Capacitive Fuel Level Sensor Development in Automotive Applications

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Doctor of Philosophy (PhD)

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Declaration

This thesis contains no material that has been accepted for the award of any other degree or diploma in any university or college of graduated education and to the best of my knowledge contains no material previously published by another person except where due reference is made.

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Signed:

Dated:
I would like to thank Prof. Romesh Nagarajah from Swinburne University of Technology for his support and guidance during research work and completion of this thesis. I would also like to thank Delphi Automotive Systems Australia for providing the facilities for experimental work and testing.
ABSTRACT

This thesis describes the research and development of a fluid level measurement system for dynamic environments. The measurement system is based on a single tube capacitive sensor. An Artificial Neural Network (ANN) based signal characterization and processing system has been developed and used to compensate for the effects of sloshing, temperature variation, and the influence of contamination in fluid level measurement systems operating in dynamic environments, particularly automotive applications. It has been demonstrated that a simple backpropagation neural network coupled with a Moving Median filter could be used to achieve the high levels of accuracy required, for fluid level measurement in dynamic environments including those relating to automotive applications.
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LIST OF ACRONYMS

ANN      Artificial Neural Network
BP       Backpropagation Neural Network
DAQ      Data Acquisition
dB       Decibel (logarithmic unit)
DCT      Discrete Cosine Transform
DFT      Discrete Fourier Transform
DOE      Design of Experiments
DSP      Digital Signal Processing
DST      Discrete Sine Transform
DWT      Discrete Wavelet Transform
FFT      Fast Fourier Transform
FS       Fourier Series
FT       Fourier Transform
FTDNN    Focused Time-Delay Neural Network
FWT      Fast Wavelet Transform
IDCT     Inverse Discrete Cosine Transform
IFFT     Inverse Fast Fourier Transform
NARX     Nonlinear Autoregressive Network with Exogenous Inputs
NN       Neural Network
OEL      Occupational Exposure Limit
PCMCIA   Personal Computer Memory Card International Association
PLC      Programmable Logic Controller
RBF      Radial Basis Function
TDNN     Distributed Time-Delay Neural Network
WT       Wavelet Transform
### LIST OF VARIABLES

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<th>Symbol</th>
<th>Description</th>
<th>Unit</th>
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<tr>
<td>A</td>
<td>Area of the capacitive plate</td>
<td>m²</td>
</tr>
<tr>
<td>a</td>
<td>Vehicle Exerted Acceleration</td>
<td>m/s²</td>
</tr>
<tr>
<td>C</td>
<td>Capacitance</td>
<td>F</td>
</tr>
<tr>
<td>C₀</td>
<td>Capacitance in the absence of dielectric or fluid</td>
<td>F</td>
</tr>
<tr>
<td>Cₜ</td>
<td>Total Capacitance</td>
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<td>f</td>
<td>Linear Frequency; Slosh Frequency</td>
<td>Hz</td>
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<tr>
<td>f₀</td>
<td>Fundamental Frequency</td>
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<td>Capacitive Tube Length</td>
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<tr>
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<td>Electrical Resistance</td>
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<tr>
<td>rₐ, rₐ</td>
<td>Inner and outer radii of the capacitive tube</td>
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</tr>
<tr>
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<td>s</td>
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<tr>
<td>T</td>
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<td>°C</td>
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<td>L</td>
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<tr>
<td>$v$</td>
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<td>$\omega$</td>
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<tr>
<td>$\omega$</td>
<td>Frame size of the signal during windowing</td>
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CHAPTER 1 - INTRODUCTION

1.1 OVERVIEW

This thesis documents a research program undertaken to design and develop a capacitive sensor based fluid level measurement system for dynamic environments, in particular automotive applications. The research work presented herein is based on the use of a single capacitive sensor coupled with an artificial neural network based signal processing system for accurately determining the fluid level in dynamic environments. The objective of this research project is to design and develop a fluid level sensor system without moving parts to accurately determine the level of fluid in a dynamic environment, especially in vehicular fuel tanks. The motivation for this research is the automotive industry's requirement for a robust and accurate fuel level measurement system that would function reliably in the presence of slosh, temperature variation, and contamination.

This chapter provides a background to the research project and an overview of the problems experienced in fluid level measurement. The objectives of the research and the outline of this thesis are also described in this chapter.
1.2 BACKGROUND

Modern automotive vehicles are equipped with digital gauges as well as with additional functionalities that inform drivers about their vehicle's fuel consumption and the remaining distance that the vehicle can travel without the need for refuelling. The high precision digital displays and additional functionalities have to rely on the accuracy of the fuel level measurement sensor. The reliability and accuracy of the fluid level measurement system in the context of a dynamic environment, which primarily depends on the level sensor, is increasingly becoming a concern for the automotive industry as well as everyday vehicle users.

The existing fluid level sensor technology is mainly based on resistive type potentiometers. The resistance value of the potentiometer changes with the fluid level. A float interconnected with the potentiometer changes the position of the terminals that are in contact with the resistive track. As the fluid level rises from empty to full, the contacts on the resistive track slide from one end to the other, forming a complete swing. The resistive type level sensors are mechanical devices that are prone to wear and corrosion [1]; hence, such mechanical sensors have a limited functional life. The rubbing of the contacts across the resistive track creates wear, which leads to a reduction in the accuracy of the level sensing mechanism over a short period of time.

The conventional level sensor systems used in automotive applications also occupy a significant amount of space because of the mechanical design that is associated with
them. The importance of level sensor accuracy and their reliability in hostile environments over long periods of time has lead to the investigation of various forms of motionless level sensors. Capacitive type level sensor is one such example that is increasingly being investigated as a substitute for mechanical level sensors in industrial and particularly automotive applications. The use of capacitive sensor for this purpose is based on the fact that the electrical capacitance value of the capacitive sensors changes in response to the changes in the capacitor’s physical parameters [2].

Capacitive sensors can directly sense a variety of parameters, such as motion, chemical composition, electric field; and they can also indirectly sense many other variables which can be converted into motion or dielectric constant, such as pressure, acceleration, fluid level, and fluid composition [2-3]. Capacitive sensors are made up of sensing electrodes that operate with excitation voltage and a detection circuit. The detection circuitry modulates the variations in capacitance into a voltage, frequency, or pulse width modulated signal. Capacitive sensors have a broad range of applications that range from motion detection to proximity sensing. Some of these applications are described below: [4]

- Motion detectors can detect 10-14 meter displacements with good stability, high speed, and wide extremes of environment, and capacitive sensors with large electrodes can detect an automobile and measure its speed
- Capacitive technology is displacing piezoresistance in silicon implementations of accelerometers and pressure sensors, and innovative applications like fingerprint detectors and infrared detectors are appearing on silicon with sensor dimensions in the microns and electrode capacitance of $10^{-15}$ Farad, with resolution to $5^{-18}$ Farad
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- Capacitive sensors in oil refineries measure the quantity of water in oil, and sensors in grain storage facilities measure the moisture content of wheat.
- In the home, cost-effective capacitive sensors operate soft-touch dimmer switches and provide the home craftsman with wall stud sensors and digital construction levels.
- Laptop computers use capacitive sensors for two-dimensional cursor control, and transparent capacitive sensors on computer monitors are found in retail kiosks.

Tubular capacitive sensors are generally used for fluid level sensing applications. The sensor determines the fluid level by measuring dielectric constant, which, in the case of fluid level sensing, is essentially the fluid in the tank filled in between two cylindrical tubes of radii $r_a$ and $r_b$. If $L_0$ is the length of the capacitive sensing tube, $\varepsilon_0$ is the permittivity of free space, and $\varepsilon_r$ is the dielectric constant of the fluid being then the capacitance value can be calculated using [5][6]:

$$
C = \varepsilon_r \left( \frac{\pi \varepsilon_0 L_0}{\ln \frac{r_b}{r_a}} \right) F \quad \text{(1.1)}
$$
Figure 1.1. Tubular capacitive sensor for fluid level sensing applications.

Figure 1.1 shows (a) the basic structure of the tubular capacitive sensor and (b) its application in a fluid level measurement system. If the geometry of the sensing tube remains constant, the capacitance of the sensing tube is proportional to the dielectric constant \( \varepsilon_r \), as shown in (1.2):

\[
C \propto \varepsilon_r
\]  

(1.2)

The dielectric constant is influenced by atmospheric changes such as temperature, humidity, pressure and composition [8]. Environmental factors such as temperature, pressure and humidity can affect the dielectric constant value of a capacitor and therefore these effects can severely deteriorate the precision of the level measurement system [8]. Since capacitance is dependant on the dielectric constant \( \varepsilon_r \), any variation in the dielectric constant of the fluid will lead to errors in the level sensing measurements. These variations can be caused by contamination or different fluids with different dielectric constants being mixed together, i.e. the mixture of fuel and water contents in an automotive fuel tank will lead to inaccurate results. Temperature variation is another factor that reduces the sensor accuracy by shifting the value of the dielectric constant. Changes in temperature can also alter the distance and area of the conducting plates of a capacitor. In summary, the output of the capacitive sensor will be subject to inaccuracy, due to the influence of contamination and temperature factors. As capacitive sensors typically exhibit non-linear response characteristics, an exact mathematical model describing the
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relationship of the sensor response to the effects of environmental factors becomes more difficult to develop. Reference capacitive sensors [9-13] have been used in the past that recalibrate the dielectric constant parameter to improve the capacitive sensor accuracy, however, the cost associated with such a configuration that requires an additional reference capacitor prohibits its wider use in applications where the cost factor plays an important role.

Apart from the accuracy of the level sensor itself, the fluid level measurement system operating in dynamic environments (i.e. automotive fuel tank) is influenced by sloshing. In automotive fuel tanks, the vehicle acceleration induces slosh waves with natural frequencies dependent on the magnitude of the acceleration, geometry of the tank and the amount of fluid contained in the tank [14-15].

To compensate for the effects of sloshing in fluid level measurement systems, various mechanical dampening methods consisting of baffles, electrical dampening techniques utilising low-pass filters, and statistical averaging methods have been used in the past. However, all these approaches lead to higher production cost, and yet the accuracy of these measurement systems under sloshing conditions is not improved significantly. The electrical dampening techniques and the statistical averaging methods primarily perform averaging on the raw sensor signals over some period of time. Averaging over a variable time frame has also been used in the past [16-18] to improve the level sensor accuracy under sloshing conditions. This is done by determining the running state of the vehicle using the vehicle speed data from the
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speed sensor. The fluid measurement system described by Kobayashi et al [17] employs a vehicle speed sensor to determine the running state of the vehicle. When the vehicle is operating at low speed (i.e., static condition), the averaging period is reduced to small values, and when the vehicle is operating at a higher speed, the averaging period is prolonged up to 90 seconds. Despite the dependence of the measurement system on the speed sensor, after analysing the raw sensor data from a resistive type fuel level sensor in a moving vehicle, it has been observed that the averaging method still produces significant error after averaging the raw sensor signal over a longer period of time. Figure 1.2 illustrates the raw volume signal obtained from a vehicle in motion, and two averaged signals calculated after averaging the raw signal over twenty seconds, which is the typical averaging time used in an automotive instrument cluster; and the second signal is an averaged signal over ninety seconds, which is a reasonably long period of time.

![Figure 1.2](image)

**Figure 1.2.** Raw sensor signal and an averaged sensor signal from a resistive type level sensor.

To improve the accuracy of fluid level measurement systems in dynamic environments in a cost effective manner, a novel approach based on Artificial Neural
CHAPTER 1 - INTRODUCTION

Networks (ANN) is researched and described in this thesis. Artificial Neural Networks (ANNs) have the ability to learn and recognise patterns. ANNs have been successfully used in many applications to understand complicated problems and accurately predict a solution. Some applications of Artificial Neural Networks are voice recognition, face recognition, character recognition, meteorological forecasting, etc [19-22]. Intelligent machines and sensors that are intended to operate in dynamic environments can be developed with neural networks without compromising accuracy. Patra et al. [23] and Song et al. [24] have used neural networks to develop intelligent sensors that compensate for nonlinear environmental parameters. Neural networks can recognise patterns; and with sufficient number of hidden neurons having *sigmoidal* functions, they can be trained to produce any continuous multivariate function with any desired level precision [25]. The complex behaviour of sensors in harsh environments as well as the phenomena of sloshing can be analysed using artificial neural networks and any compensation for sensor inaccuracies can also be made using this approach. The sensing approach developed in this research is also applicable to non-capacitive sensors such as ultrasonic and hall-effect sensors.

Additionally, prior to classifying the sensor signals with neural networks, the systems approach described in this thesis performs signal enhancement on raw sensor signals. Three commonly used signal smoothing filters are investigated through experimentation. The investigated filters consist of Moving Mean, Moving Median, and Wavelet filters. These filters provide the following enhancements [26]:

---

26
In this research, various configurations of capacitive sensors are investigated to determine the most appropriate, yet cost effective setup of the capacitive type level measurement system. Various limitations of capacitive sensors when operating in dynamic environments are identified in the literature review section to assist in the development of a robust system that will perform to an acceptable level of accuracy. 

The experimental program for this research is designed and conducted using the Design of Experiments (DOE) methodology. DOE involve different scenarios consisting of various combinations of input factors to test the effects of those combinations of factors on the outcome (response factor) [27]. DOE is the most appropriate way to measure ‘main effects and interactions’ of the factors that influence the accuracy of a fluid level measurement system [27]. To determine the most appropriate configuration of the Artificial Neural Network (ANN), experiments are performed to compare the performance of various neural network architectures. Further experiments are conducted to compare the performance of the three investigated signal smoothing filters, namely, Moving Mean, Moving Median, and Wavelet Filter. Finally, based on the experimental results, a robust fluid level measurement system with high accuracy is developed and analysed using an extensive field trial program. To investigate the performance of the proposed system,
several field trials are carried out by driving a vehicle with the developed sensor installed on suburban areas based in Melbourne. This thesis also provides a detailed comparison of the developed neural network based fluid level measurement system with the currently used system. The results from this research indicate that the proposed system is able to determine the fluid level in dynamic environments with high accuracy and is superior in performance to existing systems.

1.3 AIMS AND OBJECTIVES

The purpose of this research is to investigate the use of artificial intelligence based techniques in combination with a capacitive type sensor technology to achieve accurate fluid level measurements in dynamic environments. The research involves the design, development, and validation of a fluid level measurement methodology and system that is applicable in the context of potentially hazardous fluids and in dynamic environments.

The research aims to develop a robust fluid level sensor that maintains its performance and preserves its accuracy over a long period of time. The sensor is required to accurately determine fluid level under dynamic operating conditions especially, temperature variation, contamination, and slosh. To validate the artificial intelligence based fluid level measurement system under dynamic environment, several field trials are carried out experimentally on a running vehicle, where the goal is to accurately determine the fuel level in the vehicle fuel tank under sloshing
and dynamic conditions. It is expected that the harshness of the ambient environment would not adversely affect the accuracy of the sensor.

In summary, the research addresses the following aims:

- To make a significant contribution to understanding of the possible weaknesses and drawbacks of using a capacitive sensor as a fluid level measurement sensor,

- To make a significant contribution to understanding of the effects of liquid sloshing, temperature variations, and contaminants on the sensor response,

- To make a significant contribution to the understanding of the effectiveness of using Artificial Neural Networks as a signal processing technique to overcome the effects that sloshing and environmental changes might have on the level sensor readings, and

- To make a significant contribution to the enhancement of the accuracy of the measurement system by using different pre-processing filters on the sensor signal.

It is intended that the knowledge gained through this project will have the broadest possible application in intelligent sensor design. Below is the summary of objectives nominated for this research and respective outcomes in relation to these objectives.
CHAPTER 1 - INTRODUCTION

METHODOLOGY AND APPROACH

To achieve the aforementioned research objectives, an approach consisting of the following steps is undertaken:

- Examining the relationship between the capacitive sensor output and the influential factors such as temperature, slosh, and contamination by adopting the Design of Experiment (DOE) methodology,

- Understanding the characteristics of slosh waves at different levels of fluid in a storage tank,

- Understanding the patterns of the capacitive sensor output under dynamic conditions in both time and frequency domains,

- Determining the effectiveness of neural network based signal processing technique in improving the accuracy of the capacitive sensor based fluid level measurement system,

- Determining the most suitable neural network topology by investigating different types of artificial neural networks using experimental slosh data,

- Developing and training a set of selected neural network topologies using the data samples obtained from the field trials,

- Investigating the influence of different signal enhancement techniques in improving the performance of the Artificial Neural Network based fluid level measurement system under dynamic real-life conditions.
CHAPTER 1 - INTRODUCTION

1.4 OUTLINE OF THE THESIS

This thesis is comprised of eight chapters that are briefly introduced below:

CHAPTER 1 - INTRODUCTION provides an introduction to the background problem and to the project. An overview of the research program, covering the objectives and methodology of this research are detailed in this chapter.

CHAPTER 2 – CAPACITIVE SENSING TECHNOLOGY provides a review of capacitive sensor technology, the details of capacitive type sensors and their application in industrial environments. This chapter also describes the limitations of capacitive sensors in the context of industrial applications.

CHAPTER 3 – FLUID LEVEL SENSING USING ARTIFICIAL NEURAL NETWORKS - This chapter focuses on the basics of Artificial Neural Networks, including its various architectures, and its use in industrial applications. This chapter also focuses on the signal processing and classification aspects of Artificial Neural Networks in level sensing applications. A background to various signal classification approaches is also provided in this chapter.

CHAPTER 4 – METHODOLOGY – This chapter introduces the concept of having a capacitive sensor combined with Artificial Neural Network based signal processing for accurate and reliable fluid level measurement in dynamic environments. The methodology underpinning the proposed system is detailed in this chapter.
CHAPTER 5 – EXPERIMENTATION – This chapter describes the experimental setup of the research work. The Design of Experiments (DOEs) approach and the equipments used for the experiments are described in Chapter 5. In brief, it covers all major experiments that are performed:

1. To analyse the sensor response under dynamic conditions;
2. To determine the performance of different neural network topologies in relation to the capacitive sensor signals under slosh;
3. To understand the improvements provided by the three signal smoothing functions (Moving Mean, Moving Median, and Wavelet filter).

CHAPTER 6 – RESULTS – This chapter presents the experimental results for three major sets of experiments performed using the proposed approach to level sensing. It details experimentation results of the three experiments in the presentation of Main Effects plots, Interaction plots, Observed sensor signals, Frequency Coefficients plot, and Validation results using various configurations of the Artificial Neural Network based signal classification technique.

CHAPTER 7 – DISCUSSION – This chapter provides a detailed discussion of the experimental results. The influence of the three influential factors (temperature, slosh, contamination) on the response of the capacitive sensor is discussed. The results obtained using different artificial neural network topologies are also compared and discussed in this chapter. The influence of signal enhancement on the performance of the neural network based signal classifier is also discussed and
CHAPTER 1 - INTRODUCTION

finally the results are compared with current averaging based fluid level measurement systems.

CHAPTER 8 – CONCLUSIONS AND FUTURE WORK - This chapter provides the final conclusions of the research investigation. The summary of the findings of this research and suggestions for possible future improvements to the proposed approach to fluid level sensing in dynamic environments are presented here.
CHAPTER 2 – CAPACITIVE SENSING TECHNOLOGY

2.1 OVERVIEW

This chapter describes the basic properties of capacitive sensor technologies and their use in various kinds of sensors in industrial applications. Physical properties as well as some limitations of capacitive sensing are described here. The use of capacitive sensors with hazardous fluids, such as gasoline based fuels, and various configurations of capacitive sensors used in the application of fluid level measurement in dynamic environments are described. In brief, this chapter provides information on capacitive sensing technology and its use in dynamic and hostile environments.

2.2 CHARACTERISTICS OF CAPACITORS

2.2.1 Overview

Capacitors are the basic building blocks of the electronic world. To understand how capacitive sensors operate, it is important to understand the fundamental properties and principles of capacitors. This section provides details on the underlying principles of the capacitor. The physical, geometrical, and the electrical properties of capacitors are discussed in this section.
2.2.2 A Capacitor

A capacitor is a device that consists of two electrodes separated by an insulator [28]. Capacitors are generally composed of two conducting plates separated by a non-conducting substance called dielectric ($\varepsilon_r$) [28-29]. The dielectric may be air, mica, ceramic, fuel, or other suitable insulating material [29]. The electrical energy or charge is stored on these plates. Figure 2.1 illustrates a basic circuit configuration that charges the capacitor as soon as the switch is closed.

![Figure 2.1. Capacitor used in a circuit to store electrical charge.](image)

Once a voltage is applied across the two terminals of the capacitor, the conducting plates will start to store electrical energy until the potential difference across the capacitor matches with the source voltage. The electrical charge remains on the plates after disconnecting the voltage source unless another component consumes this charge or the capacitor loses its charge because of leakage, since no dielectric is a perfect insulator. Capacitors with little leakage can hold their charge for a considerable period of time [29]. The plate connected with the positive terminal
stores positive charge (or +Q) on its surface and the plate connected to the negative terminal stores negative charge (or -Q).

The time required to fully charge a capacitor is determined by Time Constant (τ). The value of the time constant describes the time it takes to charge a capacitor to 63% of its total capacity [28]. The time constant (τ) is measured in seconds and can be defined as in equation (2.1), where, \( R \) is the resistor connected inline with the capacitor having \( C \) capacitance.

\[
\tau = RC
\]  

(2.1)

2.2.3 Capacitance

Capacitance is the electrical property of capacitors. It is the measure of the amount of charge that a capacitor can hold at a given voltage [29]. Capacitance is measured in Farad (F) and it can be defined in the unit coulomb per volt as:

\[
C = \frac{Q}{V}
\]

(2.2)

where,

- \( C \) is the capacitance in farad (F),
- \( Q \) is the magnitude of charge stored on each plate (coulomb)
- \( V \) is the voltage applied to the plates (volts)

A capacitor with the capacitance of one farad can store one coulomb of charge when the voltage across its terminals is one volt [29]. Typical capacitance values range from about 1 pF (10^{-12} F) to about 1000 µF (10^{-3} F) [30]. An electric field will exist between the two plates of a capacitor if the voltage is applied to one of the plates
The resulting electric field is due to the difference between the electric charges stored on the surfaces of each plate. The capacitance describes the effects on the electric field due to the space between the two plates.

The capacitance depends on the geometry of the conductors and not on an external source of charge or potential difference [7, 29]. The space between the two plates of the capacitor is covered with dielectric material. In general, the capacitance value is determined by the dielectric material, distance between the plates, and the area of each plate (illustrated in Figure 2.2). The capacitance of a capacitor can be expressed in terms of its geometry and dielectric constant as [31]:

\[
C = \varepsilon_r \frac{\varepsilon_0 A}{d}
\]  

(2.3)

where,

- \(C\) is the capacitance in farads (F),
- \(\varepsilon_r\) is the relative static permittivity (dielectric constant) of the material between the plates,
- \(\varepsilon_0\) is the permittivity of free space, which is equal to \(8.854 \times 10^{-12}\) F/m,
- \(A\) is the area of each plate, in square metres and
- \(d\) is the separation distance (in metres) of the two plates.
The capacitance phenomenon is related to the electric field between the two plates of the capacitor [32]. The electric field strength between the two plates decreases as the distance between the two conducting plates increases [28]. Lower field strength or greater separation distance will lower the capacitance value. The conducting plates with larger surface area are able to store more electrical charge; therefore a larger capacitance value is obtained with greater surface area.

Figure 2.2. Factors influencing capacitance value.
2.2.4 Capacitance in parallel and series circuits

The net capacitance of two or more capacitors, connected next to each other, depends on their connection configurations [30]. If two capacitors are connected in parallel, they both will have the same voltage across them; therefore, their net capacitance will be the sum of the two capacitances. The net capacitance of a parallel combination of capacitors is given as [7]:

\[
\begin{align*}
C_T &= \frac{Q_1}{V} + \frac{Q_2}{V} + ... + \frac{Q_n}{V}, \text{ or } (2.4) \\
C_T &= C_1 + C_2 + ... + C_n \quad (2.5)
\end{align*}
\]

where, \(C_T\) is the total capacitance of the capacitors connected in parallel.

Figure 2.3. Net capacitance of capacitors connected in parallel.

Figure 2.3 shows the circuit configuration of multiple capacitors having capacitances \((C_1, C_2, ..., C_4)\). Both circuits (a) and (b) have the equivalent capacitance \(C_T\), which is the sum of all capacitances. However, if two or more capacitors are connected in series, the voltage across the two terminals may be different for each capacitor; although, the electric charge will be same the on all of them [7]. The equivalent capacitance of capacitors connected in series can be stated as:

\[
\frac{1}{C_T} = \frac{V_1}{Q} + \frac{V_2}{Q} + ... + \frac{V_n}{Q}, \text{ or } (2.6)
\]
CHAPTER 2 – CAPACITIVE SENSING TECHNOLOGY

\[
\frac{1}{C_T} = \frac{1}{C_1} + \frac{1}{C_2} + \ldots + \frac{1}{C_n}
\]  

(2.7)

\[\begin{array}{c}
V \\
C_1 \\
C_2 \\
\hline
\end{array} \quad \begin{array}{c}
C_3 \\
\hline
\end{array} \quad \begin{array}{c}
\rightleftharpoons \quad V \\
C_T \\
\hline
\end{array}
\]

(a) \hspace{5cm} (b)

Figure 2.4. Net capacitance of capacitors connected in series.

2.2.5 Dielectric constant

The gap between the two surfaces of a capacitor is filled with a non-conducting material such as rubber, glass or, wood that separates the two electrodes of the capacitor [7]. This material has a certain dielectric constant. The dielectric constant is the measure of a material’s influence on the electric field. The net capacitance will increase or decrease depending on the type of dielectric material. Permittivity relates to a material's ability to transmit an electric field. In the capacitors, an increased permittivity allows the same charge to be stored with a smaller electric field, leading to an increased capacitance.

According to equation (2.3), the capacitance is proportional to the amount of dielectric constant. As the dielectric constant between the capacitive plates of a capacitor rises, the capacitance will also increase accordingly. The capacitance can be stated in terms of the dielectric constant, as [7]:

\[C = \varepsilon_r \cdot C_0\]

(2.8)
where, $C$ is the capacitance in Farads, $\varepsilon_r$ is the dielectric constant and $C_0$ is the capacitance in the absence of dielectric constant.
Different materials have different magnitudes of dielectric constant. For example, air has a nominal dielectric constant equal to 1.0, and some common oils or fluids such as gasoline have nominal dielectric constant of 2.2. If gasoline is used as dielectric instead of air, the capacitance value using the gasoline as dielectric will increase by a factor of 2.2. This factor is called *Relative dielectric constant or Relative Electric Permittivity* [29]. Some commonly used dielectric materials and their corresponding dielectric values are listed in Table 2-1.

<table>
<thead>
<tr>
<th>Material</th>
<th>Dielectric constant</th>
<th>Material</th>
<th>Dielectric constant</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accetone</td>
<td>19.5</td>
<td>Mica</td>
<td>5.7 – 6.7</td>
</tr>
<tr>
<td>Air</td>
<td>1.0</td>
<td>Paper</td>
<td>1.6 – 2.6</td>
</tr>
<tr>
<td>Alcohol</td>
<td>25.8</td>
<td>Petroleum</td>
<td>2.0 – 2.2</td>
</tr>
<tr>
<td>Ammonia</td>
<td>15 – 25.0</td>
<td>Polystyene</td>
<td>3.0</td>
</tr>
<tr>
<td>Carbon dioxide</td>
<td>1.0</td>
<td>Powdered milk</td>
<td>3.5 – 4.0</td>
</tr>
<tr>
<td>Chlorine liquid</td>
<td>2.0</td>
<td>Salt</td>
<td>6.1</td>
</tr>
<tr>
<td>Ethanol</td>
<td>24.0</td>
<td>Sugar</td>
<td>3.3</td>
</tr>
<tr>
<td>Gasoline</td>
<td>2.2</td>
<td>Transformer oil</td>
<td>2.2</td>
</tr>
<tr>
<td>Glycerin</td>
<td>47.0</td>
<td>Turpentine oil</td>
<td>2.2</td>
</tr>
<tr>
<td>Hard paper</td>
<td>4.5</td>
<td>Water</td>
<td>80.0</td>
</tr>
</tbody>
</table>

*Table 2-1. Commonly used dielectric materials and their values [4, 32].*

### 2.2.6 Dielectric strength

The electrical insulating properties of any material are dependent upon dielectric strength [33]. The dielectric strength of an insulating material describes the
maximum electric field of that material. If the magnitude of the electric field across the dielectric material exceeds the value of the dielectric strength, the insulating properties of the dielectric material will break down and the dielectric material will begin to conduct [28]. The breakdown voltage or rated voltage of a capacitor represents the largest voltage that can be applied to the capacitor without exceeding the dielectric strength of the dielectric material [28]. The applied voltage across a capacitor must be less than its rated voltage. The operating voltage across a capacitor can be increased depending on the insulating material or the dielectric constant. Teflon and Polyvinyl chloride have greater dielectric strength. The dielectric constant can be increased by adding high dielectric constant filler material [34]. Table 2-2 lists the dielectric strength values for different types of materials at room temperature.

<table>
<thead>
<tr>
<th>Material</th>
<th>Dielectric Strength (10^6 V/m)</th>
<th>Material</th>
<th>Dielectric Strength (10^6 V/m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Air (dry)</td>
<td>3</td>
<td>Polystyrene</td>
<td>24</td>
</tr>
<tr>
<td>Bakelite</td>
<td>24</td>
<td>Polyvinyl chloride</td>
<td>40</td>
</tr>
<tr>
<td>Fused quartz</td>
<td>8</td>
<td>Porcelain</td>
<td>12</td>
</tr>
<tr>
<td>Mylar</td>
<td>7</td>
<td>Pyrex glass</td>
<td>14</td>
</tr>
<tr>
<td>Neoprene rubber</td>
<td>12</td>
<td>Silicone oil</td>
<td>15</td>
</tr>
<tr>
<td>Nylon</td>
<td>14</td>
<td>Strontium titanate</td>
<td>8</td>
</tr>
<tr>
<td>Paper</td>
<td>16</td>
<td>Teflon</td>
<td>60</td>
</tr>
<tr>
<td>Paraffin-impregnated paper</td>
<td>11</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 2-2. Approximate dielectric strengths of various materials [7].
Factors such as thickness of the specimen, operating temperature, frequency, and humidity can affect the strength of the dielectric materials.
2.3 CAPACITIVE SENSOR APPLICATIONS

2.3.1 Overview

A capacitive sensor converts a change in position, or properties of the dielectric material into an electrical signal [35]. According to the equation (2.3) in section 2.2.3, capacitive sensors are realised by varying any of the three parameters of a capacitor: distance \( d \), area of capacitive plates \( A \), and dielectric constant \( \varepsilon_r \); therefore:

\[
C = f(d, A, \varepsilon_r)
\]  

(2.9)

A wide variety of different kinds of sensors have been developed that are primarily based on the capacitive principle described in equation (2.3). These sensors’ functionalities range from humidity sensing, through level sensing, to displacement sensing [2]. A number of different kinds of capacitance based sensors used in a variety of industrial and automotive applications are discussed in this section.

2.3.2 Proximity Sensing

A proximity sensor is a transducer that is able to detect the presence of nearby objects without any physical contact. Normally a proximity sensor emits an electromagnetic or electrostatic field, or a beam of electromagnetic radiation (e.g. infrared), and detects any change in the field or return signal. Capacitive type proximity sensors consist of an oscillator whose frequency is determined by an inductance-capacitance (LC) circuit to which a metal plate is connected. When a conducting or partially conducting object comes near the plate, the mutual
CHAPTER 2 – CAPACITIVE SENSING TECHNOLOGY

capacitance changes the oscillator frequency. This change is detected and sent to the controller unit [36]. The object being sensed is often referred to as the proximity sensor's target. Figure 2.5 shows an example of the capacitive proximity sensor. As the distance between the proximity sensor and the target object gets smaller, the electric field distributed around the capacitor experiences a change, which is detected by the controller unit.

![Figure 2.5. Capacitance based Proximity Sensor.](image)

The maximum distance that a proximity sensor can detect is defined as ‘nominal range’. Some sensors have adjustments of the nominal range or ways to report a graduated detection distance. A proximity sensor adjusted to a very short range is often used as a touch switch. Capacitive proximity detectors have a range twice that of inductive sensors, while they detect not only metal objects but also dielectrics such as paper, glass, wood, and plastics [6]. They can even detect through a wall or cardboard box [6]. Because the human body behaves as an electric conductor at low frequencies, capacitive sensors have been used for human tremor measurement and in intrusion alarms [6]. Capacitive type proximity sensors have a high reliability and
long functional life because of the absence of mechanical parts and lack of physical contact between sensor and the sensed object.

An example of a proximity sensor is a limit switch, which is a mechanical push-button switch that is mounted in such a way that it is actuated when a mechanical part or lever arm gets to the end of its intended travel [37]. It can be implemented in an automatic garage-door opener; where the controller needs to know if the door is all the way open or all the way closed [37]. Other applications of the capacitive proximity sensors are:

- **Spacing** – If a metal object is near a capacitor electrode, the mutual capacitance is a very sensitive measure of spacing [4]
- **Thickness measurement** – Two plates in contact with an insulator will measure the insulator thickness if its dielectric constant is known, or the dielectric constant if the thickness is known [4].
- **Pressure sensing** – A diaphragm with stable deflection properties can measure pressure with a spacing-sensitive detector [4]

### 2.3.3 Position Sensing

A position sensor is a device that allows position measurement. Position can be either an absolute position or a relative one [38]. Linear as well as angular position can be measured using position sensors. Position sensors are used in many industrial applications such as: Fluid level measurement, shaft angle measurement, gear position sensing, digital encoders and counters, and touch screen coordinate systems.
Traditionally, resistive type potentiometers were used to determine rotary and linear position. However, the limited functional life of these sensors caused by mechanical wear has made resistive sensors less attractive for industrial applications. Capacitive type position sensors are normally non-mechanical devices that determine the position based on the physical parameters of the capacitor. Position measurement using a capacitive position sensor can be performed by varying the three capacitive parameters: Area of the capacitive plate, Dielectric constant, and Distance between the plates. The following applications are some examples of the utilisation of capacitive position sensors in:

- **Liquid level Sensing** – Capacitive liquid level detectors sense the liquid level in a reservoir by measuring changes in capacitance between conducting plates which are immersed in the liquid, or applied to the outside of a non-conducting tank [4].

- **Shaft angle or linear position** – Capacitive sensors can measure angle or position with a multi-plate scheme giving high accuracy and digital output, or with an analogue output with less absolute accuracy but faster response and simpler circuitry.

- **X-Y tablet** – Capacitive graphic input tablets of different sizes can replace the computer mouse as an x-y coordinate input device. Finger-touch-sensitive devices such as iPhone [39], z-axis-sensitive and stylus-activated devices are available.
CHAPTER 2 – CAPACITIVE SENSING TECHNOLOGY

- **Flow meter** – Many types of flow meters convert flow to pressure or displacement, using an orifice for volume flow or Coriolis Effect force for mass flow. Capacitive sensors can then measure the displacement.

### 2.3.4 Humidity Sensing

The dielectric constant of air is affected by humidity. As humidity increases the dielectric increases [8]. The permittivities of atmospheric air, of some gases, and of many solid materials are functions of moisture content and temperature [2]. Capacitive humidity devices are based on the changes in the permittivity of the dielectric material between plates of capacitors [2]. Capacitive humidity sensors commonly contain layers of hydrophilic inorganic oxides which act as a dielectric [40]. Absorption of polar water molecules has a strong effect on the dielectric constant of the material [40]. The magnitude of this effect increases with a large inner surface which can accept large amounts of water [40].

The ability of the capacitive humidity sensors to function accurately and reliably extends over a wide range of temperatures and pressures. They also exhibit low hysteresis and high stability with minimal maintenance requirements. These features make capacitive humidity sensors viable for many specific operating conditions and ideally suitable for a system where uncertainty of unaccounted conditions exists during operations. There are many types of capacitive humidity sensors, which are mainly formed with aluminium, tantalum, silicon, and polymer types. [2]
2.3.5 Tilt Sensing

In recent years, capacitive-type micro-machined accelerometers are gaining popularity. These accelerometers use the proof mass as one plate of the capacitor and use the other plate as the base. When the sensor is accelerated, the proof mass tends to move; thus, the voltage across the capacitor changes. This change in voltage corresponds to the applied acceleration. Micro-machined accelerometers have found their way into automotive airbags, automotive suspension systems, stabilization systems for video equipment, transportation shock recorders, and activity responsive pacemakers. [41]

Capacitive silicon accelerometers are available in a wide range of specifications. A typical lightweight sensor will have a frequency range of 0 to 1000 Hz, and a dynamic range of acceleration of ±2 g to ±500 g [41]. Analogue Devices Inc [42] has introduced integrated accelerometer circuits with a sensitivity of over 1.5g [4]. With this sensitivity, the device can be used as a tiltmeter [4].

2.4 CAPACITORS IN LEVEL SENSING

2.4.1 Overview

The general properties of the capacitor described in section 2.2.3 can be used to measure the fluid level in a storage tank. In a basic capacitive level sensing system, capacitive sensors have two conducting terminals that establish a capacitor. If the gap between the two rods is fixed, the fluid level can be determined by measuring
the capacitance between the conductors immersed in the liquid. Since the capacitance is proportional to the dielectric constant, fluids rising between the two parallel rods will increase the net capacitance of the measuring cell as a function of fluid height. To measure the liquid level, an excitation voltage is applied with a drive electrode and detected with a sense electrode. Figure 2.6 illustrates a basic set-up of a liquid level measurement system.

![Figure 2.6. Basic liquid level sensing system](image)

In this section, various aspects and configurations of capacitive fluid level measurement systems has been described in detail.

### 2.4.2 Sensing electrodes

The sensing electrodes of the capacitive sensor could be shaped into various forms and structures. The geometry of the sensing electrodes influences the electric field between them. For example, the capacitance between two parallel rods will be different from that between two parallel plates because of the nature of electric field
distribution around an electrically charged object. A few types of sensing electrodes, such as cylindrical rods, rectangular plates, helixical wires, and tubular shaped capacitors are described in this subsection.

### 2.4.2.1 Cylindrical Rods

Cylindrical rods are made of conductors, where the negative electrode stores the negative charge and the positive electrode stores the positive charge. An electrical field will exist between the two electrodes if a voltage is applied across them.

![Figure 2.7. Cylindrical sensing electrodes.](image)

Figure 2.7 illustrates the two cylindrical rods separated by distance $d$. The capacitance between the two parallel rods can be determined by the following rule [43]:

\[
C = \frac{\pi \varepsilon_0 \varepsilon_r}{L} \ln \frac{d}{r}, \quad \text{If } d \gg r
\]  

(2.9)

\[
C = \frac{\pi \varepsilon_0 \varepsilon_r}{\ln \left(\frac{d + \sqrt{d^2 - 4r^2}}{2r}\right)} L, \quad \text{where } d \ll r
\]

(2.10)

\(C\) is the capacitance in farads (F),

where,

$d$ is the distance between the rods,

$r$ is the radius of the rods,

$\varepsilon_0$ is the permittivity of free space,

$\varepsilon_r$ is the relative permittivity of the medium between the rods.
\( \varepsilon_r \) is the relative static permittivity (dielectric constant) of the material between the plates.

\( \varepsilon_0 \) is the permittivity of free space, which is equal to \(8.854 \times 10^{-12} \) F/m,

\( L \) is the rod length in meters

\( d \) is the separation distance (in metres) of the two rods.

\( r \) is the radius of the rod in meters

### 2.4.2.2 Cylindrical Tubes

Cylindrical tube based electrodes are commonly used in tubular capacitive sensors. Tubular capacitive sensors have a simple design, which makes them easier to manufacture. Maier [44] has used capacitive sensors that are formed as concentric, elongated cylinders for sensing the fuel level in aircraft fuel tanks. The capacitance of the sensor varies as a function of the fraction of the sensor wetted by the fuel and the un-wetted fraction in the airspace above the fuel/air interface [44].
Figure 2.8. Cylindrical tube capacitor.

Figure 2.8 shows an illustration of the cylindrical tube capacitor. A cylindrical capacitor can be thought of as having two cylindrical tubes, inner and outer. The inner cylinder can be connected to the positive terminal, whereas the outer cylinder can be connected to the negative terminal. An electric field will exist if a voltage is applied across the two terminals. If \( r_a \) is the radius of the inner cylinder and \( r_b \) is the radius of the outer cylinder then the capacitance can be calculated by using:

\[
C = \frac{\pi \varepsilon_0 \varepsilon_r \ln \frac{r_b}{r_a}}{L} \text{ F} \tag{2.11}
\]

Qu et al. [45] used an electrode arrangement having a plurality of electrodes arranged next to each other to measure the liquid level. The device measures the capacitance between a first (lowest) electrode, which is the measurement electrode, and a second electrode as the counter-electrode. A controllable switching circuit connects the electrodes to the measurement module. The connection can be switched in a definable manner by the switching module. As the switching module controls
the electrodes, each electrode of the electrode arrangement can be switched in alternation as the measurement electrode. At least one of the other electrodes can thereby be switched as the counter electrode to a definable reference potential [45]. The distance between the electrodes is preferred to be the smallest possible. Several electrodes can be implemented in groups to increase the measurement accuracy. By grouping the electrodes, each electrode group can then be alternately switched as a measurement electrode. At least one of the other respective electrode groups will be switched as the counter electrode to the definable reference potential by the switching device [45].

The signals induced on the cable or wire connecting a probe could disturb the analogue measurement signal. The signal disturbances can be caused by an external electromagnetic field, such as generated by a vehicle radio set. In order to reduce these disturbances, the use of coaxial cables is often preferred [46]. Pardi et al. [46] described a capacitive level sensing probe of a coaxial cylindrical type having a constant diameter. The probe comprises a pair of spaced coaxial electrodes constituting a cylindrical plate capacitor between the plates of which the fuel enters to vary the probe capacitance as a function of fuel level [46]. Yamamoto et al. [47] described a capacitive sensor, where the detecting element comprises: a film portion made of a flexible insulating material extending in a longitudinal direction; and a pair of detecting electrodes juxtaposed to each other on a layer of the film portion and extending in the longitudinal direction. The detecting electrodes are immersed at least partially in the liquid to be measured. The state of the measured liquid is
detected on the basis of an electrostatic capacity between a pair of detecting electrodes. The liquid state detecting element further comprises reinforcing portions made of a conductive material and disposed on the layer of film portion on an outer side of the detecting electrodes. The reinforcing portions include: a grounding terminal for being connected with a ground line; and a pair of parallel reinforcing portions extending in the longitudinal direction along side edges of the film portion so as to sandwich the pair of detecting electrodes [47].

2.4.2.3 Multi-plate capacitors

Capacitive type fluid level measurement systems can be constructed to have multiple capacitors. There are various advantages of having multiple capacitors such as increased capacitance value. Multi-capacitor systems share the common dielectric constant, which is essentially the fluid itself in capacitive type fluid level measurement systems.

![Multi-plate capacitor](image)

Figure 2.9. Multi-plate capacitor [31].

If a capacitor is constructed with \( n \) number of parallel plates, the capacitance will be increased by a factor of \((n-1)\). For example, the capacitor illustrated in Figure 2.9 has
seven plates, four being connected to A and three to B. Therefore, there are six layers of dielectric overlapped by the three plates, thus the total resultant area of each set is $(n-1)A$, or \[ (2.12) \]

$$C = \frac{\varepsilon_r \varepsilon_0 (n-1)A}{d}$$

Tward [13, 48] described a multi-capacitor sensor that is tubular in shape. The designs are in association with a simple alternating current bridge circuit, including detector and direct readout circuitry, which is insensitive to changes in the environmental characteristics of such fluid, to the fluid motion and disorientation of the container, or to stray capacitance in the sensor-bridge system. Figure 2.10 shows an illustration of this multi-capacitor system.

\[ \text{Figure 2.10. Tubular shaped multi-capacitor level sensor. [48]} \]
Wood [49] described a capacitive type liquid level sensor, where the sensor housing is described as being cylindrical and includes multiple capacitors being configured as "Y", triangular, and circular. Its configuration extends from the top of a liquid storage tank in a direction generally normal to the horizontal plane level that the liquid seeks. The sensor capacitor plates monitor liquid levels at the separate locations and associated circuitry interrogates these sensor capacitors to derive output pulse characteristics of their respective capacitance values (liquid level). As a result of interrogation, pulses having corresponding pulse widths are produced and are compared to derive the largest difference between them. The largest difference is then compared with a predetermined maximum difference value. If the maximum difference value is greater, the capacitance values of the sensor capacitors are considered to be close enough for the system to read any one of them and determine the quantity of liquid remaining in the tank. Hence, an enabling signal is generated and one of the pulses from a sensor capacitor is read to determine the liquid level [49].

2.4.2.4 Helixical capacitors

Peter [50] described a capacitive probe that is comprised of two rigid wires formed in a bifilar helix. The use of a bifilar helix structure enables small changes in fluid level to produce relatively large changes in probe capacitance [50]. Another advantage of the helixical geometry is that the sensing probe is compact, stable, rugged and low in cost. Since the helix can be fabricated from any conductive
material, the probe may be adapted to virtually any operating environment. The helix may also be entirely self-supporting or may be formed around a tubular support structure. [50]

2.4.3 Conducting and non-conducting liquids

A dielectric material that can conduct electric current will decrease the performance of the capacitor. The dielectric material should ideally be an insulator. But, the water content and other components mixed with the fluid can increase the conductivity of electrons in the fluid material. Several methods have been proposed for using a capacitive sensor to measure the fluid level in conducting and non-conducting liquids. A common method used places an insulating layer onto the conducting rods. The insulating layer will prevent the flow of electrons; hence a stable electric field could be produced.

Lee et al. [51] described a capacitive liquid-level sensor that consists of a low-cost planar electrode structure, a capacitance-controlled oscillator and a microcontroller. The sensor described is able to measure absolute levels of conducting and non-conducting liquids with high accuracy [51]. Qu et al. [45] describe a level sensor, where the electrodes are insulated with low dielectric constant material. Lenormand et al. [52] described a capacitive probe for measuring the level in conducting and non-conducting fluids. The probe comprises a tubular insulating layer made of a dielectric heat-resisting material baked at a high temperature.
Tward [48] described a fluid level sensor for mounting in a fluid storage vessel for sensing the level of the fluid within the vessel which is comprised of four similar electrically conductive capacitor elements each formed to present two electrically connected capacitive plates disposed at angles to each other. A material of known constant dielectric value fills two of the dielectric spaces thereby forming with their respective space defining capacitive plates two capacitors of known fixed and substantially similar capacitive value. The remaining two dielectric spaces are open to receive varying levels of fluid thereby forming with their respective capacitive plates, and the fluid within the spaces, two capacitors of variable capacitive value. [48]
2.5 EFFECTS OF DYNAMIC ENVIRONMENT

2.5.1 Overview

Environmental factors such as temperature, pressure and humidity affect the dielectric constant of a capacitor and therefore these effects severely deteriorate the precision of level measurement [8]. Changes in temperature can alter the distance and area of the conducting plates of a capacitor. The dielectric constant is subject to atmospheric changes such as temperature, humidity, pressure and composition [8]. These factors influence the resulting capacitance value. Several methods have been employed to compensate for these factors. A reference probe can be used to recalibrate the dielectric constant, which can compensate for the changes in dielectric constant.

2.5.2 Effects of Temperature Variations

Changes in the temperature of the liquid or gas can result in significant shifts in the dielectric constant of the liquid or gas, which introduces inaccuracies in the sensor readings. This section describes some methods and techniques that have been used in the past to overcome the effects of temperature changes on sensing devices.

Variations in temperature values can alter the geometry and size of the capacitive sensor. Any change in the electrode gap will alter the value of the capacitance and therefore an inaccurate or even invalid level measurement will be obtained. The electronic components can also behave differently at different temperatures. The
sensing electronics used to determine fluid level can therefore produce inaccurate level readings at different temperatures. Peter [50] described a method than can be used to monitor the level of a fluid in elevated temperature environments. The design consists of a high-performance thermal insulator for thermally insulating the system's electronic circuitry from the sensor probe. Atherton et al. [53] described a sensor based on the design described by Peter [50] for sensing the level of oil or transmission fluid under both normal and extreme temperature conditions. The active components of the sensor have input and leakage currents substantially lower than those of diodes and current sources under high temperature conditions.

Lawson [54] described a method for collecting liquid temperature data from a fuel tank by using a thermal sensitive resistive element that produces a value proportional to the liquid's temperature, a capacitor for storing a charge representative of this value, and a resistor through which the capacitor is discharged. Circuitry and software are provided that compares the voltage across the resistor to a reference as the capacitor discharges. This determines the number of clock counts for which a predetermined relationship exists between the voltage across the resistor and the reference and then consults a table to determine an absolute temperature based on this clock count. [54]

Other methods that use a reference capacitor such as described by McCulloch et al. [10], can eliminate the effects of a changing dielectric constant at different temperatures. The recalibration method calculates the dielectric constant at any
temperature to avoid the effects of temperature changes that can shift the values of the dielectric constant.

### 2.5.3 Effects of Contamination

It was described in Section 2.2.3 that the capacitance is dependant on the dielectric constant. Any change in the dielectric material will influence the capacitance value. To avoid the effects of the dielectric material on the capacitance value, several methods have been described that either eliminate the effects of the dielectric material, or recalibrate the dielectric parameter.

Hochstein [9] described a capacitive level gauge which determines the level of substance in the container. The gauge includes a measurement capacitor for measuring the level. Unlike conventional capacitance level gauges which may not detect changes in dielectric constant, this gauge includes a reference capacitor for determining the dielectric constant of the substance. A controller is responsive to the capacitors for producing a level signal which simultaneously indicates the level and dielectric constant of the material. The level signal incorporates a frequency which is representative of the dielectric constant and a pulse width representative of the level. The gauge supports a first pair of parallel conductive members to establish the measurement capacitor and a second pair of parallel conductive members spaced along the gauge and below the measurement capacitor to establish the reference capacitor. An advantage of this device is that its use does not require a predetermined
shaped container. Additionally, the level signal simultaneously indicates the level capacitance and reference capacitance for accurate indication of the level.

Fozmula [55] described a capacitive liquid level sensor that can be calibrated using a push button. The sensor works with various fluid types such as oil, diesel, water and water based solutions. The calibration option allows the sensor to determine the dielectric constant of the fluid and adjust the output accordingly.

The consequences of neglecting the safety of brake fluid can lead to some serious problems, i.e., water content leads to corrosion in the brake system components. The on-line monitoring of oil quality and level eliminates the inconvenience to check brake fluid manually. It makes the vehicles safer and avoids additional waste by providing a more scientific maintenance interval. Shida et al. [56] described a method for on-line monitoring of the liquid level and water content of brake fluid using an enclosed reference probe as the capacitive sensing component. The probe has an enclosed cavity at the end which is designed to hold fresh brake fluid as an on-line reference. Three capacitances formed by four electrodes are used for the liquid level, water content and reference measurement and form the mutual calibrating output functions of the sensing probe. The liquid level measurement is calibrated to the permittivity changes by the capacitance for water content measurement. Simultaneously, the water content measurement is calibrated to temperature changes and variety of fluids by the capacitance of the reference measurement. Therefore, once the permittivity characteristics of brake fluids are experimentally modeled, the proposed method has a self-calibration ability to
accommodate influencing factors including temperature, water content and variety of brake fluids without an additional sensor supported by a database as in conventional intelligent sensor systems.

McCulloch et al. [10] described a way to overcome the level reading errors caused by variations in the dielectric constant of the fluid. The system is designed to measure liquid level with a high degree of accuracy regardless of dielectric changes which may occur in the liquid or gas due to temperature changes, pressure changes, and other changes affecting the dielectric constant. The primary sensor is an elongated capacitive probe positioned vertically within the container so that the lower portion of the probe is in liquid and the upper portion of the probe extends above the surface of the liquid. A capacitive liquid reference sensor is near the lower end of the probe, and a capacitive gas reference sensor is at the upper end of the probe. A controller is provided for driving each of the sensors with an electrical signal and reading a resultant value corresponding to the capacitance of each of the sensors. The controller is configured to enable the system to be calibrated prior to installation by placing each of the sensors in a calibration or identical medium, reading sensor values corresponding to capacitances for each of the sensors, and calculating and storing calibration values based on the sensor values [10].

Wallrafen [57] described a sensor for measuring the filling level of a fluid in a vessel. The sensor has an electrode group which extends vertically over the fill-able vessel height, and dips into the fluid and forms electrical capacitors whose
Capacitances change in a measurable fashion when there are changes in the filling level. The capacitances are determined by a connected evaluation circuit and are represented as a signal which describes the filling level. There is at least one measuring electrode which extends over the entire fillable vessel height. A plurality of reference elements are arranged at different reference heights within the fillable vessel height. Optionally, a plurality of measuring electrodes are arranged in such a way that each measuring electrode has a significant change in width at a reference height assigned to it, and wherein the entire fillable vessel height is passed over by the measuring electrodes. The measuring electrode, the opposing electrode, and five reference electrodes are printed on to a carrier which is bent in a U-shape. The electrodes are connected to an electronic circuit on the carrier by means of lines which are also printed on.

Takita [11] described a capacitive sensor that provides a high level of precision by taking the effects of environmental changes into consideration and compensating for any and all changes to the plate area and to the value of the dielectric constant before determining an accurate measurement. Such compensation can be achieved through use of a plurality of environmental sensors to mathematically calculate the change according to the variant conditions surrounding the capacitive sensor. However, the compensation would be made through the use of a reference capacitor with a fixed gap between the plates that is otherwise identical in both form and reaction to environmental changes as the capacitive sensor that it monitors in order to
CHAPTER 2 – CAPACITIVE SENSING TECHNOLOGY

compensate for all environmental parameters other than the parameter of interest.\[11\]

Other methods described by Wells \[12\], Tward \[48\], Stern \[58\], Gimson \[59\], and Park et al. \[60\] all use a reference capacitor to compensate for the effects of contamination in the fluid.

2.5.4 Influence of Other Factors

2.5.4.1 Sensitivity to noise

Sensor plates may have signal capacitances in the fractional picofarad (pF) range, and connecting to these plates with a 60 pF per meter coaxial cable could totally obscure the signal. However, with correct shielding of the coaxial cable as well as any other stray capacitance one can almost completely eliminate the effects of noise. \[61\]

2.5.4.2 Sensitivity to stray capacitance

One hazard of the oscillator circuits is that the frequency is changed if the capacitor picks up capacitively coupled crosstalk from nearby circuits. The sensitivity of an RC oscillator to a coupled narrow noise spike is low at the beginning of a timing cycle but high at the end of the cycle. This time variation of sensitivity leads to beats and aliasing where noise at frequencies which are integral multiples of the oscillator frequency is aliased down to a low frequency. This problem can usually be handled with shields and careful power supply decoupling \[62\].
2.5.4.3 Distance between the electrodes

The capacitance is dependent on the gap or distance between the conducting electrodes. This distance can however increase or decrease, depending on the environmental conditions and the material, which could incorporate inaccuracies in the level readings. In some cases, movement of the fluid container can skew or bend the sensor, which will alter the distance between the electrodes, thereby errors will be produced in the capacitance value and hence the fluid level.

2.6 EFFECTS OF LIQUID SLOSHING

2.6.1 Overview

In mobile fluid tanks, such as automotive fuel tanks, acceleration will induce slosh waves in the storage tank. This phenomenon of fluid fluctuation is called sloshing. The magnitude of sloshing is dependent on the value of the acceleration or deceleration that may be caused by braking, speeding, and irregular terrain. A level measurement device observing the fluid level under sloshing conditions will produce erroneous level readings.

The sloshing phenomenon in moving rectangular tanks, e.g. automotive fuel tanks, can be usually described by considering only two-dimensional fluid flow, if the width of the tank is much less than its breadth [63]. The main factors contributing to the sloshing phenomenon are the acceleration exerted on the tank, amount of existing fluid, internal baffles, and the geometry of the tank [14, 64]. A detailed analysis of
liquid sloshing using the numerical approach for various tank configurations has been provided in the literature [14-15, 64-70].

Different designs of fluid level measurement systems have used different techniques to compensate for the erroneous reading of liquid level due to the effects of sloshing. This section of the literature review focuses on some level sensing devices that attempt to operate effectively in both static and dynamic environments.

### 2.6.2 Slosh Compensation By Dampening Methods

Fluid sloshing can be physically and electrically dampened to suppress the sloshing effects. Electrical damping methods include the use of low-pass filters and numerical averaging on digital sensor readings. Physical or mechanical damping of slosh includes the use of baffles and geometrical methods. The following diagram shows a basic geometrical dampening method. The sensor is placed inside a vessel, where fluid can enter from the bottom of the vessel. The fluid stored in the vessel will experience less slosh than the fluid outside the vessel. Therefore, the fluid inside the vessel will be stable relative to the outside level.

![Diagram of Slosh Compensation by Dampening Methods](image_url)
Wood [49] described a capacitive type liquid level sensor that is useful for both stationary and mobile storage tanks. The sensor is sensitive when the fuel is disoriented with respect to a reference level. Its configuration extends from the top of a liquid storage tank in a direction generally normal to the horizontal plane level that the liquid seeks. The sensor capacitor plates monitor liquid levels at the separate locations and associated circuitry interrogates these sensor capacitors to derive output pulses characteristic of their respective capacitance values. As a result of interrogation, pulses having corresponding pulse widths are produced and are compared to derive the largest difference between them. The largest difference is then compared with a predetermined maximum difference value. If the maximum difference value is greater, the capacitance values of the sensor capacitors are considered to be close enough for the system to read any one of them and determine the quantity of liquid remaining in the tank. Hence, an enabling signal is generated and one of the pulses from a sensor capacitor is read to determine the liquid level [49].

Tward et al. [48] described methods to solve the problem of liquid sloshing and liquid level shift. They also address the effects on liquid level and volume measurement of changes in the physical and chemical characteristics of the liquid.
being measured and of the multiple characteristics of the environment of the liquid and its container. Multiple capacitors can provide improved liquid level measurement in both stationary and dynamic conditions for liquid storage containers and tanks [48].

2.6.3 Tilt Sensor

Another method used to compensate for the dynamic effects determines the tilt angle, usually by incorporating an inclinometer. Nawrocki [71] described a method that incorporates an inclinometer in the fuel gauging apparatus. A signal from a fuel quantity sensor can be transmitted to a fuel gauge or display only when the vehicle is tilted less than a predetermined degree. To accomplish this, a signal from the fuel sensor is passed through to the display by a microprocessor only when the vehicle is substantially level and not accelerating or decelerating. When the level condition is met, the signal indicative of the amount of fuel left in the tank is stored in the microprocessor memory and displayed on the fuel gauge, and is updated again when the vehicle reaches the next level condition. Alternatively, a correction factor matrix stored in memory can be applied to the signal received from the fuel sensor to calculate a corrected signal indicative of the amount of fuel remaining in the fuel tank. Figure 2.12 shows an overview of the method described by Nawrocki [71].
Lee [72] described a digital tilt level sensing probe system comprising a set of multiple capacitor elements in a fluid container arranged along an axis of measurement where each multiple capacitor element represents a discrete level increment in dielectric material fluid to be measured. Individual capacitors in each element are horizontally spaced to reflect a level differential upon tilting of the fluid container from its normal attitude. In the case of a probe for sensing tilt angle in a single plane, the device includes integral capacitor elements, mounting pad, connector, custom IC pad, and circuitry moulded into the body [72]. Figure 2.13 shows the diagram of the devices described by Lee [72].
Shiratsuchi et al. [73] described a capacitive type fuel level sensing system that uses three capacitors to determine the fuel surface plane angle, and a fourth capacitor is used as a reference capacitor to compensate for the variations in the dielectric constant. The high cost associated with having multiple capacitors makes this approach impractical. Furthermore, Shiratsuchi et al. [73] have assumed the fuel surface as always a plane, whereas, even under normal driving conditions, the surface of the fuel actually portrays slosh waves that fluctuate at a varying rate. The method described by Shiratsuchi et al. [73] determines the fluid level when the slope angle of the fluid level is at zero, which relates to the static state condition and does not accurately determine fluid level under dynamic conditions.

### 2.6.4 Averaging Methods

The *Averaging Method* is another method besides the mechanical dampening approach that can compensate for the sloshing effects and produce better fuel level
readings. The averaging method is basically a statistical averaging method that generally collects the past level readings and determines the future level reading by using different calculation techniques. There are a few different averaging techniques that have been applied in the past that include a simple Arithmetic Mean, Weighted Average, and Variable Averaging Interval.

### 2.6.4.1 Arithmetic Mean

Arithmetic mean or simply mean is the traditional method of averaging the level sensor readings. The mean value of the sampled signal \( x = [x_1, x_2, x_3, \ldots, x_n] \) for \( n \) number of samples is calculated using:

\[
\text{mean}(x) = \bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i
\]  

(2.13)

The downside of averaging is that it produces a significant error for a momentarily large spike or an abnormal data entry in the elements of \( x \). For example, if a sampled signal is given as:

\[
x = [1.21, 1.30, 1.25, 1.27, 1.23, 1.91]
\]  

(2.14)

\[
\bar{x} = \frac{1.21 + 1.30 + 1.25 + 1.27 + 1.23 + 1.91}{6} = 1.36
\]  

(2.15)

\[
\bar{x} = \frac{1.21 + 1.30 + 1.25 + 1.27 + 1.23}{5} = 1.25
\]  

(2.16)
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The average value obtained in the presence of an abnormal entry ‘1.91’ in signal $x$ is given in (2.15), which is significantly larger than the average value when obtained without ‘1.91’ element in $x$ (2.16).

An improved version of averaging is described by Tsuchida et al. [74] who presented a method that determines the center value of the past sensor readings. The center value is assumed to be the accurate level reading. The method includes the operations of performing sampling detection of an amount of fuel remaining in the fuel tank of a vehicle, determining a center value for a plurality of remaining fuel quantity values detected by a microcomputer, determining limit values each thereof being apart from the center value by a predetermined amount, using any subsequent detected value exceeding the limit values as a new limit value, computing an average value of a predetermined number of detected sampling values, and indicating it on a display. It also performs the function of discriminating and eliminating any suddenly changed abnormal detected values due to changes in the attitude of the vehicle thereby producing stable measurement readings of the remaining fuel quantity [74].

2.6.4.2 Weighted Average

Weighted average is similar to the simple averaging method, except that there are additional weights ($w$) assigned to each element in the sample signal $x=[x_1,x_2,x_3,...,x_n]$. In the absence of the weights, all data elements in $x$ contribute equally to the final average value. But, with the usage of the additional weights ($w$), the final average can be controlled. If all the weights are equal, then the weighted
mean is the same as the arithmetic mean. The weighted average of a signal $x=[x_1,x_2,x_3,...,x_n]$ and the weights $w=[w_1,w_2,w_3,...,w_n]$ for $n$ number of sampled points can be calculated using:

$$W_{mean}(x) = \bar{x} = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i} , \quad w_i > 0$$  \hspace{1cm} (2.17)

2.6.4.3 Variable Averaging Interval

In the *Variable Averaging* method, raw sensor readings are averaged at different time-intervals depending on the state or motion of the vehicle. During static conditions, when the vehicle is stationary or when the vehicle is operating at a low speed, the time constant or the averaging period is reduced to a small interval to quickly update the sensor readings by assuming that there will be negligible slosh. During dynamic conditions, the averaging period is increased to average the sensor readings over a longer period of time. To determine the running state of the vehicle, normally a speed sensor is used.

Kobayashi et al. [16] described a sensor that uses digital signals as opposed to analogue signals to determine the fluid volume in a fuel storage tank. The digital fuel volume measuring system can indicate the amount of fuel within a fuel tank precisely in the unit of 1.0 or 0.1 litres. The volume detection signals are simply averaged during a relatively-short averaging time period at regular measuring cycles when the vehicle is being refuelled, and further weight-averaged or moving-averaged at regular measuring cycles when the vehicle is running. Therefore, fuel volume can be indicated quickly at a high response speed when the vehicle is being refuelled and
additionally, fluctuations in the fuel volume readings can be minimized when the vehicle is running. Further, the system discloses the method of detecting the state where the vehicle is being refuelled on the basis of the fact that the difference between at-least one of the current data signal indicative of fuel volume and at-least one of the preceding data signal indicative of fuel volume exceeds a predetermined value. [16]

Guertler et al. [18] described a process that determines the quantity of a liquid situated in a largely closed system. The liquid fluctuations in a dynamic or a moving vehicle can produce erroneous results. The process described Guertler et al. [18] determines the running state of the vehicle, the momentary driving condition, and, at least during selected driving conditions in the driving operation. The process continuously senses the filling level, as well as determines the momentary filling quantity via a given dependence of the liquid quantity reading on the driving condition and on the filling level. These fluctuations can be calculated as the result of the predetermined dependence of the liquid level and therefore of the amount of fluid on the driving condition. In addition, the level can be statistically averaged because of the continuous obtaining of measuring values. This permits the reliable determination of the fluid quantity whose level fluctuates as a function of the driving condition by way of level measurements. This occurs not only when the vehicle is stopped and the engine is switched-off, but also in the continuous driving operation.[18]
Kobayashi et al. [17] utilised the information about the various states of the vehicle, such as ignition ON-OFF, idle state, up and down speeding. The fuel level readings are averaged over time intervals which vary according to whether the liquid level of the fuel in the tank is stable or unstable. A fuel quantity is calculated and displayed according to the averaged value. The stable or unstable condition of the fuel level is discriminated in accordance with vehicle speed, and the position of the ignition switch. Accordingly, when the fuel level is unstable, the signal value is averaged over a time interval which is longer than that used when the fuel level is stable so that the response of display to variation of the fuel level is improved [17].
2.7 SUMMARY

A detailed investigation of the capacitive sensing technology as described in this chapter reveals the fact that capacitive technology is increasingly being used in a broad range of applications due to its non-mechanical characteristic, robustness in harsh environments, its ability to work with a wide range of chemical substances, compact and flexible size, and, longer functional life.

Even though the use of capacitive sensing technology in fluid level measurement systems has produced satisfactory outcomes in a broad range of applications, the literature review has highlighted some of the limitations of capacitive sensing technology in relation to its accuracy in fluid level measurements pertaining to dynamic environments. Level sensing in dynamic environments is characterized by three factors:

- Slosh
- Temperature variation
- Contamination

Solutions provided to address each of these three above mentioned factors have been reviewed in this chapter. In most cases common solutions to overcome these environmental factors require an additional capacitive sensor to be included to serve as a reference capacitor. The purpose of this reference capacitor is to provide additional measurement signal taking into account factors above. This measurement is then used to calculate offset in combination with the main capacitive sensor in order to improve the accuracy of overall measurement system. However, these solutions entail either higher production cost because of the requirement for an...
additional sensor, or they provide only marginal improvement in terms of accuracy compared to current systems.

The table below summarises research objectives of this thesis:
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<table>
<thead>
<tr>
<th>Objective</th>
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<th>Reference Number</th>
<th>Author</th>
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<td>Fischer-Cripps, Anthony C. <em>Force, pressure and flow</em>. Newnes interfacing companion. Oxford; Newnes. p. 54-70; 2002.</td>
<td>1</td>
<td>Fischer-Cripps, Anthony C.</td>
<td>well understood for general type of fluids except automotive fuels</td>
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<td>Dunn, William C. <em>Introduction to instrumentation, sensors and process control</em>. Boston: Artech House; 2005.</td>
<td>3</td>
<td>Dunn, William C.</td>
<td>well understood for general type of fluids except automotive fuels</td>
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<tr>
<td>Comparison of capacitive sensors in fuel tanks with other type of sensors</td>
<td>Hochstein, Peter A., inventor TELEFLEX INC (US), assignee. <em>Capacitive liquid sensor patent 5005409</em>. 1990 02/07/1990</td>
<td>9</td>
<td>Hochstein, Peter A.</td>
<td>work insufficient to meet nominated objective for automotive fuels and contaminants common in automotive fuels</td>
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<td></td>
<td>Guertler, Thomas, Hartmann, Markus, Land, Klaus, and Weinschenk, Alfred, inventors; DAIMLER BENZ AG (DE) assignee. <em>Process for determining a liquid quantity, particularly an engine oil quantity in a motor vehicle patent 5831154</em>. 1997, 01/27/1997.</td>
<td>18</td>
<td>Guertler, Thomas, Hartmann, Markus, Land, Klaus, and Weinschenk, Alfred,</td>
<td>level of accuracy not acceptable for automotive use in dynamic conditions (sport driving)</td>
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<td>n/a</td>
<td>nil</td>
<td>work insufficient to meet nominated objective</td>
</tr>
<tr>
<td>Enhancement of accuracy of the measurement system using different pre-processing filters in combination with ANN</td>
<td>n/a</td>
<td>n/a</td>
<td>nil</td>
<td>work insufficient to meet nominated objective</td>
</tr>
</tbody>
</table>

Table 1.1 Research objectives
CHAPTER 3 – FLUID LEVEL SENSING USING ARTIFICIAL NEURAL NETWORKS

3.1 OVERVIEW

The basic principles and applications of capacitive type sensors including some issues relating to application of capacitive type level sensing systems in dynamic environments were discussed in Chapter 2. In this chapter, firstly, the fundamental principles of signal classification and processing are discussed. Then the background and applications of Artificial Neural Networks (ANN) in the context of this research are described. Finally, the use of neural networks in providing solutions to the problems encountered in fluid level measurement in dynamic environments is described.

3.2 SIGNAL PROCESSING AND CLASSIFICATION

3.2.1 Overview

Signal processing and signal classification plays a crucial role in the improvement of the accuracy of any fluid level measurement system, particularly, in dynamic environments. This section broadly focuses on various aspects of signal processing and classification techniques. Various components of signal pre-processing such as Data collection methods, Feature extraction methods, and Signal filtration methods are discussed. Thereafter, a diverse range of signal classification techniques are described in this section.
3.2.2 Data Collection

Typically, the output from a fluid level sensor is in the form of continuous voltage over time. However, to digitally process the sensor’s analogue signal, the signal needs to be converted into a discrete signal by sampling it at some constant sampling frequency $f_s$ [75]. The sampling interval $T_s$ is the time between two sampled points, which is simply equal to:

$$T_s = \frac{1}{f_s} \quad (3.1)$$

Figure 3.2 shows a continuous analogue signal and its sampled version when sampled at a sampling frequency of 20 Hz. If $x(t)$ is the analogue sensor output signal, the discrete sampled signal $x[n]$ at sampling frequency $f_s$ can be described as [76]:

$$x[n] = x(nT_s) = x\left(\frac{n}{f_s}\right), \text{ where } n = 0, 1, 2, 3, \ldots \quad (3.2)$$
3.2.3 Signal Filtration

The signal values obtained from the level sensor are processed with different signal filtration functions to enhance the performance of the signal classification system before the signal is interpreted [77]. The signal feature coefficients obtained from a signal containing noise in it can have an adverse effect on signal classification accuracy if used in the classification process [77-78]. Noisy signals can be filtered using different approaches, such as low-pass filter, high-pass filter, or band-pass filter. A low-pass filter can be used to eliminate high frequency noise, especially when the level sensor signal consists of low frequency content (i.e. slosh waves). Band pass filters can be very useful if the range of effective frequency of interest is
known. Variable filters such as *adaptive filter* can be very useful for the reduction of white-noise [79].

### 3.2.4 Feature Extraction

Apart from signal filtration, another operation performed in signal pre-processing is the selection of features from and reduction of the size of the input signal, while at the same time trying to preserve the information contained in the input signal. The reduction in the signal size will reduce the input size of the classification network, if one is used, as well as increase the network performance [78]. Trunk [80] has demonstrated that use of large quantities of data may be detrimental to classification, especially if the additional data is highly correlated with previous data [78]. The following methods are commonly used to extract number of features from the input signal [78]:

- Fast Fourier Transform (FFT)
- Discrete Cosine Transform (DCT) [81]
- Wavelet Transform (WT)
- Principle Component Analysis (PCA)
- Fisher Discriminant Analysis (FDA)
- Independent Component Analysis (IDA)

#### 3.2.4.1 Fast Fourier Transform

The Fast Fourier Transform (FFT) algorithm is widely used to transform a time domain signal into the frequency domain [82]. The Fourier transform of a signal involves decomposing the waveform into a sum of sinusoids of various frequencies.
CHAPTER 3 – FLUID LEVEL SENSING USING ARTIFICIAL NEURAL NETWORKS

A time domain signal \( y(t) \) can be transformed into the frequency domain as \( Y(\omega) \) [83]:

\[
Y(\omega) = \int_{-\infty}^{\infty} y(t)e^{-j\omega t} dt
\]  

(3.3)

Discrete Fourier Transform (DFT) is used where the input signal is discrete or sampled at fixed intervals. The DFT rule is described by the following equation, where \( Y(k) \) is the transformed function of \( y(t) \) for frequency \( k \) [84].

\[
Y(k) = \frac{1}{N} \sum_{n=0}^{N-1} y(n)e^{-j2\pi(k-1)\frac{(n-1)}{N}} \quad 1 \leq k \leq N
\]  

(3.4)

Once a signal has been transformed into a form that contains discrete frequency coefficients using the FFT function, feature selection can be applied by selecting only the desired range of frequency components. In fuel level systems, the slosh waves produced in the tank consist of low frequency components. Therefore, only the lower frequency range (0 – 10 Hz) can be selected and fed into the signal classification unit (i.e. neural network).

3.2.4.2 Discrete Cosine and Since Transforms

A sequence of finite data points can be expressed in terms of a sum of cosine functions oscillating at different frequencies using the Discrete Cosine Transform (DCT) function. The DCT has been used in numerous applications in the fields of science and engineering, from digital compression of images and audio, to spectral methods for the numerical solution of partial differential equations. DCT plays a
vital role in JPEG [85] and MPEG [86] type still images and multimedia compression.

In principle, the Discrete Cosine Transform (DCT) is related to Fourier Transformation (FS), however, DCT only operates on the real data with even symmetry. Discrete Cosine Transform (DCT) of a sample signal \( x(0), x(1), \ldots, x(N-1) \) consisting of \( N \) number of samples is defined as [87]:

\[
y(k) = \alpha(k) \sum_{n=0}^{N-1} x(n) \cos \left( \frac{\pi(2n+1)k}{2N} \right), \quad k = 0, 1, \ldots, N - 1
\]  

(3.5)

The Inverse Discrete Cosine Transform (IDCT) function can be given as:

\[
x(n) = \sum_{k=0}^{N-1} \alpha(k) y(k) \cos \left( \frac{\pi(2n+1)k}{2N} \right), \quad n = 0, 1, \ldots, N - 1
\]  

(3.6)

where,

\[
\alpha(k) = \begin{cases} \frac{1}{\sqrt{N}}, & k = 0 \\ \frac{2}{\sqrt{N}}, & k \neq 0 \end{cases}
\]

The transformation in vector form is written as [87]:

\[
y = C^T x,
\]  

(3.7)

where, the elements of the matrix \( C \) are given by:

\[
C(n, k) = \begin{cases} \frac{1}{\sqrt{N}}, & k = 0, \quad 0 \leq n \leq N - 1 \\ \frac{2}{\sqrt{N}} \cos \left( \frac{\pi(2n+1)k}{2N} \right), & 1 \leq k \leq N - 1, \quad 0 \leq n \leq N - 1 \end{cases}
\]  

(3.8)
The Discrete Sine Transform (DST) is similar to DCT, however, it operates on the real-odd portions of the DFT. Discrete Sine Transform (DST) is defined via the transform matrix [87]:

\[
S(k,n) = \sqrt{\frac{2}{N+1}} \sin\left(\frac{\pi(k+1)(n+1)}{N+1}\right), \quad k, n = 0,1,\ldots, N-1
\] (3.10)

The DCT and DST belong to the family of transforms that can be computed via a fast method in \(O(N \log_2 N)\) operations [88]. The Discrete Cosine Transform (DCT) [81] is a real transform that has great advantages in energy compaction [89]. The use of DCT rather than DST is preferred in data compression applications, since the cosine functions (used in DCT) are much more efficient in transformation and require fewer data points to approximate a typical signal.

### 3.2.4.3 Wavelet Transform

The Wavelet Transform is similar in concept to FFT however with the exception that WT not only provides the frequency representation of the signal but also retains the time information [90]. It uses the windowing technique with variable sized regions to provide a time-frequency representation of the input signal. It is useful for analysing non-stationary signals, where the frequency varies over time [90]. Therefore, local analysis can be performed using the WT method. Wavelet Transform of a continuous signal \(y(t)\) can be defined as:
\[ C(s, p) = \int_{-\infty}^{\infty} y(t) \psi(s, p, t) \, dt \] (3.11)

where \( \psi(s, p, t) \) is the mother wavelet with \( s \) as the scale and \( p \) the position at time \( t \).

To transform signals that are discontinuous (sampled signals), Discrete Wavelet Transform (DWT) algorithm is used that analyses signals at different frequency bands by de-composing them into coarse information and detail information sets [91]. The coarse information set contains the low-frequencies, whereas, the detail information contains the high-frequency components of the input signal. To decompose an input signal into high-frequency and low-frequency components, DWT employs two sets of functions known as the scaling functions and wavelet functions, where the functions can be viewed as low-pass and high-pass filters, respectively [91].

![Figure 3.3. Decomposition of signal S into high and low frequency portions [91].](image)

Figure 3.3 shows the input signal \( S \), consisting of 1000 sample points, being decomposed and down-sampled into high-frequency (\( cD \)) and low-frequency (\( cA \)) components. Down-sampling is useful in compressing the signal by discarding the higher frequency component, which is usually the noise [91]. The coefficients \( cA \)
and $cD$ represent the features of the original signal. After performing DWT on the input signal, the $cA$ coefficients can be fed into the signal classification unit.

### 3.2.5 Signal Classification

Pattern classification methods are divided into two classes [92]:

- Supervised Classification
- Data Clustering (unsupervised classification)

Supervised classification methods require both the input and the target output data. It consists of the assignment of labels to the test pattern based on the training patterns. There are two phases in supervised classification methods: learning and classification. The pattern classifier system learns the system based on the training data, and after training, it can be used to classify the test patterns. There are several different data classification methods, each method has different benefits and disadvantages. Table 3-1 lists a few classification methods and provides a comparison of their performance, computational cost and other factors [78].

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Classification Error</th>
<th>Computational Cost</th>
<th>Memory Requirements</th>
<th>Difficult to implement</th>
<th>On-line</th>
<th>Insight from the classifier</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expectation maximization (EM)</td>
<td>Low</td>
<td>Medium</td>
<td>Small</td>
<td>Low</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Nearest Neighbour</td>
<td>Med-Low</td>
<td>High</td>
<td>High</td>
<td>Low</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Decision trees</td>
<td>Medium</td>
<td>Medium</td>
<td>Medium</td>
<td>Low</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Parzen windows</td>
<td>Low</td>
<td>High</td>
<td>High</td>
<td>Low</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Linear least squares (LS)</td>
<td>High</td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>
### Table 3-1. Comparison of various classification algorithms [78].

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Med-Low</th>
<th>Medium</th>
<th>Low</th>
<th>High</th>
<th>Yes</th>
<th>No</th>
<th>Some</th>
</tr>
</thead>
<tbody>
<tr>
<td>Genetic Programming</td>
<td>Low</td>
<td>Medium</td>
<td>Low</td>
<td>High</td>
<td>Yes</td>
<td>No</td>
<td>Some</td>
</tr>
<tr>
<td>Ada-Boost</td>
<td>Low</td>
<td>Medium</td>
<td>Medium</td>
<td>Medium</td>
<td>No</td>
<td>No</td>
<td></td>
</tr>
<tr>
<td>Support vector machines (SVM)</td>
<td>Low</td>
<td>Medium</td>
<td>Low</td>
<td>Medium</td>
<td>Yes</td>
<td>Some</td>
<td></td>
</tr>
</tbody>
</table>

In data clustering (unsupervised classification), the target value is not used while training. The clustering method clusters the sample data points according to their correlation with different cluster centers so as to attain a good partition of the data. There are many different types of data clustering methods available, some well known methods are listed below [78]:

- K-means [93]
- Fuzzy k-means [94]
- Kohonen maps [95]
- Competitive learning [96]

Supervised feed-forward neural networks are more flexible and can yield much better results when compared with the data clustering methods such as K-means [97].

### 3.3 ARTIFICIAL NEURAL NETWORKS

Artificial Neural Network (ANN) is an information processing technique that is inspired by the way biological nervous systems process information. It consists of neurones, a large number of highly interconnected elements working to solve specific problems. Similar to humans, ANNs learn by example. A learning process configures ANN for a specific application such as pattern recognition or data
classification. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurones, which is also true for ANNs [98].

Neural networks have a remarkable ability to derive meaning from complicated or imprecise data. ANN can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. A trained neural network can be thought of as an expert in the categorisation of information it has been given to analyse [98]. With a sufficient number of hidden neurons, neural networks can be trained to produce any continuous multivariate function with any desired level of precision [25].

Commonly neural networks are adjusted, or trained, so that a particular input leads to a specific target output. Such a situation is shown below. The network is adjusted, based on a comparison of the output and the target, until the network output matches the target. Typically many such input/target pairs are needed to train a network. [99]

![Figure 3.4. Typical configuration of an ANN](image-url)
CHAPTER 3 – FLUID LEVEL SENSING USING ARTIFICIAL NEURAL NETWORKS

3.3.1 Neuron Model

The neuron receives inputs and produces an output that can be adjusted according to the training or teaching parameters. Figure 3.5 illustrates a simple neuron model. The output values can be adjusted using the weights W1, W2… Wn.

![Neuron Model Diagram](image)

**Figure 3.5. A simple neuron model.**

The output $a$ of the neuron in Figure 3.6 is the function of input $p$ multiplied by the weight $w$, or $a=f(wp)$. The neuron on the right has a scalar bias $a$, which is seen as simply being added to the product $wp$ or as shifting the function $f$ to the left by an amount $b$. The sum of the weighted inputs and the bias $b$ feeds into the transfer function $f$. 
CHAPTER 3 – FLUID LEVEL SENSING USING ARTIFICIAL NEURAL NETWORKS

The function $f$ is the transfer function, normally a step function or a sigmoid function. The central idea of neural networks is that such parameters can be adjusted so that the network exhibits some desired or interesting behaviour. The network can be trained to produce a particular function by adjusting the weight or bias parameters.

3.3.2 Transfer function

The transfer function plays an important role in producing the output of a neural network. The transfer function combines the inputs and the weights values to deliver a signal to the output. This function typically falls into one of the three categories:

- Linear (or ramp)
- Threshold
- Sigmoid
CHAPTER 3 – FLUID LEVEL SENSING USING ARTIFICIAL NEURAL NETWORKS

3.3.2.1 **Linear Transfer Function**

The output activity is proportional to the total weighted input. It is referred in MATLAB as *purelin* function.

\[ a = \text{purelin}(n) \]

![Figure 3.7. Linear transfer function. [99]](image)

3.3.2.2 **Threshold Transfer Function**

Threshold transfer function sets the output to one of the two levels, depending on whether the total input is greater than or less than some threshold value. It is known as *hard limit* or *hardlim* function in MATLAB.

\[ a = \text{hardlim}(n) \]

![Figure 3.8. Threshold transfer function. [99]](image)

3.3.2.3 **Sigmoid Transfer Function**

For sigmoid units, the output varies continuously but not linearly as the input changes. Sigmoid units bear a greater resemblance to real neurones than do linear or
threshold units. [98] It is also known as Log-Sigmoid or logsig function in MATLAB.

\[ a = \text{logsig}(n) \]

Figure 3.9. Sigmoid transfer function. [99]

### 3.3.3 Perceptron

A perceptron neuron, which uses the threshold or hard-limit transfer function \( \text{hardlim} \), is shown in Figure 3.10.

Each external input is weighted with an appropriate weight \( w_{i,j} \), and the sum of the weighted inputs is sent to the hard-limit transfer function, which also has an input of \( l \) transmitted to it through the bias. The hard-limit transfer function returns a 0 or a 1. The perceptron neuron produces a 1 if the net input into the transfer function is equal to or greater than zero; otherwise it produces zero at the output. [99]
In MATLAB, the perceptron networks can be trained with the *adapt* function. This function presents the input vectors to the network one at a time and makes corrections to the network based on the results of each presentation. The use of the *adapt* function in this way guarantees that any linearly separable problem is solved in a finite number of training presentations. [20]

### 3.4 NEURAL NETWORK ARCHITECTURES

#### 3.4.1 Overview

A brief description of neural networks has been provided in the previous section. This section focuses on different architectures or topologies of neural networks that can be used in this research.

#### 3.4.2 Network layers

Commonly there are three main layers in neural networks, where each layer is connecting to the neighbour layer [92]:

- *Input layer* – contains raw information of the input
- *Hidden layer* – is based on inputs and weights between input and hidden layer
- *Output layer* – depends on the activity of the hidden layer and the weights between hidden and output layer.
A neural network can have several layers. The use of layer notation can be seen in the three-layer network shown in Figure 3.12 [99]. Each layer has a weight matrix $W$, a bias vector $b$, and an output vector $a$. The outputs of each intermediate layer are the inputs to the following layer.

**Figure 3.11. Three main layers of ANN.**

**Figure 3.12. Multiple layers of neurons.**[99]

### 3.4.3 Network Topologies

Two commonly used topologies of artificial neural network are:

- Feed-Forward Network, and
- Dynamic Neural Network
CHAPTER 3 – FLUID LEVEL SENSING USING ARTIFICIAL NEURAL NETWORKS

3.4.3.1 Feed-forward neural network

In feed-forward neural network topology, signals travel in one direction only, i.e. from input to output. There is no loop or feedback between the neurons and their inputs and outputs. This network topology is also called static network and it is extensively used in pattern recognition. Backpropagation (BP) is the most popular type of feed-forward neural network. Figure 3.13 illustrates an example of a static feed-forward neural network topology.

![Figure 3.13. Feed-forward static neural network.](image)

3.4.3.2 Dynamic neural network

Neural networks can be classified into dynamic and static categories. Static (feedforward) networks have no feedback elements and contain no delays; the output is calculated directly from the input through feedforward connections. In dynamic networks, the output depends on not only the current input to the network, but also on the current or previous inputs, outputs or states of the network. Dynamic neural networks are divided into two types [92]:
CHAPTER 3 – FLUID LEVEL SENSING USING ARTIFICIAL NEURAL NETWORKS

- **Time-delay neural networks** – Those that only have feed-forward connections, and
- **Recurrent neural networks** – Those that have feedback or recurrent connections.

**Time-delay neural networks**

Focused Time-Delay Neural Network (FTDNN) and Distributed Time-Delay Neural Network (TDNN) are examples of feed-forward dynamic neural networks. FTDNN has an additional delay line at the input only, whereas, TDNN has a tapped delay line memory at the input as well as throughout the network. [92]. There is no feedback connection in these networks. These networks are well suited for applications involving time-series prediction. TDNN networks attempt to recognise the frequency content of the input signals, which suggests the suitability of these networks in determining time-varying sloshes. Figure 3.14 illustrates the Distributed Time-delay Neural Network.

![Distributed Time-Delay Neural Network](image)

**Figure 3.14. Distributed Time-Delay Neural Network.**
Recurrent neural networks

In recurrent neural network topology, signals can travel in both directions, i.e. forward and backward. The neurons may be connected with each others forming loops or feedback, as shown in Figure 3.15. This is a powerful method to control dynamic systems; however, it can also get quite complicated. The dynamic state of this network continuously changes until it reaches an equilibrium state. The system state stays at equilibrium until another input is received which causes the system to reconsider its state and a new equilibrium state is produced.

Figure 3.15. Recurrent Neural Network.
The output of the NARX can be described as:

\[ y(t) = f(y(t-1), y(t-2), \ldots, y(t-n_y), u(t-1), u(t-2), \ldots, u(t-n_u)) \]  

(3.6)

### 3.5 TRAINING PRINCIPLES

#### 3.5.1 Overview

Neural networks can be trained to perform a specific task. There are several engineering tools available to train neural networks. MATLAB is one such powerful tool that includes a neural network module that trains, analyses and simulates the neural network. Training procedure follows a learning rule or training algorithm, which is defined as a procedure for modifying the weights and biases of a network [99]. Learning rules fall into two broad categories: Supervised learning and
3.5.2 Supervised learning

Supervised learning incorporates an external teacher, so that each output unit is told what the desired response to input signals ought to be [98]. The learning rule is provided with a set of examples (known as training set) of proper network behaviour:

\[ \{p_1, t_1\}, \{p_2, t_2\}, \ldots, \{p_Q, t_Q\} \]  

where, \( p_q \) is an input to the network, and \( t_q \) is the corresponding correct (target) output.

As the inputs are applied to the network, the network outputs are compared to the targets. The learning rule is then used to adjust the weights and biases of the network in order to move the network outputs closer to the targets.

3.5.3 Unsupervised learning

Unsupervised learning method does not use an external teacher and it is based only upon local information. It is also referred to as self-organisation, in the sense that it self-organises data presented to the network and detects their emerging collective properties [98]. The weights and biases are modified in response to network inputs only. There are no target outputs available. Most of these algorithms perform clustering operations. They categorize the input patterns into a finite number of classes. This is especially useful in such applications as vector quantization. [99]
CHAPTER 3 – FLUID LEVEL SENSING USING ARTIFICIAL NEURAL NETWORKS

3.6 NEURAL NETWORKS IN DYNAMIC ENVIRONMENTS

3.6.1 Overview

The use of neural networks in providing solutions to capacitive sensing level measurement applications is discussed in this subsection. Furthermore, applications that describe solutions to the issues pertaining to the accuracy of measurement sensors in dynamic environments are discussed in this section.

3.6.2 Temperature Compensation with Neural Networks

Patra et al. [101] proposed a scheme for an intelligent capacitive pressure sensor (CPS) using an artificial neural network (ANN). A switched-capacitor circuit (SCC) converts the change in capacitance of the pressure-sensor into an equivalent voltage. The effect of change in environmental conditions on the CPS and subsequently upon the output of the SCC is nonlinear in nature. Especially, change in ambient temperature causes response characteristics of the CPS to become highly nonlinear, and complex signal processing may be required to obtain the correct readout.

The proposed ANN-based scheme incorporates intelligence into the sensor. It is mentioned that this CPS model can provide a correct pressure readout within 1% error (full scale) over a range of temperature from 20°C to 70°C. Two ANN schemes, direct modelling and inverse modelling of a CPS, are reported. The former modelling technique enables an estimate of the nonlinear sensor characteristics, whereas the latter technique estimates the applied pressure which is used for direct digital readout. When there is a change in ambient temperature, the ANN
automatically compensates for this change based on the distributive information stored in its weights. [101]

Another method described by Patra et al. [102] also uses an artificial neural network (ANN). The described neural network based sensor model automatically calibrates and compensates with high accuracy for the nonlinear response characteristics and nonlinear dependency of the sensor characteristics on environmental parameters. It was shown that the NN-based capacitive pressure sensor (CPS) model can provide pressure readout with a maximum full-scale error of only 1.5 % over a temperature range of -50 to 200 degree Celsius for the three forms of nonlinear dependencies [102].
CHAPTER 4 – METHODOLOGY

4.1 OVERVIEW

This chapter discusses the characteristics of the capacitive sensor signal obtained from a fuel level sensor under dynamic conditions. It also describes a methodology to be used to develop a fluid level measurement system that compensates for the effects of a dynamic environment. This involves using an intelligent signal classification approach based on an Artificial Neural Network. Signal smoothing functions that will be implemented to enhance the performance of the artificial neural network based signal classification system are also described.

4.2 CAPACITIVE SENSOR BASED LEVEL SENSING

4.2.1 Capacitive Sensor Signal

The output of the capacitive sensor is normally a continuous voltage signal over time. The voltage signal is the representation of the fluid level observed by the sensor. The range, resolution and the linearity of the output signal could be different from one type of manufacturer to another. The sensor signal representing the fluid level is illustrated in Figure 4.1.
Figure 4.1. Capacitive signal representing fluid level in voltage.

If $L$ is the length of the capacitive tube filled with the fluid, and $v$ is its represented level in voltage, assuming the sensor response to be linear, the resolution can be given as:

$$\text{Resolution} = \frac{\Delta L}{\Delta v} \text{ metre per volt} \quad (4.1)$$

The capacitive tube immersed in the liquid tank will detect the maximum level, hence the maximum voltage, when the fluid is filled up to the top of the sensing tube. Likewise, the minimum level will be detected when there is no fluid filling the sensing tube. The maximum and minimum level is dependent on the placement and length of the capacitive tube in the tank.

4.2.2 Sensor Response under Slosh Conditions

Slosh waves will be produced in a tank filled with liquid when an external force is applied to it. Representation of these slosh waves in a digital signal can be carried
out using a tubular capacitive sensor as the waves propagate through the capacitive tube within the tank. If the capacitive sensor can produce instantaneous readings of the fluid level in an electrical unit, a replica of these slosh waves could be observed on the oscilloscope. Figure 4.2 shows the output of the capacitive sensor reading that will be seen on an oscilloscope under both static and dynamic conditions. Figure 4.2 (a) shows that the sensor response is fairly constant under static conditions; Figure 4.2 (b) shows that the sensor response produces a replica of the actual slosh waves.

Figure 4.2. Sensor response in static and dynamic conditions.

As the fluid fluctuates, the sensor output produces a replica of the slosh waves that contains the following two components:
CHAPTER 4 – METHODOLOGY

• Oscillating wave, and
• Bias shift

Figure 4.3. Two components of the slosh wave.

The frequency response of the oscillating slosh waves can be observed by transforming the capacitive signal into the frequency domain. Fast Fourier Transform (FFT) function can be used to obtain the frequency coefficients. The magnitude of these frequency coefficients and the median value (bias shift) can be used to describe the slosh pattern that exists in the fluid container. These signal characteristics can be processed through an Artificial Neural Network (ANN) to eliminate the effects of dynamic slosh. Additionally, along with the frequency coefficients and bias shift, temperature and contamination values could also be processed through the artificial neural network to eliminate their effects on signal measurement accuracy.

4.3 DESIGN OF METHODOLOGY
The observation and analysis of the slosh pattern produced under the effects of acceleration in a closed container, instigated an approach that can eliminate the sloshing effects on level measurement. Thereby accurate fluid level measurements would be possible in dynamic environments. If the fluid quantity in a storage container remains constant, the instantaneous fluid level in a dynamic environment can be defined as:

\[ L(t) = L_0 \cdot f \]  

(4.2)

Where \( L_0 \) is the tank fluid level under static conditions, and \( f \) is the unknown sloshing function that depends on the acceleration effects exhibited on the tank, the existing fluid level, and the tank geometry. The goal is focused on determining the actual level \( L_0 \) using the sensor output \( L(t) \) and the function \( f \). The output of the fluid level sensor is observed to have a direct relationship with the vehicle acceleration when observed in a running vehicle, as shown in Figure 4.4.
CHAPTER 4 – METHODOLOGY

Figure 4.4. Vehicle acceleration and the raw sensor signal.

If the value of sloshing function \( f \) is known for every corresponding value of sensor output \( L(t) \) the effect of fluid slosh can be eliminated.

\[
L_0 = \frac{L(t)}{f} = \text{constant}
\]

(4.3)

The unknown function \( f \) is solved by experimentation with the aid of a neural networks based approach. A neural network can be constructed and trained with the actual driving data obtained through several field trials to produce accurate level readings under the effect of liquid sloshing. Figure 4.5 demonstrates a method that can be adopted to develop an accurate fluid level measurement system.
The capacitive level sensor signal, denoted as $s(t)$, is typically a voltage signal in the range from 0 – 5 V, which represents the minimum and maximum of the level range respectively. A more detailed description of the methodology is provided in Chapter 5. The sensor signal $s(t)$ is sampled at 100 Hz. The sampled signal is accumulated in a $w_i$ second window frame ($w_i$). The optimal value of $w_i$ will be determined by experimentation as described in Chapter 5. After collecting the sensor data over $w_i$ seconds, the $w_i$ second data is filtered using the investigated filters. Then the signal features are extracted using the three feature extraction methods FFT, DCT, and WT. The performance and influence of these three feature extraction functions will be investigated to determine the optimal feature extraction method for the ANN based measurement system. The coefficients ($coef$) obtained from the feature extraction functions, the median value ($med$) of the $w_i$ –second capacitive sensor signal, the temperature readings $T$, and the contamination factor $K$ are all contained.
in a vector forming input features for the ANN model. The ANN input vector $x_i$ can be represented as:

$$x_i = \{\text{coef}_1, \text{coef}_2, \ldots, \text{coef}_n, \text{med}, T, K\}$$  \hspace{1cm} (4.4)

### 4.4 FEATURE SELECTION AND REDUCTION

Signal feature extraction, selection and reduction play an important role in signal classification systems. An introduction to feature extraction was given in Section 3.2.4. Improper format of input signals supplied to the classifier can result in a poorly constructed classification problem. As Trunk [80] has demonstrated, data can be detrimental to classification, especially if the data is highly correlated [78]. Apart from the correlation of data, the size of the input feature dataset is also important in determining the performance of signal classification systems. An increase of the input feature dimension ultimately causes a decrease in performance [103]. Hence, the correlation of the input data and the number of input features to be selected will be investigated during the development of the neural network based classification system.

The process of choosing a subset of the features is referred as 'feature selection', and the process of finding a good combination of features is known as 'feature reduction' [104]. The goal of feature selection and reduction in signal pre-processing is to choose a subset of features or some combination of the input features that will best represent the data [104]. According to Yom-Tov [104], finding the best subset of features by testing all possible combinations is practically impossible even when the
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number of input features is modest. For example, to test all possible combinations of the input data with 100 input features will require testing $10^{30}$ combinations [104].

According to Richards et al. [105], feature reduction can be effectively performed by transforming the data to a new set of axes, where patterns within the transformed dataset could be more easily distinguished than with the original dataset [105]. Therefore, in the capacitive type fluid level sensing system, the raw time-based level signals will be converted into the frequency-domain using the Fast Fourier Transform (FFT) function described in Section 3.2.4. By carrying out the Fourier Transformation, the raw signal contents that will be used as an input to the neural network will be represented by frequency-coefficients. Figure 4.6 shows an example of the raw time-domain signal from the capacitive sensor over 60 seconds, and the frequency response of the same signal obtained using the FFT function. The frequency spectrum of the raw sensor signal under the influence of slosh describes the fluctuations or slosh frequencies in the fuel tank. The frequency spectrum shown in Figure 4.6 displays two large spikes at 0.4 and 0.8 Hz, which represent two harmonics waves of the slosh.
According to Richards et al. [105], features which do not aid discrimination, by contributing little to the separability of spectral classes, should be discarded. Richards et al. [105] describe feature selection as the process in which the least effective features are removed. Feature selection methods can be divided into three main types [77]:

1. **Wrapper methods**: The feature selection is performed around (and with) a given classification algorithm. The classification algorithm is used for ranking possible feature combinations.

2. **Embedded methods**: The feature selection is embedded within the classification algorithm.

3. **Filter methods**: Features are selected for classification independently of the classification algorithm.
In the proposed capacitive type fluid level sensing system, the Filter method is used to perform feature selection because this is the method that is independent of the classification algorithm, while the other two methods incorporate learning or regression analysis. Additionally, filter methods are currently widely used in fuel tank level sensing (without neural networks) to compensate for the effect of the slosh. They generally result in higher inaccuracy in dynamic environments. In this work comparison will be made between various filters with and without use of the neural networks to understand the effectiveness of each method. Based on the knowledge of the maximum slosh frequency attainable in a vehicle's fuel tank, a low-pass filter method can be used to extract only selected number of fft coefficients that would actually represent the sloshing and hence the undesired range of frequency will not be taken into consideration during signal processing through the neural network.
Figure 4.7. Typical range of slosh frequency in the fuel tank during normal driving.
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After transforming the time-based sensor signal into the frequency-spectrum, the undesired portion of frequencies mainly consisting of low-amplitude noise is omitted. To determine the range of frequencies that may be exhibited in the fuel tank, a sixty-kilometre test drive was run in a suburban area, where occasional stops were made. Figure 4.7a shows the typical range of slosh frequencies observed in the vehicular fuel tank using the capacitive type level sensor during a sixty-kilometre test drive. A close-view of the 0 to 2 Hz slosh frequency range is shown in Figure 4.7b. By using a low-pass filter, frequencies having lower amplitudes (i.e. noise) can be removed prior to processing the signals through an artificial neural network.

4.5 SIGNAL FILTRATION

In the signal smoothing process, the raw signal is filtered to remove the signal noise by smoothening it with the three investigated methods: Moving Mean, Moving Median and Wavelet Transform. A raw signal over $\omega$-second is passed through the investigated filters. The moving mean and moving median filters slide across the raw signal and calculate the mean/median values in the neighbouring sampled points. If $x$ is the sampled raw signal of $N$ length, and $w$ is size of the moving window, then the filtered output $y$ using mean and median can be obtained using equations (4.5) and (4.6), respectively. The width of the moving window $w$ will be determined by experimentation (Chapter 5). The sliding window (moving window) function takes $w$ samples of the raw signal and produces a *mean* or *median* value at the output.

\[
\begin{align*}
y[i] &= mean(x[i-1], x[i-2], ..., x[i-w]), \quad \text{for } w \leq i \leq N \\
y[i] &= mean(x[1], x[2], ..., x[i]), \quad \text{for } 1 \leq i < w
\end{align*}
\]
\begin{equation}
\begin{align*}
y[i] &= \text{median}(x[i-1], x[i-2], \ldots, x[i-w]), \quad w \leq i \leq N \\
y[i] &= \text{median}(x[1], x[2], \ldots, x[i]), \quad \text{for } 1 \leq i < w
\end{align*}
\end{equation}

The value of $N$ for a signal frame of $\tilde{\omega}$–second at 100 Hz is calculated as:

\[ N = 100 \ \text{samples/s} \times \tilde{\omega} \ s = 100 \tilde{\omega} \ \text{samples} \]  

Figure 4.8 illustrates the \textit{moving mean} and \textit{moving median} filters when applied to the raw signal data. As the moving window slides across the twenty second ($\tilde{\omega}=20$) long raw signal, mean/median functions are applied to the raw signal values within the window range and a smooth signal is produced. The filtered versions of the raw signal using both filters do not contain high frequency noise.

![Figure 4.8. Illustration of the moving mean and moving median filters.](image-url)
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Another filter investigated is the Wavelet Transform (WT) filter that analyses signals at different frequency bands by de-composing them into coarse information and detailed information sets. The coarse information set contains the low-frequencies, whereas, the detailed information set contains the high-frequencies of the input signal. Only the low frequency components, which reflect a smoothened version of the raw signal, are used and the high frequency components of the raw signal, which usually contain noise, are discarded. Hence, a smooth signal is produced using the Wavelet Transform function, as shown in Figure 4.9. The Wavelet Transformation is processed through MATLAB using \texttt{dwt} \cite{106} function with Daubechies \cite{107} Wavelet (\texttt{db1}).

Figure 4.9 shows the high frequency signal (b) and the low-pass filtered signal (c) when the raw sensor signal (a) is processed with the Discrete Wavelet Transform (DWT) function.
All filtered signals using the investigated filtration methods are transformed into the frequency domain and the frequency coefficients obtained, which are then fed into the ANN based signal processing system.

### 4.6 INFLUENTIAL FACTORS ANALYSIS

An analysis on the influential factors will be carried out before the development of the ANN based capacitive signal processing system. In the influential factors analysis, the effects and interaction between the influential factors will be investigated by observing the response of the capacitive sensor. It was proposed in Chapter 2 that the main factors influencing the accuracy of the measurement system are: Slosh, Temperature, and Contamination. The results from the factors analysis experiment will provide an understanding of the magnitude of the effects that these
three influential factors may contribute to the response of the capacitive sensor output. According to Dean et al. [108], it is more effective to examine all possible causes of variation simultaneously rather than one at a time. Therefore, all three influential factors will be simultaneously analysed by developing a two-level ($2^n$) factorial design experiment. Factorial experiments include all possible combinations of factor–level in the experimental design [109]. Detailed information on the factorial design is provided in Section 5.4.2.

Factorial experiments provide an opportunity to study not only the individual effects of each factor but also their interactions [110]. The results obtained from the factorial analysis experiment will be used to generate Main Effects Plots and Interaction Plots of the three main influential factors. Main effects plot provides detailed measures of the influence of each influential factor on the response of the capacitive sensor output. Interaction Plots on the other hand provide details of interaction that may be found between the influential factors. The Main Effects Plots and Interaction Plots will provide a better understanding of the impact of the three influential factors on the capacitive sensor output. These plots will be generated with Minitab software [111]. Minitab is a very sophisticated and easy to use software, which has also been adopted by most Six Sigma practitioners as a preferred tool [112, 113].
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5.1 OVERVIEW

The implementation of the Artificial Neural Network (ANN) based capacitive signal classification system requires some training samples of the system with actual sample data obtained under various dynamic conditions. A detailed description of the experimental set-up used to conduct the research is provided in this section. There are three major experiments performed during this research. All experiments are carried out using a regular standard automobile fuel tank. The first set of experiments determine the influence of contamination, temperature and sloshing factors. The second set of experiments determine the suitability and performance of the static and dynamic neural networks. Finally, extensive experimentation is carried out with a range of different fluid levels in the tank to observe slosh pattern at different fluid levels. The data obtained from the third set of experiments will be used to train the backpropagation neural network while performing signal smoothening using the Moving mean, Moving median, and Wavelet filters.

5.2 METHODOLOGY

In order to develop and enhance the performance of the neural network based fluid level measurement approach, there are three sets of experiments performed in this research. These experiments involve the study of the effects of a dynamic environment on the capacitive sensor based fluid level measurement system. The methodology used to run the experiments and validation plan is shown in the
CHAPTER 5 - EXPERIMENTATION

The test conditions given in Table 5-1 are applied to the measurement system during the experiments to study the response of the capacitive sensor output under dynamic conditions.

<table>
<thead>
<tr>
<th>Tested Fluid Levels</th>
<th>Test Conditions</th>
<th>Output Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>EXPERIMENT SET A</td>
<td>• Slosh</td>
<td>Capacitive Sensor -</td>
</tr>
<tr>
<td></td>
<td>• Temperature</td>
<td>Response without ANN</td>
</tr>
<tr>
<td></td>
<td>• Contamination</td>
<td></td>
</tr>
<tr>
<td>40, 45, 50, 55 L</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EXPERIMENT SET B</td>
<td>• Slosh</td>
<td>Capacitive Sensor -</td>
</tr>
<tr>
<td></td>
<td>• Different ANN architectures (BP, DTDNN, NARX)</td>
<td>Response to Slosh with different neural network architectures</td>
</tr>
<tr>
<td>40, 45, 50, 55 L</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EXPERIMENT SET C</td>
<td>• Slosh</td>
<td>Capacitive Sensor -</td>
</tr>
<tr>
<td></td>
<td>• Backpropagation ANN</td>
<td>Response to Slosh with Backpropagation ANN</td>
</tr>
<tr>
<td></td>
<td>• Different Window sizes ((\hat{w}))</td>
<td>and different Filtration functions</td>
</tr>
<tr>
<td>5-9L, 15,20, 25,30L</td>
<td>• Different feature extraction functions (FFT, DCT, DWT)</td>
<td></td>
</tr>
<tr>
<td>35-40L, 45-50L</td>
<td>• Different Signal Smoothing functions (Moving mean, Moving Median, Wavelet)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Different filter tap sizes</td>
<td></td>
</tr>
</tbody>
</table>

Table 5-1 . Methodology of Experiments with Test conditions, and Output parameters.
Table 5-1 shows the overview of the experimental setup for the development and validation of the neural network based fluid level measurement system. The experiments are configured into three discrete sections, which are labelled as Experiment Set A, Experiment Set B, and Experiment Set C. The overview and purpose of the three parts of the experimental program are described below. The detailed descriptions of these three experiments will be provided later in this chapter.

Experiment Set A is performed to study the interactions and the effects of the influential factors, which were proposed in Chapter 2 to be: Slosh frequency, Temperature and Contamination, on the capacitive sensor output. In order to understand the behaviour of the capacitive sensor in a dynamic environment, it is
important to determine the magnitude of the influence that the environmental factors contribute to the response of the capacitive sensor in a dynamic environment.

Experiment Set A is designed using the Design of Experiments (DOE) methodology to observe the Main Effects Plot and the Interaction Plot of the influential factors. To set and control the Slosh frequency factor, Experiment Set A is conducted on-site using a Linear Actuator (see Section 5.3.3). A fuel tank filled with fluid is mounted on the Linear Actuator. The Linear Actuator is controlled with a digital timer, which could be configured to generate a particular slosh frequency in the liquid container. A heater is used to set the Temperature factor. To observe the sensor response under the effects of contamination, Arizona dust sample of varying quantity is mixed in the fluid. The detailed description of Experiment Set A is given in Section 5.4.

Experiment Set B is performed to determine the most suitable neural network topology from a set of commonly used neural network configurations. To compare the performance of the different neural network topologies under the influence of the Slosh factor, Experiment Set B is conducted in a similar manner to Experiment Set A. However, the Contamination and Temperature factors are kept constant during Experiment Set B, as the Slosh factor in Experiment Set A results (see Section 6.2) is observed to be the prominent contributor to the accuracy of the measurement system. The primary focus of Experiment Set B is to examine the performance of different neural network topologies under the influence of sloshing. The data obtained from Experiment Set B is used to develop and validate two different (static and dynamic)
topologies of artificial neural networks. The detailed description of Experiment Set B is provided in Section 5.5.

Experiment Set C is carried out to understand the effectiveness of the ANN based signal processing system on the slosh test data obtained from driving trials. The selection of the optimal parameters for the ANN based system is performed in this experiment. The influence of signal enhancement operations on the performance of the artificial neural network based signal processing system is also investigated. Signal smoothing is performed on the raw sensor signals to enhance the performance of the neural network based signal classification system. In contrast to Experiment Set A and Experiment Set B, which are both performed onsite on an experimental rig containing a linear actuator, Experiment Set C is performed on the road during field trials to examine the performance of the ANN based fluid level measurement system under actual driving conditions (i.e. dynamic environment). Extensive field trials are carried out for over twenty different tank levels in the automotive fuel tank. During these experiments the fluid temperature is created in the fuel tank due to unused return fuel coming back from the engine. Additionally the fluid slosh is created due to vehicle movement. Both temperature and slosh are recorded during the experiment. The data obtained from the field trials is used to train the Backpropagation Neural Network using different signal processing filters. The detailed description of Experiment Set C is given in Section 5.6.
5.3 DATA COLLECTION AND PROCESSING METHODOLOGY

The raw data obtained from the capacitive type level sensor using experimentation is processed using the methodology illustrated in Figure 5.2.

![Measurement System’s Signal Processing Block Diagram](image)

**Figure 5.2. Measurement System’s Signal Processing Block Diagram.**

The output from the capacitive type fluid level sensor is in the form of an analogue voltage signal. The amplitude of the sensor voltage signal denotes the level of fluid contained in the tank. The sensor signal voltage linearly ranges from 0 V (empty) to
CHAPTER 5 - EXPERIMENTATION

5 V (full). A detailed description of the capacitive level sensor used in the experiments is provided in Section 5.3.1. The level signal from the capacitive sensor is sampled at 100 Hz using a Data Acquisition Card in conjunction with the LabVIEW software program. The sampled signal is accumulated over \( \omega \) seconds and then processed through the neural network classifier. In this experiment \( \omega = 20 \) sec interval was used to limit the amount of data processing with still acceptable accuracy of the measurement system.

In Experiment Set C, where the influence of signal filtration is examined, the accumulated sensor signal over \( \omega \) seconds was processed through a signal filtration function before processing the signal data through the artificial neural network based signal processing system. Feature extraction is performed on the signals prior to processing them through the neural network.

Statistical median function is used to calculate the middle value of the raw sampled signals. The median function provides the middle value as opposed to the mean function that provides average value. In Section 2.6.4.1, it was discussed that the downside of averaging is that it produces a significant error for a momentarily large spike due to an abnormal data entry. Therefore, median value was used as the middle value or the bias value (refer Section 4.2.2) of the fluctuating fluid level (slosh wave).
CHAPTER 5 - EXPERIMENTATION

The frequency coefficients, the median value of the sampled signal, the temperature value from the temperature sensor and the contamination value are all incorporated in the feature vector. The signal feature vector is then used as input to the neural network based signal processing system for training and validation of the network. Signal processing and signal classification are both carried out using MATLAB software. Although the initially proposed neural network model included contamination as a variable it was determined in the Experiment Set A that the influence of contamination was not significant due to relatively constant temperature during the vehicle experiment. Consequently, it was excluded from the neural network model in subsequent vehicle trials in the Experiment Set C.

5.4 APPARATUS AND EQUIPMENT USED IN EXPERIMENTAL PROGRAMS

This section describes the instruments and equipment used to conduct the experiments. The assumptions made during the experiments are also described in the following subsections.

5.3.1 Capacitive Level Sensor

The capacitive level sensor used to run the experimentations is the T/LL134 Fuel level sensor built by Fozmula Ltd. The capacitive sensor is in the configuration of an elongated tube capacitor (shown in Figure 5.3).
Figure 5.3. Capacitive Sensor used in the experiments.

The length of the liquid sensing tube is approximately 28 cm. The capacitive sensor outputs 0 V at the absence of fluid; and 5 V at maximum fluid level. Therefore, the sensor produces the fluid level signal as a continuous analogue voltage signal that linearly ranges from 0-5 V. The sensor includes a manual calibration option to sense fluid levels in a variety of different kinds of fluids. With the manual calibration function, the capacitive sensor calibrates the value of the dielectric constant with reference to the dielectric constant value of its surrounding fluid. The capacitive sensor can be calibrated at both full and empty points. During full-point calibration, the capacitive sensor is fully submerged in the fluid for which the sensor is to be calibrated and then the manual calibration (Cal.) button (shown in Figure 5.3 a) is pressed for 5 seconds. However, during the empty-point calibration, the sensor is
taken out of the liquid and is made dry, then the Cal. button is pressed for 5 seconds. The manufacturer has described the calibration steps for both full and empty points [114]:

Calibration of the full point:

1. Start with the sender fitted to the tank and connected to the power supply.
2. The tank must be filled to the required full level with the liquid for which the sender is to be calibrated.
3. Depress the Cal. button on the top of the sender and hold for 5 seconds to set the full point calibration. Check that the output reads full.
4. The calibration for the full point can be re-set for a liquid of a differing dielectric constant by repeating the above procedure.

Calibration of the empty point:

1. Remove the sender from the tank, disconnect the power supply and shake off any excess liquid.
2. Depress the button on the top of the T/LL134 and hold.
3. Connect the sender to the power supply, while continuing to hold the button for a further 5 seconds. Release the button.
4. The empty calibration is now set. Check that the output reads zero.

The calibration can be performed in the automotive gasoline type fuel prior to the experiments to obtain accurate sensor readings. The sensor uses the three wire connector, where two wires are used to power it and the third wire outputs the signal as a voltage. The specification details of the capacitive sensor used in the experiments are given in the Table 5-2.
<table>
<thead>
<tr>
<th><strong>Parameter</strong></th>
<th><strong>Value</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>Supply Voltage</td>
<td>7-35 Vdc</td>
</tr>
<tr>
<td>Supply Current</td>
<td>15mA at 12 Vdc (approx.)</td>
</tr>
<tr>
<td>Operating frequency</td>
<td>8.3 kHz</td>
</tr>
<tr>
<td>Output Signal</td>
<td>0 – 5 V</td>
</tr>
<tr>
<td>Linearity</td>
<td>1%</td>
</tr>
<tr>
<td>Accuracy</td>
<td>±2.5%</td>
</tr>
<tr>
<td>Housing</td>
<td>30% glass filled Nylon 6</td>
</tr>
<tr>
<td>Sensor Tube</td>
<td>Stainless steel 316</td>
</tr>
<tr>
<td>Internal insulators</td>
<td>30% glass filled Nylon 6</td>
</tr>
<tr>
<td>Operating Temperature</td>
<td>-40°C to +85°C</td>
</tr>
<tr>
<td>Storage Temperature</td>
<td>-55°C to +100°C</td>
</tr>
<tr>
<td>Shock</td>
<td>50g 5.3mS</td>
</tr>
</tbody>
</table>

Table 5-2. Capacitive sensor detailed specifications.
5.3.2 Fuel tank

The fuel tank used in all the experiments had a storage capacity of 70 L. The fuel tank originally belonged to an utility vehicle (Ute). The tank can be approximated as a rectangular container with dimensions $34 \times 34 \times 81$ cm. The capacitive sensor is mounted on top of the tank. Figure 5.4 shows the fuel tank properly fitted on a Linear Actuator (refer to Section 5.3.3).

![Figure 5.4. Utility tank used in the experiments.](image)

The fuel tank is filled with Exxsol D-40 Stoddard solvent. Exxsol is the brand name of Exxon Mobil Corporation. Exxsol solvents are a series of de-aromatized aliphatic hydrocarbons [115], where typical Aromatic content is below 1%. These fluids maintain good solvency characteristics for many applications. Exxon describe the
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Occupational Exposure Limit (OEL) of the Exxsol fluids as relatively high, because of this advantage they often serve as replacements for more conventional solvents that might not meet health or environmental regulations. Heavier Exxsol D grades have boiling ranges between $140^\circ$ and $310^\circ$ C [116]. The Exxsol D-40 has the same properties as gasoline fluids but it is relatively safe for industrial usage. Therefore, Exxsol D-40 fluid is used in the experiments. The detailed specifications of the Exxsol D-40 solvent are provided in Appendix B.

5.3.3 Linear Actuator

The Linear Actuator used to run the slosh tests is shown in Figure 5.5 and Figure 5.6. The figures show the actuator and the frame body on which the fuel tank is mounted.

![Actuator](image)

Figure 5.5. Linear actuator used for creating slosh.
Figure 5.6. Linear actuator showing PLC Timer and Linear Actuator.

The pneumatic actuator is run by compressed air to slide the tank back and forth. The linear actuator is controlled by a Programmable Logic Controller (PLC) Timing Unit, which is shown in Figure 5.6. As the linear actuator moved back and forth, slosh waves are created and observed in the fuel tank. The back and forward strike of the actuator can be controlled by setting the timer value of the PLC Timer. The PLC Timer actuates (fires) air pressure through the Actuator Controller Cables (highlighted in Figure 5.6). The fire timing can be easily set by using the keypad located inside the PLC Timer Box.

5.3.4 Heater
To observe the effects of temperature variations on the sensor response, the heating chamber is used to heat up the fuel in some parts of the experiments.

5.3.5 Arizona Dust

Arizona dust is used as the impurity substance in experiments to examine the performance of the capacitive sensor based measurement system when alteration takes place in the value of the dielectric constant of the fluid. The response of the capacitive sensor output is observed before and after the introduction of Arizona Dust samples.

5.3.6 Signal Acquisition Card

All signals from the capacitive sensor are acquired and stored on the computer using the National Instruments Data Acquisition Card (DAQ card) and the LabVIEW software. The signal acquisition board and the power source are shown in the figures below. The power supply box is sourced by the AC mains to provide the 12V DC output for the capacitive sensor.
Figure 5.7. Signal Acquisition Board.

Figure 5.8. Power supply used to power the capacitive sensor.
5.4 EXPERIMENT SET A – STUDY OF THE INFLUENTIAL FACTORS

5.4.1 Overview

The purpose of running Experiment Set A is to study the magnitude of the interaction and the effects of the influential factors, which are proposed as described in Chapter 2 to be: Slosh frequency, Temperature and Contamination. In order to fully comprehend the behaviour of the capacitive sensor in a dynamic environment, it is important to quantify the influence of the environmental factors on the response of the capacitive sensor.
5.4.2 Factorial Design

Experiment Set A is performed to understand the interactions between the three main influential factors and determine the magnitude of the effects that these factors have on the capacitive sensor output. The experiment is designed with the Design of Experiments (DOE) methodology. There are a wide variety of experimental designs for conducting factorial experiments [109]. Completely randomized design is one of the most straightforward designs to implement [109]. Mason et al. [117] described the randomization design method as: ‘Randomization is a procedure whereby factor–level combinations are (a) assigned to experimental units or (b) assigned to a test sequence in such a way that every factor–level combination has an equal chance of being assigned to any experimental unit or position in the test sequence’[109].

The factorial design is developed in a randomized way using Minitab software [111]. The high and low values of these factors are shown in Table 5-3.

<table>
<thead>
<tr>
<th>Factors</th>
<th>Low Value</th>
<th>High Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-Slosh Frequency</td>
<td>0.5</td>
<td>2</td>
<td>Hz</td>
</tr>
<tr>
<td>2-Temperature</td>
<td>10</td>
<td>50</td>
<td>°C</td>
</tr>
<tr>
<td>3-Contamination</td>
<td>0</td>
<td>150</td>
<td>g</td>
</tr>
</tbody>
</table>

Table 5-3. High and Low values of the influencing factors.
The full factorial matrix of $2^3$ factors with one replicate is shown in Table 5-4:

<table>
<thead>
<tr>
<th>Run Order</th>
<th>Slosh Freq. (Hz)</th>
<th>Temperature (°C)</th>
<th>Contamination (g)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2.0</td>
<td>10</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>0.5</td>
<td>50</td>
<td>150</td>
</tr>
<tr>
<td>3</td>
<td>0.5</td>
<td>50</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>2.0</td>
<td>10</td>
<td>150</td>
</tr>
<tr>
<td>5</td>
<td>2.0</td>
<td>50</td>
<td>0</td>
</tr>
<tr>
<td>6</td>
<td>0.5</td>
<td>10</td>
<td>150</td>
</tr>
<tr>
<td>7</td>
<td>0.5</td>
<td>10</td>
<td>0</td>
</tr>
<tr>
<td>8</td>
<td>2.0</td>
<td>50</td>
<td>150</td>
</tr>
</tbody>
</table>

Table 5-4. Experiment Set A - Full factorial matrix.

The response variable in these designs is the fluid level, or the sensor output in voltage. Arizona Dust is used as contamination in these experiments. The full factorial DOE used in this experiment uses only extreme values for each variable to minimise the number of runs and assumes linear relationship between low and high value. The main objective is to understand the trend as to how each variable affects the accuracy (main effects) of the sensor response and interaction between variables (interactions).

5.4.3 Experimental Setup
Experiment Set A is setup to implement the aforementioned factorial design. A fuel tank with 50 litres of Exxsol D-40 Stoddard solvent is firmly mounted on the Linear Actuator, as described in Section 5.3.2. The capacitive sensor described in section 5.3.1 is mounted on top of the fuel tank. The sensor cable is connected to the Data Acquisition Card (DAQ Card). LabVIEW software is then run and the response of the sensor is obtained and stored. The capacitive sensor signal is sampled at 10 Hz sampling frequency. An overview of the experiment setup is illustrated in Figure 5.9.

![Figure 5.9. Overview of the Experimental Setup for Experiment Set A.](image)

The experiment is run according to the run order shown in Table 5-4. The linear actuator is used to create slosh waves in the fuel tank. The frequency of the slosh is controlled by the Programmable Logic Controller (PLC) Timer described in 5.3.3. For heating the fluid up to 50 °C, a heating chamber is used (refer Section 5.3.4). Each experiment order shown in Table 5-4 is run for 60 seconds and the response of the capacitive sensor is recorded throughout the run period.
5.5 EXPERIMENT SET B – Performance estimation of Static & Dynamic Neural Networks

5.5.1 Overview

Experiment Set B is performed to compare the performance of static and dynamic neural networks. The data samples obtained from these experiments are used to train and validate three different neural networks: BP network, Discrete Time-delay Network, and NARX network. For simplicity, only four volume levels are used in the experiments. The influence of Arizona Dust Samples (contaminant) on the sensor output is observed in the results of Experiment Set A to be very small; therefore the influence of the contamination factor is ignored in Experiment Set B. However, temperature changes have a significant effect on the output of the capacitive sensor and hence the temperature readings are observed and recorded during this experiment.
5.5.2 Experimental Setup

The setup for these sensor experiments is similar to the setup described for Experiment Set A. The fuel tank is filled with Exxsol D-40 at four different tank volumes: 40 L, 45 L, 50 L, and 55 L. The capacitive sensor is fitted near the center of the tank. The tank is firmly mounted onto the linear actuator. The actuator is controlled by a pulse timer. The range of slosh frequency with very significant amplitude observed during a normal drive (refer Section 4.4) is 0.0 Hz to 2.0 Hz based on the initial study performed in the vehicle (this will be explained in more detail in the Chapter 6). Hence in this experiment, the range of slosh frequency generated by the linear actuator is also fixed at 0.0 Hz to 2.0 Hz. The slosh frequency or the cycle of linear actuator could be selected from 0.0 Hz to 2.0 Hz at an interval of 0.2 Hz. The complete factorial matrix is shown in Table 5-5.
<table>
<thead>
<tr>
<th>Run Order</th>
<th>Slosh Freq. (Hz)</th>
<th>Tank Volume (L)</th>
<th>Run Order</th>
<th>Slosh Freq. (Hz)</th>
<th>Tank Volume (L)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>40</td>
<td>23</td>
<td>0</td>
<td>50</td>
</tr>
<tr>
<td>2</td>
<td>0.2</td>
<td>40</td>
<td>24</td>
<td>0.2</td>
<td>50</td>
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<tr>
<td>3</td>
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<td>0.6</td>
<td>50</td>
</tr>
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<td>5</td>
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<td>27</td>
<td>0.8</td>
<td>50</td>
</tr>
<tr>
<td>6</td>
<td>1</td>
<td>40</td>
<td>28</td>
<td>1</td>
<td>50</td>
</tr>
<tr>
<td>7</td>
<td>1.2</td>
<td>40</td>
<td>29</td>
<td>1.2</td>
<td>50</td>
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<td>1.4</td>
<td>50</td>
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<td>31</td>
<td>1.6</td>
<td>50</td>
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<td>1.8</td>
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<td>50</td>
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<td>12</td>
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<td>55</td>
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<td>35</td>
<td>0.2</td>
<td>55</td>
</tr>
<tr>
<td>14</td>
<td>0.4</td>
<td>45</td>
<td>36</td>
<td>0.4</td>
<td>55</td>
</tr>
<tr>
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<td>0.6</td>
<td>45</td>
<td>37</td>
<td>0.6</td>
<td>55</td>
</tr>
<tr>
<td>16</td>
<td>0.8</td>
<td>45</td>
<td>38</td>
<td>0.8</td>
<td>55</td>
</tr>
<tr>
<td>17</td>
<td>1</td>
<td>45</td>
<td>39</td>
<td>1</td>
<td>55</td>
</tr>
<tr>
<td>18</td>
<td>1.2</td>
<td>45</td>
<td>40</td>
<td>1.2</td>
<td>55</td>
</tr>
<tr>
<td>19</td>
<td>1.4</td>
<td>45</td>
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</tr>
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<td>21</td>
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<td>43</td>
<td>1.8</td>
<td>55</td>
</tr>
<tr>
<td>22</td>
<td>2</td>
<td>45</td>
<td>44</td>
<td>2.0</td>
<td>55</td>
</tr>
</tbody>
</table>

Table 5-5. Experiment Set B - Full factorial matrix.
Figure 5.11. Experimental Setup for Experiment Set B.

Figure 5.11 shows a block diagram of this experimental setup. The level signal from the capacitive sensor is acquired by LabVIEW using a Data Acquisition Card that is connected to the capacitive sensor. The capacitive signal indicating the fuel level is sampled and recorded at 100 Hz.

5.5.3 BP Network Architecture

The backpropagation network is constructed using MATLAB software. The network is constructed with 64 neurons at the hidden layer (63 neurons represent slosh frequency range from 0 – 6.3 Hz in increments of 0.1 Hz and 1 neuron represents signal median value after signal smoothing is performed). The number of neurons in the hidden layer is the same as the number of input neurons. The transfer functions of the hidden and the output layers are \textit{tansig} and \textit{purelin} respectively, which are
described in Section 3.3.2. An illustration of the BP network architecture is shown in Figure 5.12. The input vector \( p \) consists of a total of sixty-four signal features, where sixty-three are the frequency coefficients of the slosh signal after performing \( \text{fft} \) on it, and one vector element is the median value of the raw signal. The sixty-three value of the number of coefficients is derived from the observation described in Section 4.4. It was observed that slosh frequency response was generally less than 6.3 Hz. Hence, the frequency coefficients were filtered to 63 values before processing them through the artificial neural network.

![Backpropagation Network Architecture](image)

**Figure 5.12. Backpropagation Network Architecture.**

### 5.5.4 Distributed Time-Delay Network Architecture

The Distributed Time-Delay Neural Network (DTDNN) is developed as a two layered Distributed time-delay neural network. There were five neurons in the hidden layer (Layer 1) and one neuron in the output layer. The input vector \( p \) is the same as that used in the BP network, consisting of sixty-three frequency coefficients and one median value of the raw signal. The sixty-three frequency coefficients represent the 0–6.3 Hz range of typical slosh frequency observed during a normal
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test drive described in Section 4.4. Figure 5.13 shows an overview of the DTDNN architecture.

![Figure 5.13. Distributed Time-delay Neural Network Architecture.](image)

Table 5-6 lists the values of the Distributed Time-delay Neural Network parameters.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R$</td>
<td>Number of Input Features of the raw level signal</td>
<td>64</td>
</tr>
<tr>
<td>$p(t)$</td>
<td>Features of the raw level signal</td>
<td>Matrix of $64 \times 1$ features</td>
</tr>
<tr>
<td>$d^1$</td>
<td>Layer1 Delay Tap Line</td>
<td>0:2</td>
</tr>
<tr>
<td>$d^2$</td>
<td>Layer2 Delay Tap Line</td>
<td>0:1</td>
</tr>
<tr>
<td>$S^1$</td>
<td>Layer1 Neurons</td>
<td>5</td>
</tr>
<tr>
<td>$S^2$</td>
<td>Layer2 Neurons</td>
<td>1</td>
</tr>
</tbody>
</table>

**Table 5-6. Distributed Time-delay Neural Network Parameters.**
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5.5.5 NARX Network Architecture

The NARX network is also developed as a two layered dynamic network. There are four neurons in the hidden layer (Layer 1) and one neuron in the output layer. The input vector \( p \) is the same as that used in the BP and DTDNN networks, which have sixty-three frequency coefficients and one median value of the raw signal. The sixty-three frequency coefficients number represents the 0–6.3 Hz range of typical slosh frequency observed during a normal test drive described in Section 4.4. Figure 5.13 shows an overview of the NARX network architecture.

![Figure 5.14. NARX Network Architecture.](image)

Table 5-7 lists the values of the NARX network parameters.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( R )</td>
<td>Number of Input Features of the raw level signal</td>
<td>64</td>
</tr>
<tr>
<td>( p(t) )</td>
<td>Features of the raw level signal</td>
<td>Matrix of 64x1 features</td>
</tr>
<tr>
<td>( d^1 )</td>
<td>Layer1 Delay Tap Line</td>
<td>0:1</td>
</tr>
<tr>
<td>( d^2 )</td>
<td>Layer2 Delay Tap Line</td>
<td>0:1</td>
</tr>
<tr>
<td>( S^1 )</td>
<td>Layer1 Neurons</td>
<td>4</td>
</tr>
<tr>
<td>( S^2 )</td>
<td>Layer2 Neurons</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 5-7. NARX Network Parameters.

5.6 EXPERIMENT SET C - Performance Estimation using Signal Enhancement

5.6.1 Overview

Experiment Set C is carried out to investigate the effectiveness of using the artificial neural network based approach when the raw sensor signals are smoothened using a set of signal enhancement functions. Several consecutive field trials are carried out by driving a vehicle containing the fuel tank to obtain training and validation data from the capacitive sensor operating under the effects of sloshing. Firstly, feature extraction functions are configured and an optimal size of the input vector is determined by experimentation. Secondly, optimal configurations of the signal smoothing functions (described in Section 3.2.3) and the filter tap size are determined. Finally, the most appropriate configurations of the ANN based system is used to compare the accuracy of the ANN based measurement system with the currently used averaging methods. Figure 5.15 shows an overview of the experimental setup for Experiment C.
Figure 5.15. Experimental Setup for Experiment Set C.

The level signal from the capacitive sensor is acquired using LabVIEW and a Data Acquisition Card, which is connected to the capacitive sensor in the vehicle. The capacitive sensor signal indicating the fuel level is sampled and recorded at 100 Hz. The sampled level signal is gathered over twenty seconds, which is the typical hold-on time used in automotive vehicles for averaging the fuel level signal. This collective signal over twenty seconds is then filtered using three investigated filtration methods. After filtration, feature extraction is performed on the filtered signals using the MATLAB built-in Fast Fourier Transform (fft), Discrete Cosine Transform (dct) and Discrete Wavelet Transform (dwt) functions described in Section 3.2.4. The obtained coefficients (coef) from the transformation function, the median (med) value of the raw signal, and the value of the ambient temperature ($T$)
in the tank, are stored in the input vector for training and classification of the ANN based signal processing system.

### 5.6.2 Backpropagation Network Architecture

All four Backpropagation neural networks investigated share a common network configuration that consists of a single hidden layer with sixty-four neurons as input, which is the same as the number of input coefficients. The sixty-three frequency coefficients number represents the 0–6.3 Hz range of typical slosh frequency observed during a normal test drive described in Section 4.4. The transfer functions of the hidden and the output layers are `tansig` and `purelin`, respectively, which are described in Section 3.3.2. The structure of each BP neural network is shown in Figure 5.16.

![Figure 5.16. Architecture of the BP neural network.](image)

Input \( p \) is passed through input layer weights \( IW \), and the sum of the product \( IWp \) and the bias \( b_1 \) is fed into the `tansig` transfer function. In the output layer, the output from the `tansig` function is multiplied by the output layer weights \( LW \). Finally an output
volume is produced by the \textit{purelin} function by using \textit{LW} and bias \textit{b}_2. A general equation to determine the tank volume in a particular tank based on the slosh data \textit{p} can be described as [21] [118]:

\[
Volume(p) = \text{purelin}[LW(\text{tansig}(IW \ p + b_1)) + b_2]
\]  

The hidden layer weights (IW), output layer weights (LW) and the biases (\textit{b}_1 and \textit{b}_2) are obtained using the MATLAB Neural Network Toolbox after the network has been trained.

\textbf{5.6.3 Experimental Setup}

A fuel tank is fitted with a capacitive sensor near the center of the tank. The tank can be approximated as a rounded edge rectangle with dimensions 34 \times 34 \times 81 cm. The fuel tank is filled with fuel levels ranging from 5 – 50 L in the experiment, which corresponds to 6\% - 70\% of the tank capacity. Due to the limited length of the capacitive sensor tube used in the experiment, fuel levels below 5 L could not be determined. The fuel tank is mounted in latitudinal direction, where the longest length of the tank is in parallel to the direction of the vehicle. Table 5-8 lists all the fuel levels investigated in the experiment.

<table>
<thead>
<tr>
<th>Investigated Tank Levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>5L, 6L, 7L, 8L, 9L,</td>
</tr>
<tr>
<td>15L, 20L, 25L, 30L,</td>
</tr>
<tr>
<td>35L, 36L, 37L, 38L, 39L, 40L,</td>
</tr>
<tr>
<td>45L, 46L, 47L, 48L, 49L, 50L</td>
</tr>
</tbody>
</table>
Table 5-8. List of tank volumes investigated in the experiment.

The capacitive sensor is calibrated to the ambient temperature and the fuel. Each experiment is conducted by driving a vehicle containing the instrumented fuel tank for 3 km in a suburban residential area, where occasional stops are made at some road intersections. Figure 5.17 shows the typical speed and acceleration observed during the experiment.

![Figure 5.17. Typical speed and acceleration observed during the experiment.](image-url)

For the selection of appropriate parameter values for the input window size ($\omega$), feature extraction function, and the size of the input features, a factorial table (Table 5-10) of all feasible test values is generated according to the test conditions listed in Table 5-9. Each test in Table 5-10 is evaluated using an ANN based signal processing model and the capacitive signal samples obtained from the field trials.
### Table 5-9. Test conditions for the evaluation of ANN input configuration.

<table>
<thead>
<tr>
<th>Test #</th>
<th>Window size (sec)</th>
<th>Coef. func</th>
<th>Coef. size</th>
<th>Test #</th>
<th>Window size (sec)</th>
<th>Coef. func</th>
<th>Coef. size</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>5</td>
<td>FFT</td>
<td>63</td>
<td>16</td>
<td>10</td>
<td>DCT</td>
<td>100</td>
</tr>
<tr>
<td>2</td>
<td>5</td>
<td>FFT</td>
<td>100</td>
<td>17</td>
<td>10</td>
<td>WT</td>
<td>63</td>
</tr>
<tr>
<td>3</td>
<td>5</td>
<td>DCT</td>
<td>63</td>
<td>18</td>
<td>10</td>
<td>WT</td>
<td>100</td>
</tr>
<tr>
<td>4</td>
<td>5</td>
<td>DCT</td>
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<td>19</td>
<td>14</td>
<td>FFT</td>
<td>63</td>
</tr>
<tr>
<td>5</td>
<td>5</td>
<td>WT</td>
<td>63</td>
<td>20</td>
<td>14</td>
<td>FFT</td>
<td>100</td>
</tr>
<tr>
<td>6</td>
<td>5</td>
<td>WT</td>
<td>100</td>
<td>21</td>
<td>14</td>
<td>DCT</td>
<td>63</td>
</tr>
<tr>
<td>7</td>
<td>7</td>
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<td>DCT</td>
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<td>8</td>
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<td>100</td>
<td>23</td>
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<td>WT</td>
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<td>9</td>
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<td>14</td>
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<td>20</td>
<td>FFT</td>
<td>100</td>
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<td>12</td>
<td>7</td>
<td>WT</td>
<td>100</td>
<td>27</td>
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<td>DCT</td>
<td>63</td>
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<td>13</td>
<td>10</td>
<td>FFT</td>
<td>63</td>
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<td>100</td>
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<td>63</td>
<td>30</td>
<td>20</td>
<td>WT</td>
<td>100</td>
</tr>
</tbody>
</table>

### Table 5-10. Complete factorial table for the evaluation of ANN input configuration.
The selection of appropriate parameter values for the smoothing function, feature extraction function, and the tap size of the smoothing filter, a factorial table (Table 5-12) of all feasible test values is generated according to the test conditions listed in Table 5-11. Each test in Table 5-12 is also implemented using ANN based signal processing model and the capacitive signal samples obtained from the field trials.

<table>
<thead>
<tr>
<th>Coef. Function</th>
<th>Signal Smoothing Function</th>
<th>Filter Tap Size</th>
</tr>
</thead>
<tbody>
<tr>
<td>FFT, DCT, WT</td>
<td>Moving Mean, Moving Median, Wavelet Filter</td>
<td>5, 10, 15</td>
</tr>
</tbody>
</table>

Table 5-11. Test conditions for the evaluation of optimal signal smoothing function configurations.
## Table 5-12. Complete factorial table for the evaluation of optimal signal smoothing function configurations.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
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<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>FFT</td>
<td>Mov. Mean</td>
<td>5</td>
<td>15</td>
<td>DCT</td>
<td>Mov. Median</td>
<td>15</td>
</tr>
<tr>
<td>2</td>
<td>FFT</td>
<td>Mov. Mean</td>
<td>10</td>
<td>16</td>
<td>DCT</td>
<td>Wavelet</td>
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</tr>
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<td>3</td>
<td>FFT</td>
<td>Mov. Mean</td>
<td>15</td>
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<td>DCT</td>
<td>Wavelet</td>
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<tr>
<td>4</td>
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<td>Mov. Median</td>
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</tr>
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<td>6</td>
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<td>Mov. Mean</td>
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<tr>
<td>7</td>
<td>FFT</td>
<td>Wavelet</td>
<td>5</td>
<td>21</td>
<td>WT</td>
<td>Mov. Mean</td>
<td>15</td>
</tr>
<tr>
<td>8</td>
<td>FFT</td>
<td>Wavelet</td>
<td>10</td>
<td>22</td>
<td>WT</td>
<td>Mov. Median</td>
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<tr>
<td>9</td>
<td>FFT</td>
<td>Wavelet</td>
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<td>Mov. Median</td>
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<tr>
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<td>Wavelet</td>
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<td>Wavelet</td>
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<td>13</td>
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<td>10</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
5.7 NEURAL NETWORK DATA PROCESSING

Once the training and validation data samples are obtained from the experiments, three types of neural network architectures are investigated using the MATLAB software. The following flowchart describes the procedure adopted to train and validate the artificial neural networks.

Figure 5.18. Neural Network Training and Validation Program.
The three types of neural networks investigated in the research are the following, which are described in Section 3.4.3:

- Backpropagation Network (static)
- Distributed Time-Delay Network (TDNN, Dynamic feed-forward)
- NARX Network (Dynamic feedback/recurrent)

Investigation of each type of neural network followed the same methodology as illustrated in Figure 5.18. However, the network creation and initialisation of parameter processes are different for each network type. The complete program code for each experiment is provided in Appendix C.

5.7.1 Network Initialization

In network initialisation, the network type is defined and initialised with the required input parameters. These parameters are different for each network type. The parameters consists of the number of network layers, number of neurons in each layer, transfer functions, and the range of input-output values.

5.7.2 Raw Signal Data

The signal data is stored in files and folders that represent the conditions set in the experiment runs. Basically, the folders are named by the fluid volumes and the raw-data files are named by the slosh frequency or the set frequency of the linear actuator. Additionally, there is an extra file for each raw-data file that contains the experiment run configurations such as Volume, Slosh Frequency and Temperature values.
CHAPTER 5 - EXPERIMENTATION

The raw signals are loaded up and pre-processing is performed. The frequency coefficients are obtained using the integrated FFT function in MATLAB. The magnitude of the coefficients of the raw signal, the median value, and the temperature value are all bundled in a cell array, which is called SignalsDB. The following table shows the format of SignalsDB array consisting of \( n \) number of signals.

<table>
<thead>
<tr>
<th>Index</th>
<th>Run</th>
<th>1</th>
<th>2</th>
<th>…</th>
<th>( n )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Raw Signal Filename</td>
<td>Raw Signal Filename</td>
<td>…</td>
<td>Raw Signal Filename</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Slosh Frequency</td>
<td>Slosh Frequency</td>
<td>…</td>
<td>Slosh Frequency</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Actual Volume</td>
<td>Actual Volume</td>
<td>…</td>
<td>Actual Volume</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Temperature</td>
<td>Temperature</td>
<td>…</td>
<td>Temperature</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Average Raw value</td>
<td>Average Raw value</td>
<td>…</td>
<td>Average Raw value</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>[Input Vector ( \mathbf{x} )]</td>
<td>[Input Vector ( \mathbf{x} )]</td>
<td>…</td>
<td>[Input Vector ( \mathbf{x} )]</td>
<td></td>
</tr>
</tbody>
</table>

Table 5-13. Cell-array containing details of the training signal features.

5.7.3 Filtration

The three investigated filters used in the analysis of the neural network system are developed in MATLAB. The Moving Mean and Moving Median filters are developed using the equations (4.5) and (4.6), described in section 4.5. Whereas, the Wavelet filter used in the analysis is already contained in the Wavelet Toolbox [106] in MATLAB. The following commands are used in MATLAB to filter a signal \( s \) with the moving window size of \( w \).
Filter | Filter Call Function
---|---
Moving Mean | $\text{avgMean}(s, w)$
Moving Median | $\text{avgMedian}(s, w)$
Wavelet | $\text{waveletfilter}(s)$

Table 5-14. Call functions to smoothen the input signals.

The MATLAB code for these filtration functions is contained in Appendix D.

### 5.7.4 Feature Extraction

Feature extraction is performed using the MATLAB built-in FFT function. To obtain the magnitude of the frequency coefficients of the sampled signal $s$ consisting of $L$ number of sample points, the following MATLAB commands are used:

```matlab
% perform fft on the input signal s
fff_coefficients = abs(fft(s));

% remove symmetry due to the complex numbered values
Signal_Features = fff_coefficients (1:L/2+1)/L;

% reduce the number of coefficients to 63
Signal_Features = fff_coefficients (1:63);
```

### 5.7.5 Network Training

The neural network is trained once the training and target vectors have been loaded. Network parameters such as training function, maximum epoch, learning rate and goal are set prior to calling the training function. The training function used in MATLAB is called `train`, whose parameters are the network object, training vectors, and target vectors. These vectors are prepared from the raw sensor signals, as shown in Table 5-13.
5.7.6 Network Validation

A trained network is validated in MATLAB by using the *sim* function. The validation function uses the network object and the test signals as the function parameters. The test samples are also placed in the cell vector after pre-processing them with the FFT function. The output of *sim* function produced the predicted fluid level, which is later compared with the actual fluid level that exists in the vehicle.
CHAPTER 6 – RESULTS

6.1 OVERVIEW

This chapter discusses the results obtained from the three sets of experiments described in Chapter 5. Experiment Set A results showing the response of the capacitive sensor in a dynamic environment without using the Artificial Neural Network based signal processing system are provided in Section 6.2. Results for Experiment Sets B and C consisting of raw capacitive sensor signals, training samples, and validation results are presented in the following sections.

6.2 EXPERIMENT SET A

6.2.1 Main Effects Plot

The results obtained from Experiment Set A are used to present Main Effects plots of the three factors that influence the accuracy of the level measurement system. The importance of Main Effects and Interaction plots was discussed in Section 4.6.

The output of the capacitive sensor was recorded for each experiment trial described in Section 5.4. The capacitive sensor signal sampled at 10 Hz was averaged over 60 seconds to produce an averaged voltage that represented the fuel level. Table 6-1 shows the results obtained from Experiment A.
### Table 6-1. Average volume readings obtained in Experiment Set A.

<table>
<thead>
<tr>
<th>Run Order</th>
<th>Slosh Freq. (Hz)</th>
<th>Temperature (°C)</th>
<th>Contamination (g)</th>
<th>Avg. Volume (L)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2.0</td>
<td>10</td>
<td>0</td>
<td>47.7</td>
</tr>
<tr>
<td>2</td>
<td>0.5</td>
<td>50</td>
<td>150</td>
<td>58.8</td>
</tr>
<tr>
<td>3</td>
<td>0.5</td>
<td>50</td>
<td>0</td>
<td>58.6</td>
</tr>
<tr>
<td>4</td>
<td>2.0</td>
<td>10</td>
<td>150</td>
<td>45.2</td>
</tr>
<tr>
<td>5</td>
<td>2.0</td>
<td>50</td>
<td>0</td>
<td>48.0</td>
</tr>
<tr>
<td>6</td>
<td>0.5</td>
<td>10</td>
<td>150</td>
<td>49.9</td>
</tr>
<tr>
<td>7</td>
<td>0.5</td>
<td>10</td>
<td>0</td>
<td>51.9</td>
</tr>
<tr>
<td>8</td>
<td>2.0</td>
<td>50</td>
<td>150</td>
<td>52.7</td>
</tr>
</tbody>
</table>

The Main effects plots are shown in the following figures. The graphs show the degree of influence caused by the three influential factors: Slosh, Contamination, and Temperature. It can be observed that the fuel volume is influenced by the liquid slosh and the temperature changes. However, the main effects plot for contamination, shown in Figure 6.3, indicates that the changes in contamination level had little effect on the fuel volume.
CHAPTER 6 – RESULTS

Figure 6.1. Main Effects Plot for Slosh

Figure 6.2. Main Effects Plot for Temperature.
6.2.2 Interaction Plots

To observe the interaction between the influencing factors, results obtained from Experiment Set A were used to generate the Interaction Plot. Figure 6.4 shows the interaction plot for volume between the three influencing factors.
The interaction plot shows that there is no significant interaction between the three influential factors. However, the interaction plot revealed that there is some interaction between Temperature and Slosh factors. As the temperature increases, the volume indicated by the capacitive sensor also increases, suggesting that the response of the capacitive sensor changes with temperature.
6.2.3 Summary

The three influencing factors proposed to have an impact on the level measurement were the following:

- Liquid Slosh,
- Temperature, and
- Contamination

It can be seen from the Main effect plots that the effects of Slosh and Temperature are significant compared with the effects of Contamination. A reason for this negligible effect of contamination on the level measurement could be that the Arizona Dust did not affect the properties of the fluid. Figure 6.4 shows the interaction plot of the influential factors. The interaction plot shows that there is no significant interaction between contamination and the other two factor being slosh and temperature. Hence, according to the observed results, the contamination factor is independent of temperature and slosh. But there is some interaction observed between temperature and slosh. As the temperature increases to 50 °C, the volume signal is also observed to increase.

6.3 EXPERIMENT SET B

After obtaining the training samples from Experiment Set B, the training data at various tank volumes and slosh frequencies is stored in several files. These signals are loaded and classified in terms of their frequency response and their median value. Figure 6.5 shows the average fuel level data over 10 seconds obtained at various
initial volume levels and generated slosh frequencies with the linear actuator. It can be seen that the average volume reading at various acceleration or slosh values is not constant.

![Capacitive Slosh Test](image_url)

**Figure 6.5.** Average Volume of the tank measured over 10 seconds at selected slosh frequencies.

However, after training and validating the static and dynamic neural network models, the results indicate that the fluid levels can be ascertained to a much higher accuracy (Figure 6.31), when compared with the simple averaging method indicated in Figure 6.5.

### 6.3.1 Frequency Coefficients

The raw signals obtained from Experiment Set B are transformed into the frequency domain using the MATLAB built-in `fft` function. **Figure 6.6** shows the frequency coefficients surface plot of the raw capacitive type level sensor signals.
CHAPTER 6 – RESULTS

6.3.2 Backpropagation Network

Figure 6.6. Frequency coefficients surface plot.
Figure 6.7. Validation result for the static feed-forward backpropagation neural network.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Epochs</td>
<td>2821</td>
</tr>
<tr>
<td>Performance</td>
<td>0.01</td>
</tr>
<tr>
<td>Time</td>
<td>00:01:05</td>
</tr>
<tr>
<td>Training algorithm</td>
<td>Trainscg</td>
</tr>
<tr>
<td>Input neurons</td>
<td>64</td>
</tr>
<tr>
<td>No. of Inputs</td>
<td>64</td>
</tr>
</tbody>
</table>

Table 6-2. BP Network simulation performance results.
Figure 6.8. Backpropagation network training performance.
6.3.3 Distributed Time-Delay Network

Figure 6.9. Validation results of the Distributed Time-Delay Neural Network.

Figure 6.9. Validation results of the Distributed Time-Delay Neural Network.
6.3.4 NARX Neural Network

Figure 6.10. Validation result of the NARX (dynamic feedback) Neural network.

6.3.5 Summary

The MATLAB simulation and validation results for Experiment Set B show that the Backpropagation neural network produced the most accurate results. Both types of dynamic networks (shown in Figure 6.9 and Figure 6.10) were able to provide highly accurate results only when the input vectors were in the sequential order as the training vectors. However, the input data in these simulations was deliberately set
out-of-sequence, to create a randomized input, to compare the effects of the time delay and feedback associated with dynamic networks.

Table 6-3 summarises the error results obtained using the averaging method and the three investigated network topologies.

<table>
<thead>
<tr>
<th>Method</th>
<th>Network Type</th>
<th>Avg. Error</th>
<th>Max. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simple Averaging</td>
<td>N/A</td>
<td>32.43%</td>
<td>68.44%</td>
</tr>
<tr>
<td>Feed-Forward Back-propagation (BP)</td>
<td>Static</td>
<td>0.04%</td>
<td>0.11%</td>
</tr>
<tr>
<td>Distributed Time-Delay</td>
<td>Dynamic without feedback</td>
<td>0.84%</td>
<td>8.67%</td>
</tr>
<tr>
<td>NARX Network</td>
<td>Dynamic with feedback (Recurrent)</td>
<td>0.12%</td>
<td>2.60%</td>
</tr>
</tbody>
</table>

Table 6-3. Summary of the results obtained from three types of neural networks.

The overall results obtained from Experiment Set B using the three neural network topologies indicate remarkable reduction in slosh error, when the results are compared with the results obtained by simple averaging as is done in practice at present (see Figure 6.5).
CHAPTER 6 – RESULTS

6.4 EXPERIMENT SET C

The training samples obtained from Experiment Set C were processed with MATLAB using the methodology described in Section 5.3. The raw signals in this experiment were filtered through different filtration functions before the signals were trained by the artificial neural network based signal processing system. There were twenty test drive trials at different fuel levels that were carried out in this experiment, where each drive trial was conducted over a distance of three kilometres. This section provides details on the raw signals obtained from the capacitive sensor during the course of this experiment. The frequency coefficients plot, the network weights coefficients, the validation results, and the validation error plots for all drive trials (at different fuel quantity) are contained in this section.

6.4.1 Raw Capacitive Sensor Signals

The capacitive sensor signals throughout each drive trial are shown in the figures below. Each graph shows the trial data run for 280 seconds over the same drive route. These graphs clearly show the slosh created in the fuel tank over the drive path. The amplitude of slosh can be seen as varying for different tank volumes.
Figure 6.11. Raw capacitive sensor signals (49 and 50 L)

Figure 6.12. Raw capacitive sensor signals (47 and 48 L)
CHAPTER 6 – RESULTS

Figure 6.13. Raw capacitive sensor signals (45 and 46 L)

Figure 6.14. Raw capacitive sensor signals (39 and 40 L)
Figure 6.15. Raw capacitive sensor signals (37 and 38 L)

Figure 6.16. Raw capacitive sensor signals (35 and 36 L)
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Figure 6.17. Raw capacitive sensor signals (25 and 30 L)

Figure 6.18. Raw capacitive sensor signals (9 and 20 L)
CHAPTER 6 – RESULTS

Figure 6.19. Raw capacitive sensor signals (7 and 8 L)

Figure 6.20. Raw capacitive sensor signals (5 and 6 L)
6.4.2 Selection of Optimal Pre-Processing Parameters (Experiment Set C1)

Table 6-4 shows the results for the optimal pre-processing parameters evaluation test. The pre-processing configuration list in the table for each test number was applied on the raw capacitive sensor signals and then processed through the backpropagation neural network using MATLAB. The results obtained from each ANN test model are compared with the results obtained with standard statistical averaging methods (note: the Test # is the actual vehicle test run and Window size is the duration of test in seconds while data is recorded):

<table>
<thead>
<tr>
<th>Test #</th>
<th>Window size (ω)</th>
<th>Coef. func</th>
<th>Coef. size</th>
<th>Average Error (L)</th>
<th>Std. Deviation (L) Error</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Mean</td>
<td>Median</td>
</tr>
<tr>
<td>1</td>
<td>5</td>
<td>FFT</td>
<td>63</td>
<td>3.16</td>
<td>3.16</td>
</tr>
<tr>
<td>2</td>
<td>5</td>
<td>FFT</td>
<td>100</td>
<td>3.16</td>
<td>3.16</td>
</tr>
<tr>
<td>3</td>
<td>5</td>
<td>DCT</td>
<td>63</td>
<td>3.16</td>
<td>3.16</td>
</tr>
<tr>
<td>4</td>
<td>5</td>
<td>DCT</td>
<td>100</td>
<td>3.16</td>
<td>3.16</td>
</tr>
<tr>
<td>5</td>
<td>5</td>
<td>WT</td>
<td>63</td>
<td>3.16</td>
<td>3.16</td>
</tr>
<tr>
<td>6</td>
<td>5</td>
<td>WT</td>
<td>100</td>
<td>3.16</td>
<td>3.16</td>
</tr>
<tr>
<td>7</td>
<td>7</td>
<td>FFT</td>
<td>63</td>
<td>3.01</td>
<td>2.98</td>
</tr>
<tr>
<td>8</td>
<td>7</td>
<td>FFT</td>
<td>100</td>
<td>3.01</td>
<td>2.98</td>
</tr>
<tr>
<td>9</td>
<td>7</td>
<td>DCT</td>
<td>63</td>
<td>3.01</td>
<td>2.98</td>
</tr>
<tr>
<td>10</td>
<td>7</td>
<td>DCT</td>
<td>100</td>
<td>3.01</td>
<td>2.98</td>
</tr>
<tr>
<td>11</td>
<td>7</td>
<td>WT</td>
<td>63</td>
<td>3.01</td>
<td>2.98</td>
</tr>
<tr>
<td>12</td>
<td>7</td>
<td>WT</td>
<td>100</td>
<td>3.01</td>
<td>2.98</td>
</tr>
<tr>
<td>13</td>
<td>10</td>
<td>FFT</td>
<td>63</td>
<td>2.85</td>
<td>2.80</td>
</tr>
<tr>
<td>14</td>
<td>10</td>
<td>FFT</td>
<td>100</td>
<td>2.85</td>
<td>2.80</td>
</tr>
<tr>
<td>15</td>
<td>10</td>
<td>DCT</td>
<td>63</td>
<td>2.85</td>
<td>2.80</td>
</tr>
<tr>
<td>16</td>
<td>10</td>
<td>DCT</td>
<td>100</td>
<td>2.85</td>
<td>2.80</td>
</tr>
<tr>
<td>17</td>
<td>10</td>
<td>WT</td>
<td>63</td>
<td>2.85</td>
<td>2.80</td>
</tr>
<tr>
<td>18</td>
<td>10</td>
<td>WT</td>
<td>100</td>
<td>2.85</td>
<td>2.80</td>
</tr>
<tr>
<td>19</td>
<td>14</td>
<td>FFT</td>
<td>63</td>
<td>2.61</td>
<td>2.45</td>
</tr>
<tr>
<td>20</td>
<td>14</td>
<td>FFT</td>
<td>100</td>
<td>2.61</td>
<td>2.45</td>
</tr>
<tr>
<td>21</td>
<td>14</td>
<td>DCT</td>
<td>63</td>
<td>2.61</td>
<td>2.45</td>
</tr>
<tr>
<td>22</td>
<td>14</td>
<td>DCT</td>
<td>100</td>
<td>2.61</td>
<td>2.45</td>
</tr>
<tr>
<td>23</td>
<td>14</td>
<td>WT</td>
<td>63</td>
<td>2.61</td>
<td>2.45</td>
</tr>
<tr>
<td>24</td>
<td>14</td>
<td>WT</td>
<td>100</td>
<td>2.61</td>
<td>2.45</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Method</td>
<td></td>
<td>2.41</td>
<td>2.22</td>
</tr>
<tr>
<td>---</td>
<td>---</td>
<td>--------</td>
<td>---</td>
<td>------</td>
<td>------</td>
</tr>
<tr>
<td>25</td>
<td>20</td>
<td>FFT</td>
<td>63</td>
<td>2.41</td>
<td>2.22</td>
</tr>
<tr>
<td>26</td>
<td>20</td>
<td>FFT</td>
<td>100</td>
<td>2.41</td>
<td>2.22</td>
</tr>
<tr>
<td>27</td>
<td>20</td>
<td>DCT</td>
<td>63</td>
<td>2.41</td>
<td>2.22</td>
</tr>
<tr>
<td>28</td>
<td>20</td>
<td>DCT</td>
<td>100</td>
<td>2.41</td>
<td>2.22</td>
</tr>
<tr>
<td>29</td>
<td>20</td>
<td>WT</td>
<td>63</td>
<td>2.41</td>
<td>2.22</td>
</tr>
<tr>
<td>30</td>
<td>20</td>
<td>WT</td>
<td>100</td>
<td>2.41</td>
<td>2.22</td>
</tr>
</tbody>
</table>

Table 6-4. Results for the selection of optimal pre-processing configuration (Exp. C1).
Figure 6.21. Average Error Plot – optimal ANN pre-processing estimation.
Figure 6.22. Standard Deviation Error Plot – optimal ANN pre-processing estimation.

ANN Test - Optimal Filter Param. Estimation

Average Error (L)

Test No.

Coeff. Function

Window size
Figure 6.21 and Figure 6.22 show plots of the average and standard deviation error results obtained from the optimal ANN pre-processing estimation test. In general, both plots show significantly low error results for the ANN based signal processing model when compared with the two currently used statistical averaging methods (mean and median).

Figure 6.21 indicates that the optimal configuration for the ANN pre-processor is when it is configured with the parameters used in Test #25, which uses a window size of 20 seconds \( \omega = 20 \) sec, Fast Fourier Transform Function (FFT) as the feature extraction function and with 63 number of frequency coefficients. Figure 6.22 shows that the Standard Deviation Error was also the lowest for Test #25. Based on these observations, the optimal configuration for the ANN pre-processor system include: Fast Fourier Transform (FFT) as the optimal feature extraction functions, 63 as the number of signal coefficients, and a window size \( \omega \) of 20 seconds. The optimal configuration obtained in this test will be used to run the next test ‘C2 Selection of Optimal Signal Smoothing Parameters’. The results obtained using the Discrete Cosine Transform (DCT) function generally indicated a larger error when compared with the other two transformation functions (FFT and WT). However, by incorporating the signal smoothing technique with the DCT transformation function, the accuracy of the ANN based signal processing system might improve. Hence, DCT will also be examined along with the FFT and WT functions in the next text ‘C2 Selection of Optimal Signal Smoothing Parameters’.
6.4.3 Selection of Optimal Signal Smoothing Parameters (Exper. Set C2)

After obtaining the optimal pre-processing parameters in Experiment Set C1, Experiment set C2 was conducted to obtain optimal signal smoothing parameters. Experiment Set C2 was run to understand the significance and performance of signal smoothing technique in signal pre-processing. Table 6-5 lists the benchmark results of using different signal pre-processing approaches with the ANN based signal processing system. A graph of the results listed in this table is shown in Figure 6.23.
<table>
<thead>
<tr>
<th>Test #</th>
<th>Coef. Func.</th>
<th>Filter Func.</th>
<th>Filter Tap size</th>
<th>Avg. Error (L) [ANN]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Lower limit</td>
<td>Avg.</td>
</tr>
<tr>
<td>1</td>
<td>FFT</td>
<td>Mov. Mean</td>
<td>5</td>
<td>0.30</td>
</tr>
<tr>
<td>2</td>
<td>FFT</td>
<td>Mov. Mean</td>
<td>10</td>
<td>0.28</td>
</tr>
<tr>
<td>3</td>
<td>FFT</td>
<td>Mov. Mean</td>
<td>15</td>
<td>0.33</td>
</tr>
<tr>
<td>4</td>
<td>FFT</td>
<td>Mov. Median</td>
<td>5</td>
<td>0.23</td>
</tr>
<tr>
<td>5</td>
<td>FFT</td>
<td>Mov. Median</td>
<td>10</td>
<td>0.33</td>
</tr>
<tr>
<td>6</td>
<td>FFT</td>
<td>Mov. Median</td>
<td>15</td>
<td>0.34</td>
</tr>
<tr>
<td>7</td>
<td>FFT</td>
<td>Wavelet</td>
<td>5</td>
<td>0.31</td>
</tr>
<tr>
<td>8</td>
<td>FFT</td>
<td>Wavelet</td>
<td>10</td>
<td>0.31</td>
</tr>
<tr>
<td>9</td>
<td>FFT</td>
<td>Wavelet</td>
<td>15</td>
<td>0.32</td>
</tr>
<tr>
<td>10</td>
<td>DCT</td>
<td>Mov. Mean</td>
<td>5</td>
<td>0.41</td>
</tr>
<tr>
<td>11</td>
<td>DCT</td>
<td>Mov. Mean</td>
<td>10</td>
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</tr>
<tr>
<td>12</td>
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<td>Mov. Mean</td>
<td>15</td>
<td>0.43</td>
</tr>
<tr>
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<td>Mov. Median</td>
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</tr>
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<td>Mov. Median</td>
<td>10</td>
<td>0.43</td>
</tr>
<tr>
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<td>DCT</td>
<td>Mov. Median</td>
<td>15</td>
<td>0.44</td>
</tr>
<tr>
<td>16</td>
<td>DCT</td>
<td>Wavelet</td>
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<td>0.42</td>
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<td>Wavelet</td>
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</tr>
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<td>0.36</td>
</tr>
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<td>Mov. Mean</td>
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</tr>
<tr>
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<td>WT</td>
<td>Mov. Mean</td>
<td>10</td>
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</tr>
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<td>Mov. Mean</td>
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<tr>
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</tr>
<tr>
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<td>WT</td>
<td>Mov. Median</td>
<td>10</td>
<td>0.58</td>
</tr>
<tr>
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<td>WT</td>
<td>Mov. Median</td>
<td>15</td>
<td>0.54</td>
</tr>
<tr>
<td>25</td>
<td>WT</td>
<td>Wavelet</td>
<td>5</td>
<td>0.47</td>
</tr>
<tr>
<td>26</td>
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<tr>
<td>27</td>
<td>WT</td>
<td>Wavelet</td>
<td>15</td>
<td>0.46</td>
</tr>
</tbody>
</table>

Table 6-5. Results for the selection of optimal signal smoothing parameters (Exp. C2).
Figure 6.23. Optimal ANN pre-processing filter parameter estimation.
Figure 6.23 shows the influence of signal filtration on the ANN based signal processing system. The results shown in Figure 6.23 indicate that the ANN based system provides the best results when it is configured with the configurations used in Test #4. Test #4 was configured with the window size of 20 sec (\( \omega = 20 \)), FFT as the feature extraction function, 63 number of coefficients, and Moving Median function as the signal smoothing function with the filter tap-size of 5. Figure 6.23 also indicates that the error results obtained using FFT function were generally less than the errors obtained from the other two transformation functions WT and DCT. The WT function indicated a poor performance, when compared with FFT and DCT. The configurations used in test #4 will be used in the next test to observe the performance of the ANN based signal classification system at different tank volumes.

### 6.4.4 Final Validation Results (Experiment Set C3)

A final model of the ANN based signal processing system was synthesised based on the results observed in the previous experiments. The selected optimal values of the ANN pre-processor and the signal smoothing techniques were used to create a final version of the ANN based signal processing and classification model. The configuration of the synthesised ANN model is shown in Figure 6.24.
CHAPTER 6 – RESULTS

6.4.5 Frequency Coefficients

The raw signals obtained from the test drives were transformed into the frequency-domain using the MATLAB’s built-in Fast Fourier Transform (fft) module. The frequency coefficients plot of the capacitive sensor signals is shown in Figure 6.25.

Figure 6.24. Synthesised ANN based measurement system model.

Window size (ω) = 20 sec = 20 s * 100 samples/s = 2000 samples
Feature reduction using filtration was described in Section 4.5. It was also described in Section 4.5 that the range of significant slosh frequency is 0-6.3 Hz. In this experiment, a low-pass filter was used to filter out slosh frequencies over 6.3 Hz. This was achieved to increase the network training speed without incurring a performance penalty. The frequency coefficients and the median value of the signals were all bundled in an array of sixty-four elements, which were then used to train and validate the neural network.

Figure 6.26 shows a broader view of the raw sensor signals in the time domain that were filtered through the investigated filters and then transformed into frequency domain using the FFT function. Along with the training samples, the corresponding target value or the actual value of the initial fuel level in the tank are also shown.
6.4.6 Network Weights

After training the neural network, the network was validated using the test samples obtained from the second field trial. Table 6-6 shows the performance speed of the neural network when the four methods of signal filtration were applied. It shows that the network speed was faster with the signals that were filtered through the wavelet filter.

<table>
<thead>
<tr>
<th>Signal Filtration method</th>
<th>Epochs Elapsed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unfiltered</td>
<td>9,597</td>
</tr>
<tr>
<td>Wavelet Filter</td>
<td>7,703</td>
</tr>
<tr>
<td>Moving Median</td>
<td>10,537</td>
</tr>
<tr>
<td>Moving Mean</td>
<td>8,032</td>
</tr>
</tbody>
</table>

Table 6-6. Number of lapsed epochs until the performance goal was reached.

Table 6-7 lists the neural network weights obtained from the network on which the Moving Median filter was applied. The weights can be substituted into equation (4.1) to produce the output volume.
### Input Weights (IW)

<table>
<thead>
<tr>
<th>Neurons</th>
<th>Coef₁</th>
<th>Coef₂</th>
<th>Coef₃</th>
<th>Coef₄</th>
<th>...</th>
<th>Coef₆₄</th>
</tr>
</thead>
<tbody>
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<td>2.01490</td>
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</tr>
<tr>
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<td>...</td>
<td>-0.55357</td>
</tr>
<tr>
<td>3</td>
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</tr>
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<td>-1.57140</td>
</tr>
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</table>

### Output Layer Weights (LW)

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</tbody>
</table>

Table 6-7. List of Input and output layers weights.
6.4.7 Validation Results

Figure 6.27 to Figure 6.29 show the neural network validation results for different input signals. The graphs shown in these figures can be used to compare the performance of the measurement system at different tank levels using both statistical averaging and neural network based signal classification approaches.

Figure 6.27. Network verification results for volumes 48-50L.

≈ 5.5L error
≈ 4.7L error
≈ 1.2 L error
Chapter 6 – Results

Figure 6.27 shows the output results for selected (lower and higher) tank volumes. The output results were obtained after processing the capacitive sensor signals with different processing methods. The time length of each trial is indicated as 280 seconds. The graphs in Figure 6.27 show fuel volumes averaged over the whole drive period of 280 seconds, after processing the signals through different processing methods. To describe the steps undertaken to obtain the overall averaged volume, a closer look at the investigated 49 litre trial is also shown in Figure 6.27. The raw sensor signal illustrated in Figure 6.27 (A) was divided into twenty-second long signals, as shown in Figure 6.27 (B), which were then filtered and processed through the neural network. The overall averaged volume in Figure 6.27 (C) was calculated by averaging the neural network outputs for each trial over the whole 280 second period.
Figure 6.28. Network verification results for volumes 38-47L.
Figure 6.29. Network verification results for volumes 5-37L.
6.4.8 Validation Error

Validation error was calculated by subtracting the observed average level from the actual or initial tank level. Table 6-8 shows the volume figures obtained using the statistical averaging functions, and the neural network using different pre-processing filters. Average error values at a particular investigated tank volume are shown in Table 6-9. All values listed in Table 6-8 and Table 6-9 are in litres.

<table>
<thead>
<tr>
<th>Actual Tank Volume</th>
<th>Statistical Averaging</th>
<th>Artificial Neural Networks</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Moving Mean*</td>
<td>Moving Median*</td>
</tr>
<tr>
<td>50</td>
<td>55.96</td>
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<td>53.74</td>
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<td>49.18</td>
</tr>
<tr>
<td>47</td>
<td>44.42</td>
<td>44.41</td>
</tr>
<tr>
<td>46</td>
<td>45.64</td>
<td>45.57</td>
</tr>
<tr>
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<tr>
<td>8</td>
<td>10.85</td>
<td>10.12</td>
</tr>
</tbody>
</table>
Table 6-8. Validation results using statistical averaging methods and the neural network approach with different pre-processing filters.

<table>
<thead>
<tr>
<th>Actual Tank Volume</th>
<th>Statistical Averaging</th>
<th>Artificial Neural Networks Methods</th>
</tr>
</thead>
<tbody>
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<td>Moving Mean*</td>
<td>Moving Median*</td>
</tr>
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<td>5.96</td>
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<tr>
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<td>2.58</td>
<td>2.59</td>
</tr>
<tr>
<td>46</td>
<td>0.36</td>
<td>0.43</td>
</tr>
<tr>
<td>45</td>
<td>0.94</td>
<td>1.19</td>
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<tr>
<td>40</td>
<td>0.04</td>
<td>0.04</td>
</tr>
<tr>
<td>39</td>
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<td>1.92</td>
</tr>
<tr>
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<td>0.25</td>
</tr>
<tr>
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<td>0.03</td>
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<td>0.92</td>
</tr>
<tr>
<td>35</td>
<td>0.39</td>
<td>0.09</td>
</tr>
<tr>
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<td>0.19</td>
</tr>
<tr>
<td>25</td>
<td>2.58</td>
<td>1.77</td>
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<td>20</td>
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<td>2.12</td>
</tr>
<tr>
<td>7</td>
<td>0.47</td>
<td>0.09</td>
</tr>
</tbody>
</table>

* Averaged filter values without using neural networks
Table 6-9. Validation error results for applied statistical and neural network methods.

6.4.9 Summary

Figure 6.30 shows the overall absolute average error plots at different tank volumes using the statistical averaging methods and using the neural network approach by adapting different filters.
It can be seen from the graph in Figure 6.30 that the average error produced by the simple Moving Mean and Moving Median functions without using the neural network is substantially large for lower volume ranges (8-25 L) as well as for higher volumes (47-50 L). However, the results obtained from the investigated BP networks indicate less error compared with the simple statistical methods. All four BP networks have shown significant success in determining the fuel level with high accuracy throughout the investigated volumes and especially at low fuel volumes. Determination of fuel volumes accurately is particularly important at low fuel volumes.
CHAPTER 6 – RESULTS

To summarise all the results, a graph shown in Figure 6.31 was prepared that plots the overall average errors obtained using the statistical methods and the four investigated Artificial Neural Networks.

![Graph showing investigation summary results]

**Figure 6.31.** Investigation summary results showing the maximum and average errors.
CHAPTER 7 – DISCUSSION

7.1 OVERVIEW

This chapter discusses the design and optimal selection of parameters of the ANN based signal processing system. The selection of optimal pre-processing parameters used in the ANN based measurement system and the results obtained from the experimentations, and the possible improvements to design of the ANN based system, are all discussed in this section.

7.2 BACKPROPAGATION NETWORK CONFIGURATIONS

The fuel level measurement system designed and evaluated in this research is based on a Backpropagation type of Artificial Neural Network. It was discussed in Section 3.3 that artificial neural networks with a sufficient number of neurons in the hidden layer can be trained to produce virtually any form of output curve. The choice of selecting a particular network configuration plays a crucial role in terms of the performance of Artificial Neural Networks. Hence, field trials were conducted to experimentally determine the most suitable configuration for the artificial neural network based fuel level measurement system.

In the experiment Set A a factorial design of experiment was run to understand the influence of slosh, temperature and contamination on the accuracy of the capacitive sensor without application of neural networks. Results of this experiment indicate that fluid slosh had the most significant influence on the sensor accuracy. Temperature also has an influence especially in situations with larger temperature
variances during experiments carried out in the laboratory but the effect was not as significant. During the vehicle field trial however the temperature of fuel was relatively constant and had no significant effect on the sensor accuracy. Finally the influence of contamination was not significant and was not taken into account in subsequent experiment sets B and C.

Experiment Set B was run to investigate the performance of the neural network based signal processing system using two sets of neural network architecture configurations: Static and Dynamic Neural Networks. The findings obtained from Experiment Set B indicated remarkable reduction in slosh error, when the results were compared with the results obtained from the simple averaging method. The Experiment Set B results provided in Table 6-3 showed that under dynamic sloshing conditions, the simple averaging method produced an average error of over 30%, whereas, the maximum error figures obtained using the neural network based signal processing methods were less than 10%.

The results obtained from Experiment Set B indicated that the Feed-Forwarded Backpropagation (BP) network that produced an average error of 0.04% was the most feasible neural network architecture for the classification of the capacitive fuel level signals in the current application. However, the results obtained from the other neural network topologies such as Distributed Time-Delay and NARX showed satisfactory classification results with average error of less than 1% (see Section 6.3.5). These results obtained using several different types of neural networks
showed good consistency in terms of the response of the neural network based measurement system to the measurement of fuel levels using the capacitive sensing system.

Based on the findings of Experiment Set B, in Experiment Set C, the Backpropagation (BP) neural network architecture was selected to further investigate the performance of the neural network based signal processing system. Specifically the influence of the number of hidden neurons on the system's classification accuracy were investigated. Another objective of Experiment Set C was to observe the effects of signal smoothing of input signals on the network classification accuracy. The outcomes of Experiment Set C are discussed in the following sections.

7.3. SELECTION OF SIGNAL PRE-PROCESSING PARAMETERS

To determine an appropriate configuration for the ANN based measurement system, it was important to determine the optimal parameters for the signal pre-processing functional block. That is, to determine an appropriate feature extraction function out of the three functions (FFT, DCT, WT) described in Section 3.2.4. Furthermore, the optimal size of the input window (ώ), and the size of the feature vector was important to be determined experimentally. For this purpose, Experiment Sec C was conducted and the training and validation samples obtained from the field trials were used to investigate the performance of the ANN based system based on the different
CHAPTER 7 – DISCUSSION

Types of feature extraction functions, different sizes of the input window (\(\omega\)), and different sizes of the feature vector.

The results obtained from Experiment Set C1 indicated that the optimal solution for the signal pre-processor configuration is obtained using the Fast Fourier Transform (FFT) function as the feature extraction function, with windows size (\(\omega\)) of 20 seconds and feature vector size of 63 coefficients. The overall performance of each of these parameters is shown in the following figures. The parameters that were found to be most feasible are circled in the result figures listed below.

Figure 7.1 shows the average performance of several ANN models having different number of coefficients investigated in Experiment Set C1. The overall performance of the neural network based classification system using both 63 and 100 hidden neurons is much the same.
Figure 7.1. Overall performance of the ANN based measurement system using different input coefficient sizes (error is in litres of tank fuel volume).

Figure 7.2. Overall performance of the ANN based measurement system using different feature extraction functions.
CHAPTER 7 – DISCUSSION

Figure 7.2 shows the overall performance of the three feature extraction functions used in the ANN based measurement system. The overall performance of the ANN based system using FFT is observed to be much better when compared with using WT and DCT based feature extraction functions.

![Average Error - Window size](image)

**Figure 7.3. Overall performance of the ANN based measurement system using different window sizes compared with existing statistical averaging methods.**

Figure 7.3 shows the performance of the ANN based measurement system when implemented with different window sizes ($\omega$). A window size of 5 means that the measurement system uses 5-second sampled data to process the output. Likewise, a window size of 14 means that the measurement system uses 14-second sampled data from the capacitive sensor to process and predict the output level. The graph shown in Figure 7.3 indicates that the window sizes have an effect on the error. The
CHAPTER 7 – DISCUSSION

Performance of the ANN based fluid level measurement system having different window sizes is generally seen as consistent and superior to the two statistical averaging methods (mean and median). The performance of the statistical averaging methods (without use of ANN) improves as the size of the input window increases, which illustrates the fact that a signal averaged over a longer period of time will produce a more converged and accurate reading. This is also the case with use of ANN although the effect of window size is less significant than with statistical averaging methods (Figure 7.3).

7.4 SELECTION OF SIGNAL SMOOTHING PARAMETERS

To investigate the performance of the ANN based measurement system, when applied with the signal smoothing capability, it was important to determine appropriate parameters for the signal smoothing configuration. That is, to determine an appropriate signal smoothing (filter) function out of the three functions (Moving Mean, Moving Median, Wavelet Filter) described in Section 4.5. Furthermore, the optimal size of the filter tap, and an appropriate feature extraction function was important to be determined experimentally. For this purpose, Experiment Set C2 was conducted and the training and validation samples obtained from the field trials were used to investigate the performance of the ANN based system based on the different types of signal smoothing functions, different feature extraction functions, and different sizes of the filter tap.
The results obtained from Experiment Set C2 indicated that the optimal solution for the signal pre-processor configuration is using the Fast Fourier Transform (FFT) function as the feature extraction function, and Moving Median with tap size of 5 as the signal smoothing function. The overall performance of each of these parameters is shown in the following figures. The parameters that were found to be most feasible are circled in the result figures below.

![Average Error - Filter Tap Sizes](image)

Figure 7.4. Overall performance of the ANN based measurement system using various filter tap sizes.
Figure 7.5. Overall performance of the ANN based measurement system using different signal smoothing functions.

Figure 7.6. Overall performance of the ANN based measurement system incorporating signal smoothing techniques with different feature extraction functions.
Figure 7.6 shows the overall performance of ANN based measurement system incorporating different feature extraction functions and signal smoothing technique.

Figure 7.6 shows a general improvement in the ANN based measurement system when incorporating the signal smoothing technique. The average performance of the feature extraction functions shown in Figure 7.2 (without signal smoothing feature) Figure 7.6 (with signal smoothing) indicate that the performance of the ANN based system has improved with the inclusion of the signal smoothing technique. The overall average error for the FFT function without the signal smoothing method was observed in Experiment C1 (Figure 7.2) as 0.92 L, but with the inclusion of the signal smoothing method, it has reduced to 0.75 L. The positive effect of signal smoothing on the neural network based signal processing system are also observable for DCT and WT based systems.

<table>
<thead>
<tr>
<th>Implemented Feature Extraction Function</th>
<th>Avg. Error (without signal smoothing) (Exp. Set C1)</th>
<th>Avg. Error (with signal smoothing) (Exp. Set C2)</th>
<th>Error Reduction</th>
</tr>
</thead>
<tbody>
<tr>
<td>FFT</td>
<td>0.92 L</td>
<td>0.75 L</td>
<td>18%</td>
</tr>
<tr>
<td>DCT</td>
<td>1.07 L</td>
<td>0.91 L</td>
<td>15%</td>
</tr>
<tr>
<td>WT</td>
<td>1.17 L</td>
<td>1.11 L</td>
<td>5%</td>
</tr>
</tbody>
</table>

Table 7-1- Influence of signal enhancement on the performance of the ANN based signal processing system.
Table 7-1 shows a comparison of the ANN based signal processing system with and without the signal smoothing method. In Experiment Set C1, signal smoothing on the raw sensor signal was not implemented, whereas in Experiment Set C2, the raw input signals were smoothened using three signal smoothing functions, namely, Moving Average Filter, Moving Median Filter, and Wavelet Transform Filter. The results shown in Table 7-1 indicate a substantial error reduction of 18% in the ANN based signal processing system when configured with FFT as the feature extraction function. Although the error reduction with the DCT based ANN is also fairly significant this was not the case with the WT based ANN.
CHAPTER 8 – CONCLUSIONS AND FUTURE WORK

8.1 Conclusion

Artificial Neural Network (ANN) based signal processing and classification approach coupled with a single capacitive sensor has been used to accurately determine the fuel level in an automotive fuel tank under dynamic conditions. A comprehensive literature review was conducted on the usage of capacitive sensors in dynamic environments and on the characteristics and effective use of Artificial Neural Networks. Based on the findings of the literature review, a capacitive sensor based measurement system using Artificial Neural Network (ANN) based signal processing and classification was proposed to provide robust and accurate fuel level measurement in a dynamic environment.

Extensive experiments were performed to determine an optimal configuration for the proposed ANN based measurement system. The selection of the ANN parameters, the kernel parameters and the signal pre-processing configurations were all based on extensive experiments. To determine the performance of the ANN based fuel level measurement system, many field trials were carried out to obtain a large amount of data for the training and validation of the system. The raw capacitive sensor signals obtained from the experiments data were observed to indicate large variations in the calculated fuel volume, when the actual fuel in the tank had remained constant. This variation in the capacitive sensor output was caused by sloshing effects.
CHAPTER 8 – CONCLUSIONs AND FUTURE WORK

The overall results obtained from the ANN based measurement system, when designed to have the optimal configuration determined by experimentation, were observed to have remarkably higher accuracy in a dynamic environment when compared with the existing statistical averaging methods. The ANN model applied with the Moving Median filter (with tap size of 5) produced a significantly lower maximum average error of 1.11 litres, when compared with the statistical averaging methods of Moving Mean and Moving Median that produced a maximum average error of 5.96 litres and 5.38 litres, respectively.

The increased accuracy of the fuel level measurement system that can be achieved in dynamic environments with the configuration described in this thesis will provide more confidence to drivers regarding the actual amount of fuel indicated by the instrument panel. With the suggested fuel level measurement system, the distance-to-empty figures can be accurately computed. In particular the ANN based method is suitable for use in a professional car racing where vehicles are subjected to highly dynamic manoeuvres. Drivers of cars equipped with this measurement method can confidently drive a higher number of laps without fear of running out of fuel in situations where fuel level in the tank is low.

The neural network approach has been used to accurately determine the fuel level in an automotive fuel tank under dynamic conditions. In an initial sets of experiments (Experiment set A), the three factors that can potentially influence the level measurement were investigated, and the investigation indicated a substantial
influence of the sloshing phenomenon and temperature variation on the capacitive level sensing output.

In a second set of experiments (Experiment set B), three different neural network configurations were investigated using the data obtained from Experiment set A. These 3 networks are the most commonly used in various scientific applications and for that reason they were chosen for this analysis. A maximum error of 8.7% was obtained using the Distributed Time-Delay Neural Network and an error of 0.11% was obtained using the Backpropagation Neural Network. The error results obtained by using the three neural network topologies were substantially less than that obtained by using the averaging method without neural networks.

In Experiment set C, four identical BP neural networks were developed and an investigation was carried out by applying three filtration methods and keeping one unfiltered raw signal to analyse the performance of the BP neural network approach in improving the accuracy of the level sensor in the presence of liquid slosh. The four neural networks with applied filters Moving Mean, Moving Median, Wavelet, and Unfiltered had the same network configurations. The output response of each network with the same raw signals was also observed to be very similar. The BP network applied with the Moving Median filter produced a maximum averaged error of 1.1 litres (Figure 6.31), which is significantly better than the results obtained using the statistical and non-neural network Moving Mean, and Moving Median functions that produced a maximum averaged error of 6.0 litres and 5.4 litres, respectively.
In summary, the neural network approach to signal processing has been demonstrated to be effective in determining the fuel level in dynamic environments using a single tube capacitor. Furthermore, the BP network performance has been enhanced with the implementation of a Median filter at the pre-processing stage. Table below summarises research objectives and achieved outcomes:
### Table 8.1 Summary of Research Objectives and Outcomes

<table>
<thead>
<tr>
<th>Objective</th>
<th>Publication</th>
<th>Reference Number</th>
<th>Author</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>Comparison of capacitive sensors in</td>
<td>Fischer-Cripps, Anthony C. <em>Force, pressure and flow</em>. Newnes</td>
<td>1</td>
<td>Fischer-Cripps, Anthony C.</td>
<td>well understood for general type of fluids except automotive fuels</td>
</tr>
<tr>
<td></td>
<td>Eren, Halit, and Kong, Wei Ling. <em>Capacitive Sensors - Displacement</em>.</td>
<td>2</td>
<td>Eren, Halit, and Kong, Wei Ling.</td>
<td>well understood for general type of fluids except automotive fuels</td>
</tr>
<tr>
<td></td>
<td>In: Webster, John G., editor. The measurement, instrumentation, and sensors</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Temperature effect on capacitive sensor</td>
<td>Dunn, William C. *Introduction to instrumentation, sensors and process</td>
<td>3</td>
<td>Dunn, William C.</td>
<td>well understood for general type of fluids except automotive fuels</td>
</tr>
<tr>
<td>Contamination effect on capacitive</td>
<td>Hochstein, Peter A., inventor TELEFLEX INC (US), assignee. *Capacitive</td>
<td>9</td>
<td>Hochstein, Peter A.</td>
<td>Partially met as only Arizona dust contamination was researched and</td>
</tr>
<tr>
<td>sensor accuracy</td>
<td>liquid sensor patent 5005409. 1990 02/07/1990.</td>
<td></td>
<td></td>
<td>tested</td>
</tr>
<tr>
<td>Slosh effect on sensor accuracy -</td>
<td>Terzic, Edin; Terzic, Jenny; Nagarajah, C. Romesh and Alamgir, Muhammad.</td>
<td>4</td>
<td>Terzic, E</td>
<td>Partially met as only Arizona dust contamination was researched and</td>
</tr>
<tr>
<td>use of averaging methods</td>
<td>*“A neural Network Approach to Fluid Quantity Measurement in Dynamic</td>
<td></td>
<td></td>
<td>tested</td>
</tr>
<tr>
<td></td>
<td>Kobayashi, Hiroshi, and Obayashi, Hiroaki, inventors; Nissan Motor</td>
<td>16,17</td>
<td>Kobayashi, Hiroshi, and Obayashi, Hiroaki,</td>
<td>level of accuracy not acceptable for automotive use in dynamic</td>
</tr>
<tr>
<td></td>
<td>Company, Limited, assignee. *Fuel volume measuring system for automotive</td>
<td></td>
<td></td>
<td>conditions (sport driving)</td>
</tr>
<tr>
<td></td>
<td>Guertler, Thomas, Hartmann, Markus, Land, Klaus, and Weinschenk, Alfred,</td>
<td>18</td>
<td>Guertler, Thomas, Hartmann, Markus, Land,</td>
<td>level of accuracy not acceptable for automotive use in dynamic</td>
</tr>
<tr>
<td></td>
<td>inventors; DAIMLER BENZ AG (DE) assignee. *Process for determining a liquid</td>
<td></td>
<td>Klaus, and Weinschenk, Alfred,</td>
<td>conditions (sport driving)</td>
</tr>
<tr>
<td></td>
<td>quantity, particularly an engine oil quantity in a motor vehicle patent</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Terzic, Edin, Nagarajah, C. Romesh and Alamgir, Muhammad. “Capacitive</td>
<td>2</td>
<td>Terzic, E</td>
<td>Fully Met</td>
</tr>
<tr>
<td></td>
<td>sensor-based fluid level measurement in a dynamic environment using neural</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>network”. Engineering Applications of Artificial Intelligence; vol. 23, no.</td>
<td>2,</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Terzic, Edin; Terzic, Jenny; Nagarajah, C. Romesh and Alamgir, Muhammad.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>*“A neural Network Approach to Fluid Quantity Measurement in Dynamic</td>
<td>4</td>
<td>Terzic, E</td>
<td>Fully Met</td>
</tr>
</tbody>
</table>

| **Table 8.1 Summary of Research Objectives and Outcomes** |
Future Work

A Capacitive Sensor coupled with the Artificial Neural Network (ANN) approach to signal processing will be used to address other factors such as tilting effect that causes liquid to shift to one side. With the rapid improvements in microprocessor technology, it will be possible to automatically train the ANN model in real time, which will further increase the effectiveness of the measurement system in dynamic environments.
REFERENCES


[13.] Tward, Emanuel, and Junkins, Philip, inventors; Tward 2001 Limited (Los Angeles, CA) assignee. Multi-capacitor fluid level sensor patent 4417473. 1982, 02/03/1982


REFERENCES


[19.] Krose, Ben, and van der Smagt, Patrick. An Introduction to Neural Networks. The University of Amsterdam; 1996.


REFERENCES


REFERENCES


REFERENCES


[47.] Yamamoto, Takashi, Hayashi, Shinichi, and Kondo, Masaru, inventors; NGK SPARK PLUG CO (JP), assignee. *Liquid state detecting element and liquid state detecting sensor* patent 7064560. 2005, 01/05/2005

[48.] Tward, Emanuel inventor Tward 2001 Limited, assignee. *Fluid level sensor* patent 4417472. 1982, 02/03/1982


REFERENCES


REFERENCES


REFERENCES


[71.] Nawrocki, Ryszard, inventor FORD MOTOR CO (US) assignee. Apparatus and method for gauging the amount of fuel in a vehicle fuel tank subject to tilt patent 5072615. 1990, 12/17/1990

[72.] Lee, Calvin S., inventor Lee, Calvin S. (Laguna Niguel, CA), assignee. Variable fluid and tilt level sensing probe system patent 5423214. 1994, 04/04/1994


[74.] Tsuchida, Takashi, Okada, Kazukiyo, Okuda, Yutaka, Kondo, Nobuo, and Shinohara, Toshio, inventors; Toyota Jidosha Kogyo Kabushiki Kaisha, assignee.
REFERENCES


[77.] Blum, Avrim, and Langley, Pat. Selection of relevant features and examples in machine learning, Artificial Intelligence; vol. 97, pp. 245-271, 1997.


REFERENCES


REFERENCES


REFERENCES


[106.] Michel Misiti;Yves Misiti;Georges Oppenheim;Jean-Michel Poggi. Wavelet Toolbox 4 - Users Guide. MathWorks; 2009.


REFERENCES


APPENDICES

APPENDIX A– LIST OF PUBLICATIONS

The following papers highlight the findings of this research. These articles were published in reputed journals during the course of this research program.


4. Terzic, Edin; Terzic, Jenny; Nagarajah, C. Romesh and Alamgir, Muhammad. “A neural Network Approach to Fluid Quantity Measurement in
APPENDICES

APPENDIX B – EXXSOL D-40 FLUID SPECIFICATION

The following table provides detailed specifications for the Exxsol D-40 type Stoddard solvent used in the experimentations [116].

<table>
<thead>
<tr>
<th>Property</th>
<th>Units</th>
<th>Typical values</th>
<th>Test method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Distillation range</td>
<td>°C</td>
<td>164</td>
<td>ASTM D 86</td>
</tr>
<tr>
<td>IRP</td>
<td></td>
<td>192</td>
<td></td>
</tr>
<tr>
<td>DP</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Flash point</td>
<td>°C</td>
<td>48</td>
<td>ASTM D 56</td>
</tr>
<tr>
<td>Density @ 15°C</td>
<td>kg/dm³</td>
<td>0.772</td>
<td>ASTM D 4052</td>
</tr>
<tr>
<td>Viscosity @ 25°C</td>
<td>mm²/s</td>
<td>1.30</td>
<td>ASTM D 445</td>
</tr>
<tr>
<td>Evaporation rate (n-BuAc=100)</td>
<td>-</td>
<td>15</td>
<td>EMC-AP-F01</td>
</tr>
<tr>
<td>KB value</td>
<td>-</td>
<td>32</td>
<td>ASTM D 1133</td>
</tr>
<tr>
<td>Aniline point</td>
<td>°C</td>
<td>7.0</td>
<td>ASTM D 611</td>
</tr>
<tr>
<td>Aromatic content</td>
<td>wt%</td>
<td>0.08</td>
<td>AM-S 140.31</td>
</tr>
<tr>
<td>Colour (Saybolt)</td>
<td>-</td>
<td>30</td>
<td>ASTM D 158</td>
</tr>
<tr>
<td>Bromine index</td>
<td>mg/100g</td>
<td>15</td>
<td>ASTM D 2710</td>
</tr>
<tr>
<td>Surface tension @ 25°C</td>
<td>mN/m</td>
<td>24.7</td>
<td>EC-M-F02 (Wilhelmy Plate)</td>
</tr>
<tr>
<td>Refractive index @ 20°C</td>
<td>-</td>
<td>1.428</td>
<td>ASTM D 1218</td>
</tr>
</tbody>
</table>

Table B1 – Exxsol D-40 Fluid Specifications.
APPENDICES

APPENDIX C – MATLAB PROGRAM FOR EXPERIMENT SET B

This section contains the MATLAB program code for the three types of neural network topologies investigated in the research under Experiment Set B. The Backpropagation network program is written in several MATLAB source file with extension "mat". The other two network types, DTDN and NARX are written in single files. However, they both require the "signals_db.mat" file to load the experiment signals.

Experiment Set B - Backpropagation Network (main.m)

```matlab
% File: main.m
% Clear console window
clc;
clear;

NO_OF_LOOPS = 1;

% Load signals
SignalsDB = load_signals;

% Create a neural network
if exist('net.mat', 'file')
    load net;
else
    net = initialise_nnt(SignalsDB);
end;

% Plot signals before training NNT
plot_nnt(SignalsDB);

% Train Neural Network
for j = 1:NO_OF_LOOPS
    net = train_nnt(net, SignalsDB);
end;

% Simulate the trained NNT
RESULT = simulate_nnt(net, SignalsDB);

% Save database and variables
```
save net net;

% file: initialize_nnt.m
% Creates and Initialises a Backpropagating Neural Network
function net = initialise_nnt(SignalsDB)

%fprintf ('Initialising Neural Network...\n');
s=cell2mat(SignalsDB(6,:))';

%set number of neurons
S1 = size(s,2);     % Layer 1
S2 = 1;             % Output Layer

%set the input vector size
window_size = S1;     % 63 fft + 1 median value=64

%set range values for the input nodes
netInputs = [floor(min(s))' floor(max(s))'+1];

%create a back-propagating NNT
%net = newff(netInputs, [32 1],{'tansig','purelin'}); % 'trainlm'
net = newff(netInputs, [S1 S2],{'tansig','purelin'},'trainscg');

%initialise weights
net = init(net);

% File: load_signals.m
% Loads all the raw signals and puts them in a container called
% 'SignalsDB'. Raw signals are in time domain, this function
% converts them
% into frequency domain and stores them in the Signals Database.

function SignalsDB = LoadSignals

%fprintf ('Loading Signals\n');

%Signals database fields
num_of_fields = 6;
FIELD_FILE = 1;
FIELD_SLOSH = 2;
FIELD_VOLUME = 3;
FIELD_TEMPERATURE = 4;
FIELD_AVERAGE = 5;
FIELD_SIGNAL = 6;
FIELD_RAW = 7;
% Location of raw signal
signals_folder = 'Raw Signals\Capacitive\';
file_ext = '.txt';

%~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
if exist('signals_db.mat','file')
    load signals_db;
else
    SignalsDB = cell (num_of_fields,[]);
end

% Start of reading raw signals
for j=1:4
    volume = j*5+35;
    vol_str = sprintf('%d',volume);
    current_folder = [signals_folder,'SloshTest-081112-
    ',vol_str,'L\'];

    folder_content = dir ([current_folder,'*','file_ext]);
    nface = size (folder_content,1);

    for k=1:nface
        slosh = str2double(strrep(folder_content(k,1).name,
        '.txt', ''));

        % filename
        sFilename = [current_folder,folder_content(k,1).name];

        % time-based raw signal
        signal = load(sFilename);
        data {1} = signal(1:1000);

        % averaged raw value
        medianValue = median(data{1});

        % time domain to frequency domain
        nnt_input = fft_nnt(data{1});
        nnt_input(end+1) = medianValue;

        % store current signal file
        SignalsDB {FIELD_FILE, end+1} = sFilename;
        SignalsDB {FIELD_SLOSH, end} = slosh;
        SignalsDB {FIELD_VOLUME, end} = volume;
        SignalsDB {FIELD_TEMPERATURE, end} = temperature;
        SignalsDB {FIELD_AVERAGE, end} = medianValue;
        SignalsDB {FIELD_SIGNAL, end} = {nnt_input};
        SignalsDB {FIELD_RAW, end} = {signal(1:3000)};
    end
end
end

save signals_db SignalsDB;
end
% File: train_nnt.m
% Trains a neural network using the signals contained in the Signals
% Database.
function NET = train_nnt(net,SignalsDB)
fprintf ('Training Neural Network...
');
num_of_fields = 6;
FIELD_FILE = 1;
FIELD_SLOSH = 2;
FIELD_VOLUME = 3;
FIELD_TEMPERATURE = 4;
FIELD_AVERAGE = 5;
FIELD_SIGNAL = 6;

% Neural network training parameters
% net.trainParam.lr = 0.05;
% net.trainParam.mc = 0.9;
net.trainParam.epochs = 5000;
net.trainParam.show = 20;
net.trainParam.goal = 0.01;

% Load sample values
P{1,1} = cell2mat(SignalsDB(FIELD_SIGNAL,:));

% Load target values
T{1,1} = cell2mat(SignalsDB(FIELD_VOLUME,:));

% train the neural network
net = train(net,P,T);

NET = net;

% File: simulate_nnt.m
% Simulates a trained neural network.
function RESULT = simulate_nnt(net,SIGDB)
num_of_fields = 6;
FIELD_FILE = 1;
FIELD_SLOSH = 2;
FIELD_VOLUME = 3;
FIELD_TEMPERATURE = 4;
FIELD_AVERAGE = 5;
FIELD_SIGNAL = 6;

% Load sample values
y = cell2mat(SIGDB{FIELD_VOLUME,:});
[a,b]=size(y);

x = 1:b;
figure;
P{1,1} = [cell2mat(SIGDB{FIELD_SIGNAL,:})];
RESULT = sim(net,P);
output = cell2mat(RESULT);
plot(output, 'ro-');
hold on;
plot(x,y, 'b-');
hold off;
xlabel('Input Signals');
ylabel('Output Volume(L)');
title('Neural Network Output (after training)');

[a,b] = size(SIGDB);
x = 0:10;
y1 = output(1:11);
y2 = output(12:22);
y3 = output(23:33);
y4 = output(34:44);
figure;
x = [0 0.20 0.40 0.6 0.80 1.00 1.2 1.40 1.60 1.8 2.00];
g40 = plot(x,y1, 'ro-');
hold on
g45 = plot(x,y2, 'gd-');
g50 = plot(x,y3, 'k*-');
g55 = plot(x,y4, 'bs-');
legend([g40,g45,g50,g55], '40 L', '45 L', '50 L', '55 L', 'location', 'SouthEast')
xlabel('Slosh Frequency (Hz)');
ylabel('Volume (L)');
title('Feed-Forward Backpropagation Network Results');
hold off

% File: plot_nnt.m
% Plots raw signals using their average values.
function RESULT = plot_nnt(SIGDB)
    num_of_fields = 6;
    FIELD_FILE = 1;
    FIELD_SLOSH = 2;
    FIELD_VOLUME = 3;
    FIELD_TEMPERATURE = 4;
    FIELD_AVERAGE = 5;
    FIELD_SIGNAL = 6;
[a, b] = size(SIGDB);
x = 0:10;
y1 = [];
y2 = [];
y3 = [];
y4 = [];

for i=1:b
    avg = cell2mat(SIGDB(FIELD_AVERAGE, i));
    if (cell2mat(SIGDB(FIELD_VOLUME, i))==40)
        y1(end+1) = avg;
    elseif (cell2mat(SIGDB(FIELD_VOLUME, i))==45)
        y2(end+1) = avg;
    elseif (cell2mat(SIGDB(FIELD_VOLUME, i))==50)
        y3(end+1) = avg;
    elseif (cell2mat(SIGDB(FIELD_VOLUME, i))==55)
        y4(end+1) = avg;
    end
end

figure;

x = [0 0.20 0.40 0.6 0.80 1.00 1.2 1.40 1.60 1.8 2.00];
plot(x,y1,'ro-');
hold on
plot(x,y2,'go-');
plot(x,y3,'ko-');
plot(x,y4,'bo-');
hold off

xlabel('Slosh Frequency (Hz)');
ylabel('Averaged Volume (volt)');
title('NNT Signals (Before Training)');

RESULT = 1;
Experiment  Set  B  -  Distributed   Time-delay  Neural   Network

(nn_dynamic_IIR.m)

```
clear all;
load Signals_db;

y1 = SignalsDB{6,1}';
y2 = SignalsDB{6,2}';

y=SignalsDB(6,1:end);  %[y1 y2 y1 y2]
t1 = ones(1,size(y1,2));
t2 = 5*ones(1,size(y2,2));
t = SignalsDB(3,1:end);  %[t1 t2 t3 t4];

d1 = 0:2;
d2 = 0:1;

p = y;%con2seq(y);
t = t;%con2seq(t);
dtdnn_net = newdtdnn(p,t,5,{d1,d2});
%dtdnn_net.trainFcn = 'trainbr';
dtdnn_net.trainParam.show = 5;
dtdnn_net.trainParam.epochs = 30;
dtdnn_net = train(dtdnn_net,p,t);

yp = sim(dtdnn_net,p);
ya = sim(dtdnn_net,[p(1:5) p(9:15) p(19:25) p(29:43)]);
x = [1:5 9:15 19:25 29:43];

L40 = cell2mat(SignalsDB(5,1:11))/SignalsDB{5,1}*SignalsDB{3,1};
L45 = cell2mat(SignalsDB(5,12:22))/SignalsDB{5,12}*SignalsDB{3,12};
L50 = cell2mat(SignalsDB(5,23:33))/SignalsDB{5,23}*SignalsDB{3,23};
L55 = cell2mat(SignalsDB(5,34:44))/SignalsDB{5,34}*SignalsDB{3,34};
Raw = [L40 L45 L50 L55];
xRaw = 1:44;

yp = cell2mat(yp);
ya = cell2mat(ya);
yActual = cell2mat(SignalsDB(3,1:end));

y1 = ya(1:8);
y2 = ya(9:16);
y3 = ya(17:24);
y4 = ya(25:end);

figure;
x1 = [SignalsDB{2,1:5} SignalsDB{2,9:11}];
```
APPENDICES

```matlab
x2 = [SignalsDB{2,12:15} SignalsDB{2,19:22}];
x3 = [SignalsDB{2,23:25} SignalsDB{2,29:33}];
x4 = [SignalsDB{2,34:43}];
g40 = plot(x1,y1,'ro-');
hold on;
g45 = plot(x2,y2,'gd-');
g50 = plot(x3,y3,'k*-');
g55 = plot(x4,y4,'bs-');
legend([g40,g45,g50,g55],'40 L','45 L','50 L','55 L','location','SouthEast')
title('Distributed Time-Delay Neural Network (without feedback)');
ylabel('Volume (Litres)');
xlabel('Slosh Frequency (Hz)');
hold off;

figure;
pActual=plot(yActual,'-k.');
set(gca,'XTick',[2:2:44]);
set(gca,'XTicklabel',['0.2';'0.6';'1.0';'1.4';'1.8';'0.0';
'0.4';'0.8';'1.2';'1.6';'2.0']);
hold on;
title('Distributed Time-Delay Neural Network (Capacitive)');
ylabel('Volume (Litres)');
xlabel('Slosh Frequency (Hz)');
pRaw=plot(xRaw, Raw,'-g');
pOriginal=plot(yp,'-bo');
pDelayed=plot(x,ya,'-r*');
legend([pRaw,pActual,pOriginal,pDelayed],'Raw Signal','Expected output','Output (Sequential)','Output (Delayed)','location','SouthEast');
grid on;
hold off;
```
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Experiment Set B - NARX Neural Network (nn_dynamic_feedback.m)

clear all;
load Signals_db;

u = SignalsDB(6,1:end);
y = SignalsDB(3,1:end);

DELAYCOUNT = 2;

p = u(DELAYCOUNT:end);
t = y(DELAYCOUNT:end);
d1 = [1:DELAYCOUNT];
d2 = [1:DELAYCOUNT];
narx_net = newnarxsp(p,t,d1,d2,4);
%narx_net.trainFcn = 'trainbr';
narx_net.trainParam.show = 10;
narx_net.trainParam.goal = 0.0001;
narx_net.trainParam.epochs = 100;
Pi = [u(1:DELAYCOUNT); y(1:DELAYCOUNT)];
narx_net = train(narx_net,[p;t],t,Pi);
yp = sim(narx_net,[p;t],Pi);
ya = sim(narx_net,[p(1:5) p(9:15) p(19:25) p(29:end);
    t(1:5) t(9:15) t(19:25) t(29:end)],Pi);

i = 44 - DELAYCOUNT + 1;
x = (DELAYCOUNT -1) + [1:5 9:15 19:25 29:i];
xp = [DELAYCOUNT:size(y,2)];

L40 = cell2mat(SignalsDB(5,1:11))/SignalsDB{5,1}*SignalsDB{3,1};
L45 = cell2mat(SignalsDB(5,12:22))/SignalsDB{5,12}*SignalsDB{3,12};
L50 = cell2mat(SignalsDB(5,23:33))/SignalsDB{5,23}*SignalsDB{3,23};
L55 = cell2mat(SignalsDB(5,34:44))/SignalsDB{5,34}*SignalsDB{3,34};
Raw = [L40 L45 L50 L55];
xRaw = 1:44;

yp = cell2mat(yp);
ya = cell2mat(ya);
yActual = cell2mat(SignalsDB(3,1:end));

y1 = ya(1:7);
y2 = ya(8:15);
y3 = ya(16:23);
y4 = ya(24:end);

figure;
%x = [1:5 9:15 19:25 29:43];
x1 = [SignalsDB{2,2:5} SignalsDB{2,9:11}];
x2 = [SignalsDB{2,12:15} SignalsDB{2,19:22}];
x3 = [SignalsDB{2,23:25} SignalsDB{2,29:33}];
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```matlab
x4 = [SignalsDB{2,34:44}];
g40 = plot(x1,y1,'ro-');
hold on;
g45 = plot(x2,y2,'gd-');
g50 = plot(x3,y3,'k*-');
g55 = plot(x4,y4,'bs-');
legend([g40,g45,g50,g55], '40 L', '45 L', '50 L', '55 L', 'location', 'SouthEast')
title('Dynamic NNT with feedback - NARX Network');
ylabel('Volume (Litres)');
xlabel('Slosh Frequency (Hz)');
hold off;

figure;
pActual=plot(yActual,'-k.');
set(gca,'XTick',[2:2:44]);
set(gca,'XTickLabel', ['0.2'; '0.6'; '1.0'; '1.4'; '1.8'; '0.0'; '0.4'; '0.8'; '1.2'; '1.6'; '2.0']);
hold on;
title('Dynamic NNT with feedback - NARX Network (Capacitive)');
ylabel('Volume (Litres)');
xlabel('Slosh Frequency (Hz)');
pRaw=plot(xRaw, Raw,'-g');
pOriginal=plot(xp, yp,'-bo');
pDelayed=plot(x,ya,'-r*');
legend([pRaw,pActual,pOriginal,pDelayed], 'Raw Signal', 'Expected output', 'Output (Sequential)', 'Output (Delayed)', 'location', 'SouthEast')
grid on;
hold off;
```
APPENDIX D– MATLAB PROGRAM FOR EXPERIMENT SET C

Experiment Set C – Investigated Filters

**Moving Mean Filter**

```matlab
% File: avgMean.m
% performs averaging using taps
function [sOutput] = avgMean(Signal,NoOfTaps)

[x,y]=size(Signal);
sOutput(1,1)={1};

for j=1:y;
    %Take the signal
    s=Signal(:,j);
    o=s;
    for i=1:NoOfTaps-1
        o(i)=mean(s(1:i));
    end;
    for i=NoOfTaps:length(s);
        o(i)=mean(s(i-NoOfTaps+1:i));
    end;

    sOutput(1,j)={o};
end;

%Return
sOutput=cell2mat(sOutput);
```

**Moving Median Filter**

```matlab
% File: avgMedian.m
% performs averaging using taps
function [sOutput] = avgMedian(Signal,NoOfTaps)

[x,y]=size(Signal);
sOutput(1,1)={1};

for j=1:y;
    %Take the signal
    s=Signal(:,j);
    o=s;
    for i=1:NoOfTaps-1
        o(i)=median(s(1:i));
    end;
    for i=NoOfTaps:length(s);
        o(i)=median(s(i-NoOfTaps+1:i));
    end;

    sOutput(1,j)={o};
end;

%Return
sOutput=cell2mat(sOutput);
```
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\[
o(i) = \text{median}(s(i \text{-NoOfTaps+1:i})};
\]
end;

\[
sOutput(1,j) = \{o\};
\]
end;

% Return
sOutput = cell2mat(sOutput);

---

**Wavelet Filter**

% File: waveletfilter.m
% Produces a filtered version of input Signals using wavelet method
function [sOutput] = WaveletFilter(Signals)

[x,y]=size(Signals);
sOutput(1,1)=\{1\};

for i=1:y;
    [a,b]=dwt(Signals(:,i),'db1');
    if y>1
        sOutput(1,i)=a;
    end;
end;

if y>1;
    sOutput=cell2mat(sOutput);
else;
    sOutput=a;
end;
Experiment Set C1 – Main Program (ExpC1.m)

% ExpC1 is used to investigate appropriate pre-processing
% parameters such as window_size, feature_extraction_func,
% and size of input features.
%  
clc             %clear screen
clear all;      %clear memory
close all;      %close all figures
load sdb_expC;  %load ExpC signals
samprate  =   100;  %100 Hz sampling rate
totallen  = 28000;  %280 seconds
maxepochs = 10000;
show      =   500;  %update progress every [#] epochs

% test_param contains different parameters for
% different tests for the evaluation of optimal network performance
% param.
test_param=[
% format: windowsize,coef_func,coef_size,filter_func,filter_tapsize
  5,0,63,0,0
  5,0,100,0,0
  5,1,63,0,0
  5,1,100,0,0
  5,2,63,0,0
  5,2,100,0,0
  7,0,63,0,0
  7,0,100,0,0
  7,1,63,0,0
  7,1,100,0,0
  7,2,63,0,0
  7,2,100,0,0
  10,0,63,0,0
  10,0,100,0,0
  10,1,63,0,0
  10,1,100,0,0
  10,2,63,0,0
  10,2,100,0,0
  14,0,63,0,0
  14,0,100,0,0
  14,1,63,0,0
  14,1,100,0,0
  14,2,63,0,0
  14,2,100,0,0
  20,0,63,0,0
  20,0,100,0,0
  20,1,63,0,0
  20,1,100,0,0
  20,2,63,0,0
  20,2,100,0,0];
[noOfTests params]=size(test_param);

if exist('ExpC1_Signals.mat','file')
    %load previously generated signals for network training and validation
    load ExpC1_Signals;
else
    %generate signals
    for i=1:noOfTests
        fprintf(['Generating signal ',num2str(i),'
']);
        windowsize = test_param(i,1) * samprate; %window size in seconds
        if test_param(i,2)==0
            coef_func='fft';
        elseif test_param(i,2)==1;
            coef_func='dct';
        else
            coef_func='dwt';
        end;
        coef_size = test_param(i,3);
        if test_param(i,4)==1
            filter_func='movingmean';
        elseif test_param(i,4)==2;
            filter_func='movingmedian';
        elseif test_param(i,4)==3;
            filter_func='wavelet';
        else
            filter_func='unfiltered';
        end;
        tapsize = test_param(i,5);
        %create input and target signal vectors
        [inputs{1,i},targets{1,i}]=...
            createinputvector(sdb_expC,windowsize,...
                coef_func,coef_size,filter_func,tapsize);
    end;
    save ExpC1_Signals;
end;

%load raw signals and actual volume data from sdb_expC.
raw_signals = cell2mat(sdb_expC(7,:));
vol_levels  = cell2mat(sdb_expC(2,:));

if exist('ExpC1_Networks.mat','file')
    load ExpC1_Networks;
else
    % Run tests on BP network
    for i = 1:noOfTests
        fprintf(['\nTraining ANN# ', num2str(i), '\n']);
        windowsize = test_param(i,1) * samprate; % windowsize in seconds
        if test_param(i,2) == 0
            coef_func = 'fft';
        elseif test_param(i,2) == 1
            coef_func = 'dct';
        else
            coef_func = 'dwt';
        end;
        coef_size = test_param(i,3);
        if test_param(i,4) == 1
            filter_func = 'movingmean';
        elseif test_param(i,4) == 2
            filter_func = 'movingmedian';
        elseif test_param(i,4) == 3
            filter_func = 'wavelet';
        else
            filter_func = 'unfiltered';
        end;
        tapsize = test_param(i,5);
        division_factor = totallen/windowsize;
        % create input and target signal vectors
        inputsignals = cell2mat(inputs(1,i));
        targetsignals = cell2mat(targets(1,i));
        % train and validate the ANN based system
        neurons = size(inputsignals,2);
        net = createBPNN(inputsignals,neurons,1);
        epochs{1,i} = 0;
        % train with 50% signals
        [net, ep, perf] = trainnet(net, inputsignals(1:2:end,:),... 
            targetsignals(1:2:end,1), 0, maxepochs, show);
        [output] = sim(net, inputsignals');
        avgerror = mean(breakup(output-targetsignals, division_factor));
        % calculate statistical averaging error values
        windowed_raw_signals = breakup(raw_signals, windowsize);
        volumes = ExpandEach(vol_levels, division_factor);
offsets = ExpandEach(median(raw_signals(1:100,:)),division_factor);

mean_vol=(mean(windowed_raw_signals)./offsets).*volumes;
median_vol=(median(windowed_raw_signals)./offsets).*volumes;

%statistical mean func error
mean_vol_err= mean(breakup(abs(mean_vol-volumes),division_factor));
mean_vol_errp= 100*mean(breakup(abs(mean_vol-volumes)./volumes,...
                          division_factor));
mean_vol_errp_max = max(mean_vol_errp);
mean_vol_err_max= max(breakup(abs(mean_vol-volumes),...
                          division_factor));
mean_vol_err_overall = mean(mean_vol_err);
mean_vol_err_max_overall = mean(mean_vol_err_max);

%statistical median func error
median_vol_err= mean(breakup(abs(median_vol-volumes),...
                           division_factor));
median_vol_errp= 100*mean(...
                         breakup(abs(median_vol-volumes)./volumes,division_factor));
median_vol_errp_max = ...
                         max(median_vol_errp);
median_vol_err_max= ...
                         max(breakup(abs(median_vol-volumes),division_factor));
median_vol_err_overall = mean(median_vol_err);
median_vol_err_max_overall = mean(median_vol_err_max);

%ANN based system error
ann_vol_err = ...
ann_vol_errp= 100*mean(...
                        breakup(abs(output-targetsignals),division_factor))./vol_levels;
ann_vol_errp_max = max(ann_vol_errp);
ann_vol_err_max = ...
                        max(breakup(abs(output-targetsignals),division_factor));
ann_vol_err_overall = mean(ann_vol_err);
ann_vol_err_max_overall = mean(ann_vol_err_max);

mean_vol_errs{1,i}=mean_vol_err;
mean_vol_errps{1,i}=mean_vol_errp;
mean_vol_err_maxs{1,i}=mean_vol_err_max;
mean_vol_err_maxs{1,i}=mean_vol_err_max;
mean_vol_err_max_overalls{1,i}=mean_vol_err_max_overall;
mean_vol_err_overalls{1,i}=mean_vol_err_overall;

median_vol_errs{1,i}=median_vol_err;
median_vol_errps{1,i}=median_vol_errp;
median_vol_errp_maxs{1,i}=median_vol_errp_max;
median_vol_err_maxs{1,i}=median_vol_err_max;
median_vol_err_max_overalls{1,i}=median_vol_err_max_overall;
median_vol_err_overalls{1,i}=median_vol_err_overall;

ann_vol_errs{1,i}=ann_vol_err;
ann_vol_errps{1,i}=ann_vol_errp;
ann_vol_errp_maxs{1,i}=ann_vol_errp_max;
ann_vol_err_maxs{1,i}=ann_vol_err_max;
ann_vol_err_max_overalls{1,i}=ann_vol_err_max_overall;
ann_vol_err_overalls{1,i}=ann_vol_err_overall;

summary_errors_overall(i,1:3)=...
    [mean_vol_err_overall median_vol_err_overall
    ann_vol_err_overall];
summary_errors_max(i,1:3)=...
    [max(mean_vol_err_max) max(median_vol_err_max)
max(ann_vol_err_max)];
summary_errors_std(i,1:3)=...
    [std(mean_vol_err) std(median_vol_err)
std(ann_vol_err)];

summary_errorsp_overall(i,1:3)=...
    [mean(mean_vol_errp) mean(median_vol_errp)
mean(ann_vol_errp)];
summary_errorsp_max(i,1:3)=...
    [max(mean_vol_errp) max(median_vol_errp)
max(ann_vol_errp)];
summary_errorsp_std(i,1:3)=...
    [std(mean_vol_errp) std(median_vol_errp)
std(ann_vol_errp)];

results{1,i} = output;
epochs{1,i} = epochs{1,i} + ep;
networks{1,i} = net;
end;

table_errors_percent=...
    [summary_errorsp_overall summary_errorsp_std
summary_errorsp_max];
table_errors=...
    [summary_errors_overall summary_errors_std summary_errors_max];
save ExpC1_Networks  networks epochs;
save ExpC1_Results   results ...
table_errors table_errors_percent ...
summary_errors_max summary_errors_overall summary_errors_std ...
mean_vol_err mean_vol_errp mean_vol_errp_max mean_vol_err_max ...

mean_vol_err_max_overall  mean_vol_err_overall ...
median_vol_err median_vol_err_max median_vol_errp ...
median_vol_errp_max median_vol_err_max_overall ...
median_vol_err_overall ...
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    ann_vol_err  ann_vol_err_max  ann_vol_errp  ann_vol_errp_max  ...
    ann_vol_errp_max_overall  ann_vol_err_overall  ;

end;
APPENDICES

Experiment Set C2 – Main Program (ExpC2.m)

% ExpC2 is used to investigate appropriate pre-processing and filter parameters such as window_size, feature_extraction_func, size of input features, filter_type, and tap_size.

clc             %clear screen
clear all;      %clear memory
close all;      %close all figures

load sdb_expC;  %load signals
samprate  =   100;  %100 Hz sampling rate
totallen  = 28000;  %280 seconds
maxepochs = 10000;
show      =   500;  %update progress every [#] epochs

target_dir = [pwd,'\']; %current directory

test_param=
%format: windowsize,coef_func,coef_size,filter_func,filter_tapsize 
20,0,63,1,5
20,0,63,1,10
20,0,63,1,15
20,0,63,2,5
20,0,63,2,10
20,0,63,2,15
20,0,63,3,5
20,0,63,3,10
20,0,63,3,15
20,1,63,1,5
20,1,63,1,10
20,1,63,1,15
20,1,63,2,5
20,1,63,2,10
20,1,63,2,15
20,1,63,3,5
20,1,63,3,10
20,1,63,3,15
20,2,63,1,5
20,2,63,1,10
20,2,63,1,15
20,2,63,2,5
20,2,63,2,10
20,2,63,2,15
20,2,63,3,5
20,2,63,3,10
20,2,63,3,15];

[noOfTests params]=size(test_param);
if exist('ExpC2_Signals.mat','file')
    %load previously generated signals for network training and validation
    load ExpC2_Signals;
else
    %generate signals
    for i=1:noOfTests
        fprintf(['Generating signal ',num2str(i),'
']);

        windowsize = test_param(i,1) * samprate; %windowsize in seconds

        if test_param(i,2)==0
            coef_func='fft';
        elseif test_param(i,2)==1;
            coef_func='dct';
        else;
            coef_func='dwt';
        end;

        coef_size = test_param(i,3);

        if test_param(i,4)==1
            filter_func='movingmean';
        elseif test_param(i,4)==2;
            filter_func='movingmedian';
        elseif test_param(i,4)==3;
            filter_func='wavelet';
        else;
            filter_func='unfiltered';
        end;

        tapsize = test_param(i,5);

        %create input and target signal vectors
        [inputs{1,i},targets{1,i}] = ... 
            createinputvector(sdb_expC,windowsize,...
                coef_func,coef_size,filter_func,tapsize);
    end;
    save ExpC2_Signals;
end;

%load raw signals and actual volume data from sdb_expC.
raw_signals = cell2mat(sdb_expC(7,:));
vol_levels  = cell2mat(sdb_expC(2,:));

if exist('ExpC2_Networks.mat','file')
    load ExpC2_Networks;
else
    %Run tests on BP network

for i=1:noOfTests
    fprintf(['\nTraining ANN# ',num2str(i),'\n']);

    windowsize = test_param(i,1) * samprate; %windowsize in seconds

    if test_param(i,2)==0
        coef_func='fft';
    elseif test_param(i,2)==1
        coef_func='dct';
    else;
        coef_func='dwt';
    end;

    coef_size = test_param(i,3);

    if test_param(i,4)==1
        filter_func='movingmean';
    elseif test_param(i,4)==2;
        filter_func='movingmedian';
    elseif test_param(i,4)==3;
        filter_func='wavelet';
    else;
        filter_func='unfiltered';
    end;

    tapsize = test_param(i,5);
    division_factor = totallen/windowsize;

    %create input and target signal vectors
    inputsignals = cell2mat(inputs(1,i));
    targetsignals = cell2mat(targets(1,i));

    %train and validate the ANN based system
    neurons = size(inputsignals,2);
    net=createBPNN(inputsignals,neurons,1);

    epochs{1,i}=0;
    %train with 50% signals
    [net,ep,perf]=trainnet(net,inputsignals(1:2:end,:),...
            targetsignals(1:2:end,1),0,maxepochs,show);

    [output]=sim(net,inputsignals')';
    avgerror = mean(breakup(output-targetsignals,division_factor));

    %calculate statistical averaging error values
    windowed_raw_signals = breakup(raw_signals,windowsize);
    volumes = ExpandEach(vol_levels,division_factor);
    offsets = ExpandEach(median(raw_signals(1:100,:)),division_factor);
mean_vol=(mean(windowed_raw_signals)./offsets).*volumes;
median_vol=(median(windowed_raw_signals)./offsets).*volumes;

%statistical mean func error
mean_vol_err= mean(breakup(abs(mean_vol-volumes),division_factor));
mean_vol_errp= 100*mean(breakup(abs(mean_vol-volumes)./volumes,division_factor));
mean_vol_err_max = max(mean_vol_err);
mean_vol_err_max= max(breakup(abs(mean_vol-volumes),division_factor));
mean_vol_err_overall = mean(mean_vol_err);
mean_vol_err_max_overall = mean(mean_vol_err_max);

%statistical median func error
median_vol_err= mean(breakup(abs(median_vol-volumes),division_factor));
median_vol_errp= 100*mean(breakup(abs(median_vol-volumes)./volumes,division_factor));
median_vol_err_max = max(median_vol_err);
median_vol_err_max= max(breakup(abs(median_vol-volumes),division_factor));
median_vol_err_overall = mean(median_vol_err);
median_vol_err_max_overall = mean(median_vol_err_max);

%ANN based system error
ann_vol_err = mean(breakup(abs(output-targetsignals),division_factor));
ann_vol_errp= 100*mean(breakup(abs(output-targetsignals)./vol_levels);
ann_vol_err_max = max(ann_vol_err);
ann_vol_err_max= max(breakup(abs(output-targetsignals),division_factor));
ann_vol_err_overall = mean(ann_vol_err);
ann_vol_err_max_overall = mean(ann_vol_err_max);

mean_vol_errs{1,i}=mean_vol_err;
mean_vol_errps{1,i}=mean_vol_errp;
mean_vol_errp_maxs{1,i}=mean_vol_err_max;
mean_vol_err_maxs{1,i}=mean_vol_err_max;
mean_vol_err_max_overalls{1,i}=mean_vol_err_max_overall;
mean_vol_err_overalls{1,i}=mean_vol_err_overall;

median_vol_errs{1,i}=median_vol_err;
median_vol_errps{1,i}=median_vol_errp;
median_vol_errp_maxs{1,i}=median_vol_err_max;
median_vol_err_maxs{1,i}=median_vol_err_max;
median_vol_err_max_overalls{1,i}=median_vol_err_max_overall;
median_vol_err_overalls{1,i}=median_vol_err_overall;

ann_vol_errs{1,i}=ann_vol_err;
APPENDICES

ann_vol_errps{1,i}=ann_vol_errp;
ann_vol_errp_maxs{1,i}=ann_vol_errp_max;
ann_vol_err_maxs{1,i}=ann_vol_err_max;
ann_vol_err_max_overalls{1,i}=ann_vol_err_max_overall;
ann_vol_err_overalls{1,i}=ann_vol_err_overall;

summary_errors_overall(i,1:3)=...  
[mean_vol_err_overall median_vol_err_overall
 ann_vol_err_overall];
summary_errors_max(i,1:3)=...  
[max(mean_vol_err_max) max(median_vol_err_max)
 max(ann_vol_err_max)];
summary_errors_std(i,1:3)=...  
[std(mean_vol_err) std(median_vol_err)
 std(ann_vol_err)];

summary_errorsp_overall(i,1:3)=...  
[mean(mean_vol_errp) mean(median_vol_errp)
 mean(ann_vol_errp)];
summary_errorsp_max(i,1:3)=...  
[max(mean_vol_errp) max(median_vol_errp)
 max(ann_vol_errp)];
summary_errorsp_std(i,1:3)=...  
[std(mean_vol_errp) std(median_vol_errp)
 std(ann_vol_errp)];

results{1,i} = output;
epochs{1,i} = epochs{1,i} + ep;
networks{1,i} = net;
end;

table_errors_percent=[summary_errorsp_overall
 summary_errorsp_std summary_errorsp_max];
table_errors=[summary_errors_overall summary_errors_std
 summary_errors_max];

save ExpC2_Networks networks epochs;
save ExpC2_Results results ...
 table_errors table_errors_percent ...
 summary_errors_max summary_errors_overall summary_errors_std ...
 mean_vol_err mean_vol_errp mean_vol_errp_max
 mean_vol_err_max ...
 mean_vol_err_max_overall mean_vol_err_overall ...
 median_vol_err median_vol_err_max median_vol_err_max ...
 median_vol_err_max median_vol_err_max_overall ...
 median_vol_err_overall ...
 ann_vol_err  ann_vol_err_max ann_vol_errp ann_vol_errp_max ...

end;
Experiment Set C – Misc Functions

function [sdbOut] = breakupsdb(sdbIn,splitsize)
%breakupsdb breaks up the signals contained in 'sdbIn' into
%smaller signals of the length described by splitsize.
%
% Syntax
%
% sdbOut = breakupsdb(sdbIn,splitsize);
%
% Description
%
% breakupsdb(sdbIn,splitsize) takes two arguments,
% sdbIn - sdb type signal container,
% splitsize - split length of the new signals,
% and returns experiment signals in the sdb format.
%
if nargin < 2
    fprintf ('Invalid number of input arguments.\n');
    return;
end;

[NoOfLines NoOfSignals]=size(sdbIn);
sdbOut = cell(NoOfLines, NoOfSignals);
n=1;

for i=1:NoOfSignals
    sampling_rate = cell2mat(sdbIn(1,i));
    signal_data=breakup(cell2mat(sdbIn(7,i)),splitsize);
    [newLength,NoOfNewSignals] = size(signal_data);

    for j=1:NoOfNewSignals
        sdbOut(1,n) = sdbIn(1,i); %sampling
        sdbOut(2,n) = sdbIn(2,i); %volume
        sdbOut(3,n) = {newLength/sampling_rate}; %length
        sdbOut(4,n) = sdbIn(4,i); %slosh freq.
        sdbOut(5,n) = sdbIn(5,i); %temperature
        sdbOut(6,n) = sdbIn(6,i); %contamination
        sdbOut(7,n) = {signal_data(:,j)}; %signal
        n=n+1;
    end;
end;

function net = createBPNN(inputs,layer1neurons,layer2neurons)
% Creates and Initialises a Backpropagating Neural Network
%
% Syntax
%
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%    net = createBPNN(inputs,layer1neurons,layer2neurons)
%    Description
%    createBPNN creates and initialises a Backpropagating Neural
Network
% based on the range of the input data, having layer1 and layer
2
% neurons described by the two input parameters:
%    layer1neurons and layer2neurons
%
% Input Parameters:-
% -   inputs:         input samples
% -   layer1neurons:  No. of Layer 1 Neurons
% -   layer2neurons:  No. of Layer 2 Neurons
% Return output:-
% -   net:        Returns the BP network
netInputs = [min(inputs)'-0.5  floor(max(inputs))'+0.5];

% create a back-propagating NNT
%net = newff(netInputs, [32 1],{'tansig','purelin'});  % 'trainlm'
net = newff(netInputs, [layer1neurons layer2neurons],
    {'tansig','purelin'},'trainscg');

% initialise weights
net = init(net);

function [sdb] = createsdb(csvfile)
% createsdb Imports experiment signals from csv file to sdb.
%   Syntax
%     sdb = createsdb(csvfile);
%   Description
%     createsdb takes raw signals contained in the csvfile and
produces
%     a cell-matrix describing the properties and experiment details
for
%     the raw signals.
%     createsdb(csvfile) takes one argument,
%     csvfile - location of the csv file.
%     and returns experiment signals in the sdb format.

if nargin < 1
    fprintf ('CSV File not specified\n');
    return
APPENDICES

end

if exist(csvfile,'file')==0
    fprintf (['File not found: ',csvfile,'
']);
    return
end;

%read csv file
csvdata=csvread(csvfile);
[NoOfLines NoOfSignals]=size(csvdata);

%allocate memory space
sdb = cell(7, NoOfSignals);

for i=1:NoOfSignals
    sdb(1,i) = {csvdata(1,i)}; %sampling
    sdb(2,i) = {csvdata(2,i)}; %volume
    sdb(3,i) = {csvdata(3,i)}; %length
    sdb(4,i) = {csvdata(4,i)}; %slosh freq.
    sdb(5,i) = {csvdata(5,i)}; %temperature
    sdb(6,i) = {csvdata(6,i)}; %contamination

    %determine the length of the actual signal
    signalend=0;
    NoOfZeros=0;
    for j = 7:NoOfLines
        signalend=j;
        if csvdata(j,i)==0
            NoOfZeros = NoOfZeros+1;
            if NoOfZeros>5
                signalend=j-6;
                break;
            end;
        else
            NoOfZeros=0;
        end;
    end;

    %add signal data to sdb
    sdb(7,i) = {csvdata(7:signalend,i)}; %signal
end;

function [NET,epochs,per] = trainnet(net,inputs,targets,lr,maxepochs,show)
%trainnet trains net (Artificial neural network) using inputs and targets
%parameters
%Syntax
APPENDICES

```matlab
sdb = trainnet(net,inputs,targets,lr,maxepochs,show)

Description

trainnet trains the neural network (net)...
using the signals contained in the inputs and targets
vectors.

Input Parameters:
- net: An initialised neural network
- inputs: Training samples
- targets: Target samples
- lr: Learning rate
- maxepochs: Maximum Epochs to train
- show: display training progress after show number of
  epochs

Output Parameters:
- NET: Returns the net after it has been trained
- per: Return Network Performance value
- epochs: Return the number of epochs taken to train the
  net

fprintf ('Training Neural Network...
');

% Neural network training parameters
net.trainParam.lr = lr;       % learning rate
%net.trainParam.lr_inc = 1.05;   % variable learning rate
net.trainParam.mc = 0.9;        %
net.trainParam.epochs = maxepochs;   % maximum no. of epochs
net.trainParam.show = show;      % training window update
intervals
net.trainParam.goal = 0.001;    % target goal (mse) error
%net.trainParam.mem_reduc = 2;  % reduced memory mode

% Load sample values
%P{1,1} = cell2mat(SignalsDB(FIELD_SIGNAL,:));
P=con2seq(inputs');

% Load target values
%T{1,1} = cell2mat(SignalsDB(FIELD_VOLUME,:));
T=con2seq(targets');

% train the neural network
[net,tr] = train(net,P,T);
per=tr.perf(end);
epochs=tr.epoch(end);
NET = net;

fprintf ('Training Neural Network...
');
```