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# Application of Distributed Acoustic Sensing to Flow Regime Classification

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# Summary

Getting the most out of a hydrocarbon reservoir is not a trivial task. It takes plenty of interwoven decisions to make. There are many forms of tools that support engineers to make correct decisions. The simplest ones would only display measurements in a suitable way, and appoint the rest of the decision making process to human knowledge and experience. Complex decision support tools may implement model-based estimation and optimization. This work targets methods for optimization-based decision support, namely implementing artificial neural networks.

The objective of the thesis proposed is to investigate the potential of DAS (Distributed Acoustic Sensing) for flow regime classification. A relatively simple and cost effective experiment has been conducted in this study.

Using the results from the experiments, several artificial neural networks has been created to recognize the pattern in the one third octave band data. The results has shown a neural network is a promising tool which serves the purpose of this study.

# Preface

This specialization project report is submitted to the Norwegian University of Science and Technology (NTNU), Trondheim, Norway, for partial fulfillment of the requirements for the degree of Master of Science. The study has been conducted in collaboration between the department of Petroleum Engineering and Applied Geophysics, and Ziebel AS, under the supervision of professor Sigbjørn Sangesland.

I owe my deepest gratitude to my supervisor Professor Sigbjørn Sangesland for the opportunity given to me as his student. His valueable comments and interesting discussions as well as his patience made it possible to complete this project.

I would also like to thank the friendly and supportive team of Ziebel AS which made it possible for me to successfuly conclude the project. My sincere thanks goes to Frode Hveding whose continuous support and visits to NTNU had a huge contribution to the work. Furthermore, I deeply appreciate the endless technical support from Alex van der Spek and Kim Flatråker, and thank them for their brilliant remarks and suggestions.

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Chapter 1

# Introduction

Well intervention is referred to any operation carried out in a well during or after the productive life of the well. It has various missions including modification of the state or geometry of a well, providing well diagnostics and well production management.

One of the methods for well intervention, involves pushing down a carbon rod to total depth of the well, in order to obtain accurate temperature and acoustic measurements of the entire well length while parked downhole. This intervention method has been advanced for fiber-optic logging purposes.

Developed by Ziebel AS, Z-System is one the intervention technologies based on a semi stiff carbon rod containing fiber optic cables. Optical fibers inside the carbon rod act as an array of sensors providing live and simultaneous temperature and acoustic data from almost every 1 meter. The system has a spool containing the rod, an injector head, well control equipment on surface and a bottom hole assembly (bullnose) containing termination points for the fiber optic cables. The stiffness and light weight of the rod allows access to highly deviated, and horizontal wells in which limited depth reach is an inevitable issue.

The Z-System has significant advantages over conventional logging systems such as coiled tubing (CT) or wireline and tractor conveyed (WL) systems:

- Senses all the well all the time; Dynamic reservoir management optimization
- Ability to access horizontal wells by pushing it from surface with no need to tractor
- Very high tensile strength
- Ability to access wells with restrictions because of its slick system and small O.D (1.5 inches)
- Negligible choking effect during flowing

- Less deferred production during intervention work since it can be run in hole while producing
- Reliability of technology because of no electronics downhole (only fiber optics)
- No up and down movement during operation (no need for multiple passes) since the fiber is parked during the entire operation, and the entire rod acts as an array of sensors
- Broadband information delivered “Live" and in real time
- Multiple applications solved in one single run

This work aims at suggesting a proper method for interpreting data obtained using the Z-System. This project specifically focuses on the Distributed Acoustic Sensing feature embedded within this technology.

Chapter 2

# Fundamentals of Optical Fiber Sensing

## 2.1 History and Statistics

Optical fiber technology has been used by oil and gas industry over the last 20 years. Originally this technology was used within space and military applications. It was found out later that oil and gas industry could also benefit from employment of this technology.

The first downhole installation of optical fiber sensing system was performed in 1993. Its only mission was to act as a simple point pressure and temperature sensor in a land well in the Netherlands. Although the first steps in the development of optical fiber technology was made in the mid 1980Šs, the significant success came only in the mid-1990s. The first application of Distributed Acoustic Sensing (DAS) optical fiber technology was implemented by Shell Canada during the completion of a tight gas well in February 2009 (Molenaar et al., 2011). Since the technology inception in the 1980Šs, optical fiber sensing has been introduced in a wide range of applications, focusing on implementation in extreme operating environments with physical space limitations, and unique measurement requirements (Johannessen and Drakeley, 2012).

In conclusion, it is necessary to state that optical fiber technology implementation has found more and more applications to be introduced. Since the technology posesses a number of significant advantages over the conventional systems for monitoring and data acquisition, there is a tendency to use the technology on a permanent basis bringing as a part of completion component for smart wells.

## 2.2 Advantages of Fiber Optic Monitoring

It is evident that utilization of optical fiber technology has many proven by field experience advantages over conventional systems for data acquisition and monitoring.

The first advantage of optical fiber technology is its immunity to electromagnetic interference. The reason is that this system does not incorporate any downhole electronics. Several mesurements are made in the well, however, there is no need to have any electronic transducers or circuit boards inside te well. In other words, there is no need for electrical power. Measurements are simply made with the help of optical fiber.

Another advantage is the resistance to high temperatures. Once optical fibers are installed, they tend to work for a long time. There is some evidence that other existing technologies such as electrical and quartz sensing systems have a temperature limitation. Usually, this limitation is around 150 °C, meaning that the working period in extreme temperature conditions is short.

Finally, the optical fiber tecnology has a capability of multiplexing and making distributed measurements. These optical fiber methods provide real time monitoring, because they give such parameters as temperature, strain and acoustics. The measurement could be made over the entire length of the well, as optical fiber sensing system allows signals to be sent and received over a long distance. The system acts as an array of sensors, which is able to monitor several parameters at the same time (Carnahan et al., 1999).

## 2.3 Principles of Distributed Temperature Sensing

Distributed Temperature Sensing relies upon optical time-domain reflectometry. The sensing element is represented by the optical fiber, which is attached to a laser source emitting laser pulses. The light is shot down through the optical fiber and light returns back to the instrument that pulsed the light down. This returned light contains information that describes the conditions inside the well. Figure 2.1 illustrates the working principle of DTS. The actual fiber itself is very thin, about the width of a human hair. The pulse length is typically estimated from 1 to 2 meters.

The reflection points, which cause the light to backscatter and carry information, are minute imperfections or very small density variations distributed continuously along the core of the glass fiber. In the optimal case, the intensity of the backscattered light diminishes exponentially with time. Since the light speed within the optic fiber is known, it is possible to estimate the distance that the light pulse has moved based on the time. Under normal operational conditions, the package of light that is transmitted down reaches the far end and comes back. Only after this pulse has returned another pulse will be sent down.

At each of the imperfections there is a backscatter event called a Rayleigh backscatter. This light then returns to the detector and carries with it information. Of the very small portions of the light that will be reflected back (maybe one photon in a million photons), a

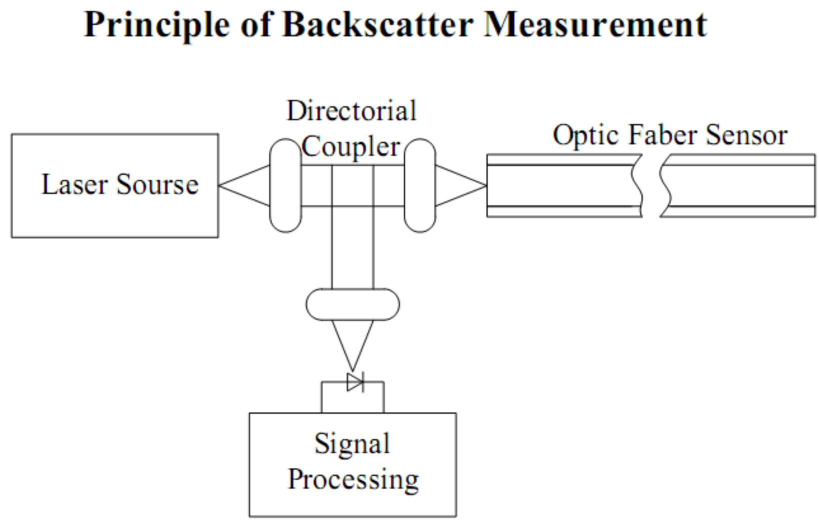



**Figure 2.1:** Principles of Distributed Temperature Sensing, (Carnahan et al., 1999)

small quantity undergoes a spectroscopic shift.

Figure 2.2 illustrates the full backscatter light spectrum. The returning light contains several different spectral components in terms of frequency: Rayleigh, Brillouin and Raman bands. The central peak in the figure is called the Rayleigh peak. It has the exact same waveleng as the incident light (the light pulse that is pumped down the fiber). A small portion of the backscattered light undergoes a Brillouin shift and another portion undergoes a Raman shift. There are two components to each of these: the stokes and the anti-stokes.

For the Raman peaks, it is observed that the anti-stokes component is strongly temperature dependent, while the stokes component is virtually unaffected by changes in temperature. Taking this into consideration, the Raman components can be used for obtaining information about temperature distribution along the optical fiber.

In the case of Brillouin peaks, the temperature affects both of the stokes and anti-stokes components. The effect will not change the amplitude but rather make a change in wavelength. As the temperature increases, the Brillouin peaks will spread outward from the center.

Using the Raman peaks, it is possible to determine the absolute temperature by analyzing the ratios of the amplitudes (intensities) of the anti-stokes to stokes components, which is done in the detector. The location along the optical fiber is determined by the time period from the pulse launch until the return of the pulse to the detector.

Brillouin peaks usually provide information about distributed temperature and distributed strain, since both temperature and strain affect the wavelength shift and those can then be deconvolved into individual temperature and strain measurements. As with the Raman

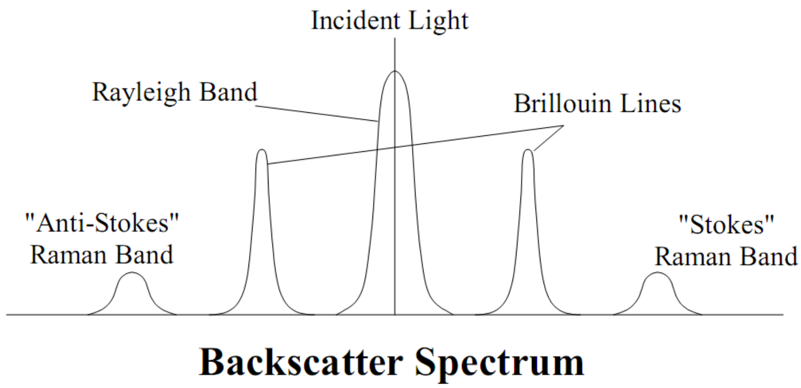



**Figure 2.2:** Backscattert light spectrum, (Carnahan et al., 1999)

components, the location of a particular measurement on the fiber is determined by the two way travel time of the pulse of light (Carnahan et al., 1999; Dria, 2014).

The accuracy of the measurements with the help of distributed temperature sensing technology should be incorporated into its description in order to be comprehensive. For DTS system the temperature can be determine at every meter along the whole length of deployed optical fiber. The surface component of equipment is sending 8ns pulses of 1064nm wavelength laser light down the fiber and provide analysis of backscattering light for each meter of the distance of interest. The intensity of the backscattering light is strongly proportional to the temperature of the optical fiber. Result of analysis of backscattering spectra directly depends on the temperature of optical fiber at the point of interest. Typical resolution for obtained measurements is 0.1 Degrees Centigrade (Brown et al., 2000).

## 2.4 Application of Distributed Temperature Sensing

DTS technology is considered to be well-known and proven by comprehensive field trials. The area of implementation for this system has covered a wide range of applications.

### 2.4.1 Conducting reservoir surveillance

One of the priorities for DTS utilization is an acquisition of reservoir surveillance data. Totally new approach for data collecting has become available to implement using of the optical fiber technology. The real-time monitoring of reservoir and well performance is usually viable by running production log on the end of the coiled tubing. Sometimes the condition makes impossible to use conventional techniques for monitoring and data acquisition, hence the new methods must be found. Permanent placement of optical fiber behind the casing enables to recognize the flow behind the casing and presence of flow during shut-in periods. Furthermore, it was made possible to identify water finger encroachment.

The accuracy of obtained measurements is dependent on many factors such as steady state thermal conditions, thermal properties of flowing fluids and assumptions. There is a number of specialized software for making comparison and interpretation of the acquired data. Consequently, data analysis is split into two parts. One of them is visual interpretation of the obtined real-time measurements and another one corresponds to utilization of fluid flow and heat transfer simulators, which provides theoretical preditions and evaluation of production scenarios.

It is obvious that only continuous temperature monitoring of the well will not resolve all the problems related to well exploitation but in combination with comprehensive thermal models and other acquired data, it is possible to develop a significant understanding of reservoir performance without frequent production logging (Brown et al., 2000).

### 2.4.2 Water injection monitoring and gas lift system optimization

One of the earliest sphere of DTS technology implementation is presumably considered to be monitoring of water injection and gas lift system optimization. Historically, DTS was used since 1930Šs for evaluation of water injection profile, flow contribution calculations and estimation of effectiveness of fracture jobs, etc.

The key to comprehension of temperature measurement challenges in the well is to understand the fluid flow behaviour and ways of heat transfer occurs taking into account Joule Thomson effect and influence of geothermal gradient. The merger of these effects generate a characteristic thermal profile, which is time dependent. It is possible to record it by using DTS system whereupon analysis of the results can be interpreted.

There are two basic concepts for water injection analysis. The first one is the technique called warm back. The main idea of it is to obtain the lower limit of injected fluid. The permeable intervals will be cooled by the fluid with greater radius than impermeable intervals. The second approach used in water injection analysis is hot slug velocity measurements. In case of well shut-in, the water inside the tubing above the reservoir will have higher temperature after sometime than underlying volume of fluid. When injection is renewed, the formed hot slug propagation can be tracked by optical fiber technology. It is also possible to estimate the velocity of the propagated slug for visual representation of flow profile into reservoir.

Regarding the gas lift optimization, the optical fiber technology is used to monitor the effectiveness of functioning of wellŠs Gas Lift Mandrels (GLMŠS). Using results of Joule Thomson effect of gas going through the mandrel, identification of the mandrel location becomes possible. This process provide a qualitative estimation of mandrels performance.

It became feasible to identify the slug flow through the mandrel using DTS system.

For injection profiling and gas lift system optimization problems, obtained results with the help of DTS technology is normally compared to utilization of wireline radioactive tracer tools and Production Logging Tool (PLT). It is worth noticing that the main challenge for PTL utilization comprise the fact that one running of the tool corresponds to obtaining of one temperature profile that makes analysis more difficult. In addition to this, it might be impossible to access the wellbore because of any obstruction such as scale build-ups, casing deformation, etc.

In contrast to traditional methods of data acquisition, the fiber optic system is able to generate multiple temperature profiles during the life of the well. The main advantage of DTS for all cases related to monitoring is capability to obtain the temperature measurements simultaneously through entire length of the well during a long period of time. This enables to perform monitoring of the work for all gas lift valves in the same time, but in case of PLT utilization, it is impossible to acquire. Indeed, the optical fiber is flexible enough to pass through tubing bends and dog-legs. Also, when the fiber is permanently installed, it is immune to subsequent casig deformation and scale formation. However, permanent installation of the optical fiber is associated with high-rate and high-cost fields mostly found off-shore.

In view of these advantages of DTS technology, it is important to mention that the results of acquired data analysis are also dependent on methods used for interpretation such as stabilized injection, thermal resolution and thermal tracer. According to field trials, it was concluded that thermal tracer or velocity tracing methodologies to be the most robust solutions, since other techniques provide questionable outcome without long period of data recording.

In other words, continuous monitoring of water injection procedure and performance of gas lift equipment using optical fiber technology provide opportunity to take corrective actions and optimize the solution for the problems based on understanding the processes occurred inside the well and reservoir. Simultaneous monitoring throughout the interior well with the help of DTS gave reliable and real-time data, which ensure robustness of technology with cost effective way of data acquisition (Brown et al., 2005; Rahman et al., 2011).

### 2.4.3 Real-time monitoring of acid stimulation

As a rule, DTS system is used for continuous monitoring purposes during different stages of well exploitation. Controlling the acid stimulation requires precise understanding of near wellbore dynamics and conditions. The acid treatment creates harsh environment, hence absence of downhole electronics and moving parts in the optical fiber system makes it suitable and reliable for utilization. In case of acid treatment stimulation, the optical fiber is used to perform monitoring of multiple non-isolated intervals.

With the help of DTS, it is attainable to collect valuable information that enables identification the zones which were taking the acid. With conventional technology for monitoring the acid stimulation, it was impossible to obtain the information about acid placement and to know whether it was effective. The information about amount of the acid consumed by each zone relatively to other can be also acquired with the DTS implementation. Obtained data allow to make on-the-fly changes for the purpose of adjusting pumping rate and make-up of the acid treatment. Furthermore, utilization of DTS system permits to develop a systematic approach for improvement in the acid treatment predictability in order to maximize efficiency of stimulation. The contrast between injection profiles before and during acid treatment helps to limit the amount of pumping fluid and prevent formation damage, thus wise enables to diminish environmental impact.

To collude, it is appropriate to state that utilization of the optical fiber technology drives industry towards smart acid placement rather than using broad brush approach (Clanton et al., 2006).

### 2.4.4 Tracking and surveillance during production and shut-in periods

One of the latest and advanced areas of implementation for DTS system is utilization during production and shut-in periods for well performance monitoring and evaluation. The technology is used to obtain a better comprehension of flow allocation in a complex reservoir structure, since possessing precise information at earlier stages of production will be a decisive foundation for further field development. Acquired data with the help of DTS enable quantitative analysis of gained fluids to be performed at any desirable time within the necessary period. Utilization of this technology will allow wells to de completed with smaller sizes because of limiting requirements for production logging. Obtained information yields improved reservoir characterization and provides opportunity to predict the dynamics of reservoir behaviour. On basis of data analysis results, it is possible to see the trend of zones depletion over time represented by pressure changes and etc. Combination of data acquired by logging operations and from DTS survey can be used in generating accurate reservoir models. These models are employed in converting temperature data to valuable flow information. Available opportunity to perform monitoring over time, started from the beginning of production period, helps to identify the main parameters that has strongest influence on the flow profile and controlling the flow.

In order to produce a fluid from a reservoir in the optimum way, there is a strong need to determine the reservoir properties such as permeability or skin since commencement of production. Changes in the parameters will inevitably occur during the production when depletion in pressure takes place. That is why reservoir models must be kept updated by input information from continuous monitoring, enabling calculation of reservoir zones contribution whenever it is required. Especially for the long-term reservoir management, it is claimed that combination of DTS measurements and other data about reservoir can be used as a foundation for realistic model of permeability and reservoir fluid dynamics (Fryer et al., 2005).

### 2.4.5 Downhole Leak detection

DTS system has increasing amount of applications. Since this technology proved its robustness in many field trials, it was also decided to use the optical fiber for leak detection and compare with conventional methods such as leak detection logs (LDLŠs). Traditional leak detection technics employed an operational diagnostic tools deployed on wireline if the annular communication is detected. However, ultrasonic leak detection logging is proved to be more effective in pinpointing the leaks under 1bpm. On the other hand, taking into account the fact that the ultrasonic tool can be attached to DTS line and it is mostly used for small leaks, it is common to use DTS for narrowing the potential intervals and ultrasonic tool for conformation the precise location of the leak.

It is claimed that the optical fiber technology is considered to be able to detect all types of leaks (small, multiple and large). In case of large leaks detection, utilization of DTS technology allows to save time for operation and required amount of injected fluid is significantly smaller than in conventional technology implementation. In case of multiple leaks detection, it is a challenge to identify small leaks in a presence of large. It is vital to provide as high a differential pressure as possible across the leaks area. When differential pressure is maintained enough high, secondary leaks will emerge and be identified. In case of small leaks detection, the question of resolution for identification technics is arisen. The leak is considered to be small when it is $< 0.1$ barrels per minute. This rate is often below the limit of resolution for conventional methods that is why the temperature anomalies can be ŞsmearedŤ. DTS makes possible to eliminate this unpleasant effect because once it is installed there is no need to move the optical fiber.

It will be appropriate to say a few words about temperature resolution of DTS for the specific area of application like leaks detection. Since the intensity of each backscattered pulse is weak, a huge amount of pulses has to be done before a complete temperature profile could be obtained. The required time for detection can be from a few seconds up to some hours, which depends on the necessary resolution to be achieved. In practice, the time of recording is an equilibrium between estimated rates of temperature change and necessary temperature resolution. To be able to detect especially small leaks, it is vital to have this balance. However, it is important to correlate acquired data with the well completion to be able accurately determine the leak point (J.Y. Julian and et al., 2007).

## 2.5 Principles of Distributed Acoustic Sensing

Distributed Acoustic Sensing (DAS) has caused immense advancement in the monitoring business, since it has provided the ability to listen to the acoustic field along the whole length of the optical fiber cable deployed into the well. DAS system allows to obtain a full-spectrum acoustic signal with a spatial resolution of almost every 1 meter. Figure 2.3 illustrates the principle of the DAS system.

A novel digital technique for storing obtained information is implemented in the DAS system. Traditionally the measuring tool consists of two main elements: the interroga-

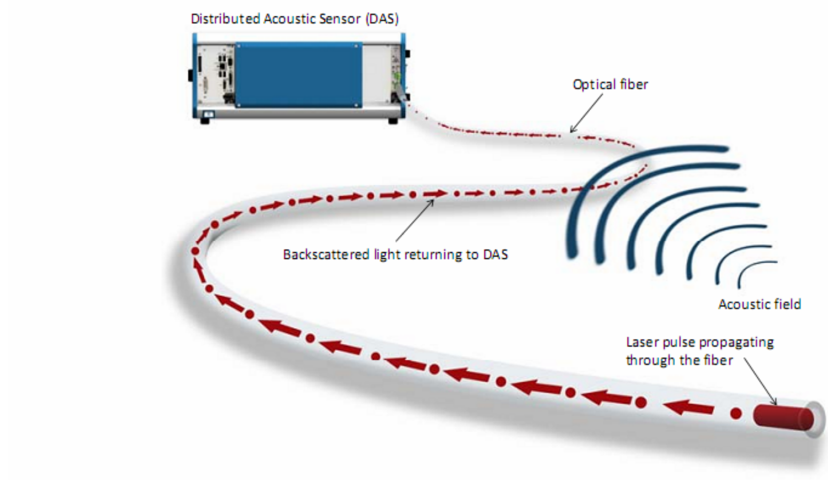



**Figure 2.3:** Principles of Distributed Acoustic Sensor, (Johannessen and Drakeley, 2012)

tor system at the surface and the downhole-deployed optical fiber. DAS system applies a technique called Coherent Optical Time Domain Reflectometry (C-OTDR). The DAS is sensitive to vibro-acoustic disturbance around the optical fiber. The disturbance occurs on a microscopic level. In contrast to DTS, which measures Raman components of backscattered light with utilization of a 50 micron core multi-mode fibre, DAS works with a 9 micron core single-mode optical fiber. The fact that DAS system uses single-mode cable allows obtaining better special resolution and reducing noise. Each small segment of the optical fiber acts as an interferometer[1]. Association of all the backscatter photons forms an interference pattern. The intensity of this pattern is determined by the localized changes in the optical fiber segment length. The microscopic change in the length of a small portion of the fiber will cause a change in the intensity of the Rayleigh backscattered laser signal. These changes in length are due to mechanical strain effects on the fiber at that point (e.g., the very small strain effect that occurs when the pressure pulse of an acoustic wave strikes the fiber). Comparing both, Rayleigh scattering is much stronger that Raman scattering. Important to mention is that the interpretable modification in backscattered light are analysed at the interrogation component of DAS. The digital optoelectronic technic implemented in the DAS system enables to record the instantaneous phase (or frequency) of light rather than the amplitude.

It is relevant to mention that this type of measurement provides at a spatial resolution as small as 1 meter a full recording possibly as high as 50 kHz over the length of the fiber. Each time fragment contains a snap shot of the acoustic field, which is averaged over the 1 meter segment of optical fiber cable at that particular fragment section.

Obtained raw data of acoustic field pass from the interrogator unit to the processing com-

[1] Interferometry is a family of techniques in which waves, usually electromagnetic, are superimposed in orde to extract information about the waves (source: Wikipedia).

ponent of DAS where the interpretation and visualization are made (Johannessen and Drakeley, 2012; Dria, 2014; Molenaar et al., 2011).

## 2.6 Processing of Acoustic Signal

One of the challenges of the DAS system utilization is processing a large volume of data collected at field conditions. As an example, it would be appropriate to consider an interval in 10 km of optical fiber, each meter of which working at 10 kHz. This can generate the minimum data rate equal to 100 MSamples/s. Some Software with implemented special signal processing techniques have been recently developed. They enable comparably fast analysis of the signal acoustic spectra along the entire length of the optical fiber. Those techniques have also the ability of identification of flow characteristics along the well.

One of the current processing techniques called coherent phase array processing technique, enables to trace the propagation of the acoustic energy along the well. This is applied in analysis implementing space-frequency domain for the speed of sound validation, and consequently, to measurements of fluid composition and velocities (Johannessen and Drakeley, 2012).

## 2.7 Applications of Distributed Acoustic Sensing

DAS system is regarded as immature technology in comparison with DTS, which has been utilized during the last 20 years. Taking this into consideration, the implementation of the DAS system in the oil and gas industry causes a lot of excitement and creates a necessity for further investigation because the technology possesses wide potential application areas. The spectrum of DAS envisages applications consists of distributed flow measurements, sand detection, smart well completion monitoring, gas breakthrough and etc.

### 2.7.1 Monitoring in-well activities and hydraulic fracturing treatment

One of the initial spheres of implementation was the utilization as a monitoring tool for in-well activities and hydraulic fracturing stimulation. The technology proved itself as sensitive and robust. Traditional diagnostic techniques such as radioactive tracers, come with certain limitation concerning shallow depth investigation.

Real-time in-well monitoring with the help of DAS demonstrated that the optical fiber technology to be able to detect precisely enough activities caused by placement of downhole tools, etc. In-well activities can be observed due to acoustic signature followed up the processes. Moreover, DAS made evident the ability of producing measurements that enables to capture the dynamic changes during the hydraulic fracturing treatment. Since the recordings are made in a broad frequency range, it allows to differentiate perforation clusters being active during acidation stage and perforation clusters taking most of propant and fluid during stimulation process. Possessing this kind of information gives opportunity to optimize the volume placement design and make improvements in the treatment. The figure below illustrates the monitoring process of hydraulic fracturing treatment.

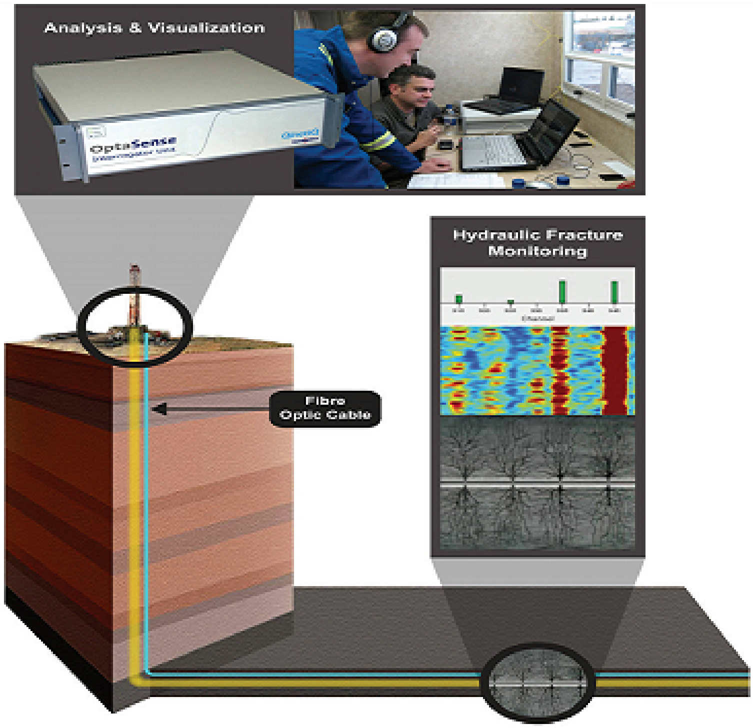



**Figure 2.4:** Monitoring process of hydraulic fracturing stimulation, (Molenaar et al., 2011)

Also, worth repeating is that passive nature and long-term reliability of DAS extend the area of applicability of this system, creating the persuasive foundation for further enhancements. The fidelity of recordings acquired during hydraulic fracturing stimulation enables to perform post-job diagnostics. The results of surveillance analyses can be further used in optimizing simulation of propant and fluid placement. In addition to this, the acquired information can enforce cost savings in real-time during the stimulation (Molenaar et al., 2011).

### 2.7.2 Advances in Distributed Acoustic Sensing for Vertical Seismic Profiling

Another area of DAS application is vertical seismic profiling (VSP)acquisition. In this sphere of implementation, DAS works as a seismic receiver array. The conventional functions of DAS can be represented by completion tasks such as checkshots, imaging and time-lapse monitoring.

To begin with, the acquired seismic data with the help of DAS possess sufficient degree of quality to be compared with traditional VSP methods such as 1C geophones. Since this is not common area of implementation for optical fiber technology, improvements in quality of acquired data went gradually. Nowadays tremendous increase in the signal-to-noise ratio is observed. Under most circumstances, the higher the signal-to-noise ratio in measurements, the more detailed picture can be obtained. Beside this, it is noticed increase in seismic signal coherence. Moreover, the new datasets possess denser receiver spacing (channel with the length of 8 meters versus 10 meters therefore). It is also claimed that DAS method in VSP acquisition gives more detailed checkshots than conventional checkshots with the help of geophones. There is absence of necessity for moving receivers and repeating shots as it was done previously.

Taking into account the fact that DAS technology does not require well interventio and measurements can be made while producing, it can be concluded that DAS will become a more popular method in VSP data acquisition and cover the type of wells previously assumed to be inaccessible (Mateeva et al., 2012).

### 2.7.3 Leaks detection with the help of Distributed Acoustic Sensing

According to the field experience, DAS is also appropriate for evaluation of abandoned gas wells condition. To be more specific, DAS was used for leak detection (small continuous leaks and large outburst). The optical fiber technology makes possible continuous full-well coverage for monitoring without necessity of moving tools in the well, which diminishes interfering with measurements. It is also important to mention that there is no need for rig-up/rig-down for data acquisition that helps save time of operation and correspondingly introduce DAS as cost-effective method for making informed decision how to detect and handle leaks.

Nowadays not enough information about acoustic signature and characteristics of various leaks types exists. More field trials and laboratory research is necessary to conduct in order to form complete database. In addition to this, data acquisition parameters and modes are required to be examined for determination of optimum framework for leak detection. It is worth noticing that there is demand for further improvement in the construction area of optical fiber, for instance, elimination of vertical striping noise by developing proper insulation (Boone et al., 2014).

### 2.7.4 Application of Distributed Acoustic Sensing for Improved Wellbore Production Surveillance

It is proved that DAS can be used for monitoring the performance of individual perforated zones during production or injection for a long period without need for well intervention.

The optical fiber can be deployed and can be left permanently behind casing due to occurrence of necessity for data acquisition at any convenient time. In addition to this, DAS system allows to track the injected fluid distribution during smart injection, and consequently to control the process by utilization of flow control valve.

In anticipation of all what was said above, it is possible to state that the advantage of DAS technology permits introducing new areas of applicability for the system. Acquired data is normally used for optimization purposes, the main objective of which is to ensure that standards of governmental regulations are met with cost-effective planning.

Due to the fact that the DAS technology is being applied to a few new fields, necessary software has been developed to properly visualize the acquired data. Further research must be conducted to make standard interpretation of the graphs available. The interpretations could then be used to perform flow regime characterization for different types of wells (van der Horst et al., 2014).

## 2.8 Distributed Temperature Sensing and Distributed Acoustic Sensing integration

Integrating the various measurements of anything to monitor the in-well conditions offers the best advantage and highest use of that information.

The idea that has been presented by several groups in the last several years is the utilization of the optical fiber for monitoring. That highlights the fact that one cable can provide the opportunity to obtain many measurements simultaneously. Combination of DTS and DAS permit the use of unique monitoring options during the whole life of the well.

For example, for an unconventional well starting from the pre-fracturing period, DTS is used for geothermal acquisition, cement monitoring (finding the top of the cement) and perforation monitoring. During this period, DAS can be used to monitor offset wells that are being fracked and to obtain vertical seismic profiling (VSP) information. For instance, fracturing operations are considered the time for the most concentrated data acquisition for both DTS and DAS. Everything from using DTS as a thermal tracer to identifying injection profile, and augmenting the temperature profiles obtained by DTS with those from the DAS.

### 2.8.1 State-of-the- art technology combined with brilliant ideas

The optical fiber technology is used worldwide for less than 30 years, and the number of applications of this technology is constantly increasing. Ziebel AS has created a new technical solution for well intervention based on utilization of the optical fiber technology. This engineering proposal is called Z-system represented by semi stiff composite carbon rod sensing with the outer diameter of 15 mm.

**Figure 2.5:** Z-System Sensing, (Ziebel, 2014).

As in all previously mentioned cases the optical fiber works as a sensing device itself but the difference of Z-system from conventional optical fiber systems is that proposed technical solution is a combination of sensing fibers. This system includes Distributed Temperature Sensing, Distributed Acoustic Sensing, Point Pressure in Bottom Hole Assembly (BHA), Point Temperature in the BHA and vibration sensor in BHA.

The acquired data are transmitted to the onshore center where the technical experts can visualise and interpret the data. Since Z-system is a combination of several sensing fibers inside one carbon rob, it provides unique opportunity to obtain more detailed information about fluid behaviour and changes in the reservoir conditions.

Chapter 3

# Experimental Setup

Despite being used in many areas including the oil and gas industry, the optical fiber technology still has a few spheres of implementation that require further laboratory research and field trials. Some of the common problems with this technology for well intervention service in the industry are lack of a complete database for aquatic signature of downhole events (e.g., during leak detection), and absence of standardized ways of interpreting the obtained graphs in order to determine integrity issues.

The objective of the laboratory experiments of this work is to investigate the potential of DAS system for flow regime classification in order to improve data analysis and interpretation processes. These tests are practical by nature and the results will be further used in the neural nets designed at Ziebel AS.

This chapter will be devoted to a description of the laboratory apparatus used in experimental investigation. It will contain a detailed description of every individual component in the experimental setup. The procedural sequence of the experiment will also be described later in the chapter.

## 3.1 Components of Experimental Setup

The experimental setup contains two groups of apparatus. The first part consists of plastic see-through vertical tubes with a manifold at the bottom, as illustrated in Figure 3.1. The second part includes components of the optical fiber system as shown in Figure 3.2.

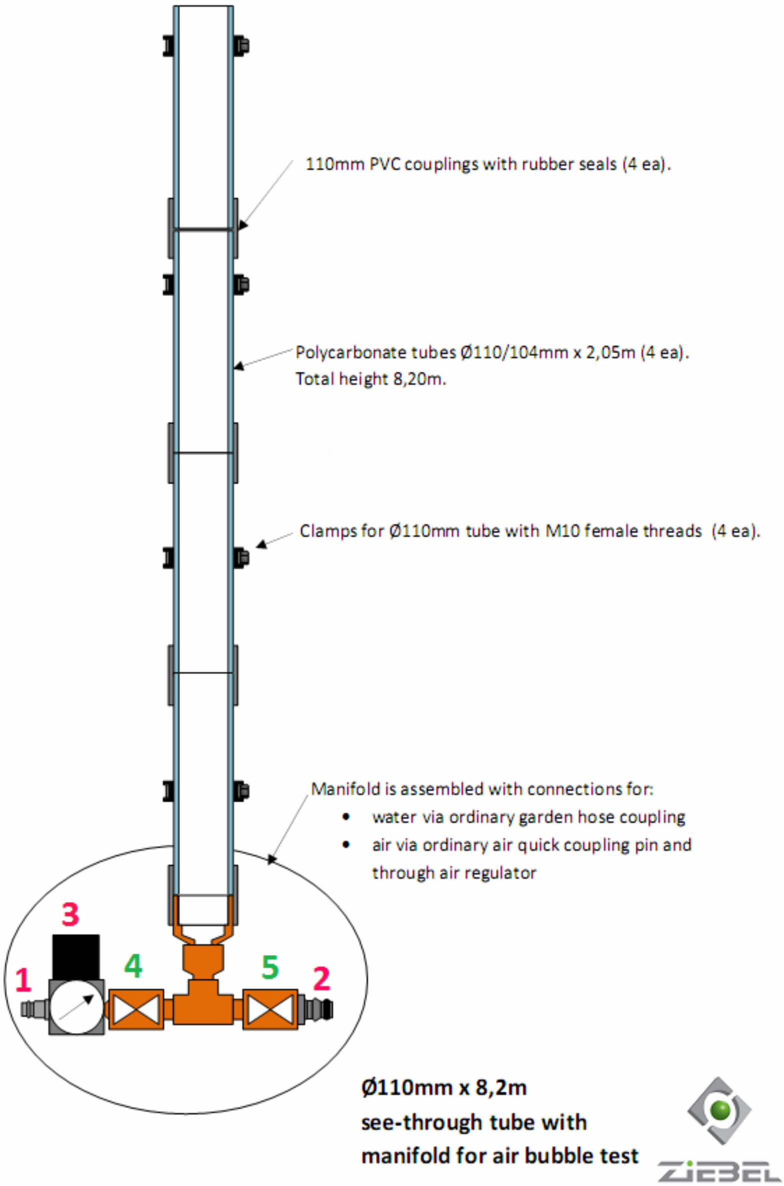



**Figure 3.1:** Vertical pipe with manifold for air bubble experiment, (Ziebel, 2014).

### 3.1.1 Vertical tube

The proposed vertical tube is intended to simulate a production tubing. The vertical section of the tube consists of four segments, each of length 2.05 m, summing to a total height

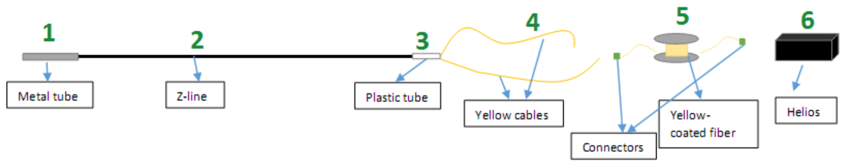



**Figure 3.2:** DAS system components, (Ziebel, 2014)

equal to 8.20 m. The diameter of the tube is ⌀110/104 mm, corresponding to the outer and inner measures, respectively.

The bottom part of the vertical tube is equipped with a manifold, which is assembled with the following connections and valves (numbers as indicated in Figure 3.1):

- #1 connection for air supply via air quick coupling pin;
- #2 connection for water supply via garden hose coupling;
- #3 pressure gauge;
- #4 ball valve;
- #5 ball valve.

In order to monitor different flow regimes, a see-through vertical tube made of polycarbonate was used. Perfectly matching the goal of this experiment, the segments from this material are easily joined together using PVT coupling with rubber seals. Since the tube is made of plastic, it possesses high tensile and impact strengths. The vertical tube has sufficient length compared to the size of laboratory room. To avoid unnecessary movements, it is required for the tube to be fixed to a metal frame. The connections are settled by means of clamps for the tube with M10 female threads. Notwithstanding the fact that the tube consists of several segments, it acts as one solid pipe due to the employed method for joining the sections. This mechanism of installation allows for creating flow regimes characterized by significant turbulence.

### 3.1.2 DAS system

In this section, the components of the DAS system within the experimental unit and procedure of its installation will be described. Figure 3.2 illustrates the order in which the elements need to be connected:

- #1 terminal end or metal tube in order to add weight to the bottom part of the Z-line;
- #2 Z-line;

- #3 plastic tube in order to protect the top terminal end of Z-line and make available access to single cables;
- #4 yellow cables;
- #5 yellow coated fiber representing Dead Zone Eliminator;
- #6 Helios or laser source.

The DAS system unit was assembled according to provided instructions from Ziebel AS. It is worth noticing the fact that the optical fiber is made of very fragile material. That is why the cables and especially the connections to the cables must be handled with extra care and not be pulled or bent severely.

The procedure for installation of the components of the DAS system is as follows. First, the Z-line was transferred inside the vertical polycarbonate tube until the terminatal end (#1) was placed at the bottom of the tube. Since the length of Z-line was 7.90 m, the Z-line was placed inside the vertical pipe so that the level of the plastic part (#3) matched the rim of the vertical tube. The purpose of the plastic part between the Z-line and cables was to protect the fiber splices. Precautions were taken regarding the yellow cables, which stuck out of the plastic tube at the top end of Z-line.

According to the experimental setup, the Z-line was provided with two cables sticking out of it, namely the “primary” and “secondary" cables. The secondary cable was placed as a backup, in case the primary cable was damaged.

The yellow coated fiber represented Dead Zone Eliminator that had to be connected in between Z-line and Helios. The coil consisted of around 460 m of the optical fiber cable. Checking whether the connectors were still intact with the fiber, was an important part of the installation procedure.

Before utilizing any of the connectors, it was necessary to clean the connectors with isopropyl alcohol only and not other cleaning agents. The cleaning procedure is as follows:

1. pour some isopropyl alcohol on the wipe;
2. open the black cap of the connector and push it down without forcing it to avoid being broken;
3. rub the wipe on the tip of the connector;
4. close the cap.

It is important to keep the connectors clean, since dust will cause power loss. After cleaning the connectors, one of the yellow cables (Primary) was connected to the end labelled as “Connect to Z-line”. Another cable was connected to Helios and labelled as “Connect to Helios”.

After connecting every part of the system as shown in the Figure 3.2, the DAS system was ready to use for experiments. Figure 3.3 illustrates the setup of the pipe and the DAS box connected together.

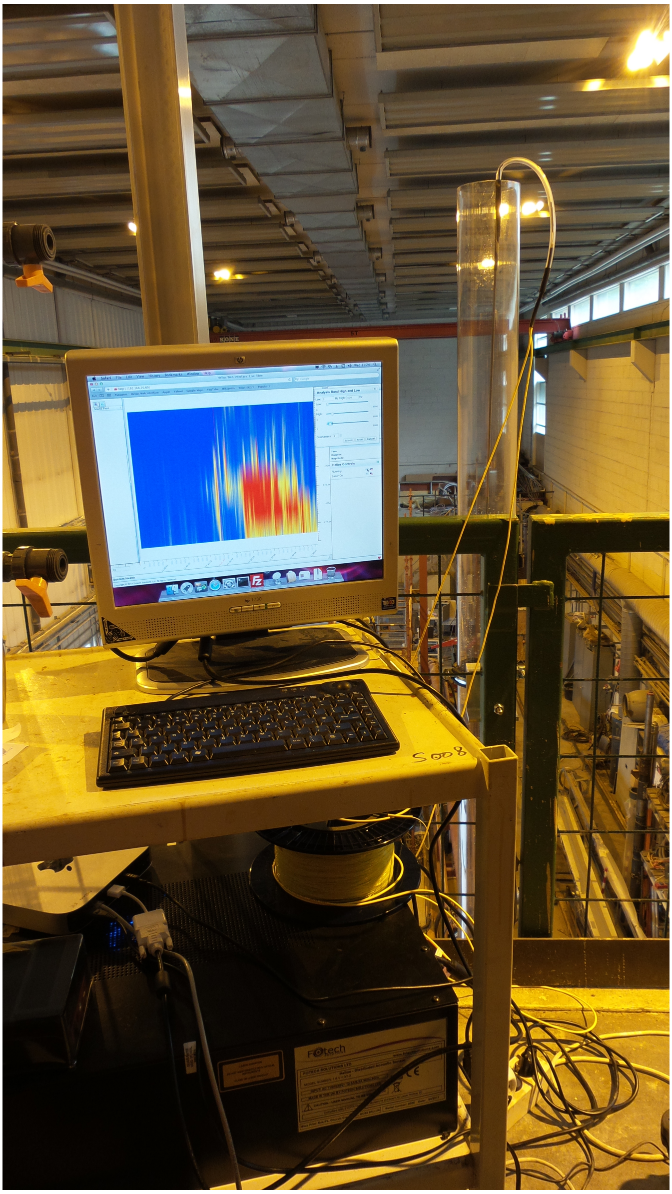


**Figure 3.3:** Z-line inside the pipe and connected to the DAS box.

## 3.2 Experimental fluids

It is common for experimental investigation to vary initial conditions and compare the results. For current studies were chosen two types fluids to create multiphase flow in the vertical pipe:

1. “water + gas”
2. “water+ pine oil+ gas”

The main purpose of adding pine oil was to decrease the size of the bubbles formed.

Pine oil (Figure 3.4) is a type of oil obtained by steam distillation of various parts of pine trees. The composition of pine oil depends on many factors. The main factors are type of the tree, place of production and source of raw material. Pine oil has the following phisical properties:

**Figure 3.4:** Pine oil

- density 950 kg/m$^3$;
- insoluble in water;
- colorless to pale yellow liquid.

## 3.3 Experimental procedure

Using verified program settings in the Helios software, it is appropriate to start the experimental investigation.

Two different experiments will be conducted. The first part of experimental work is based on using the fluid consisting of only water and air. In contrast with the first setup, the fluid for the second part includes pine oil to make multiphase flow more similar to what happens in production tubing.

The sequence for conducting the experiments is as follows:

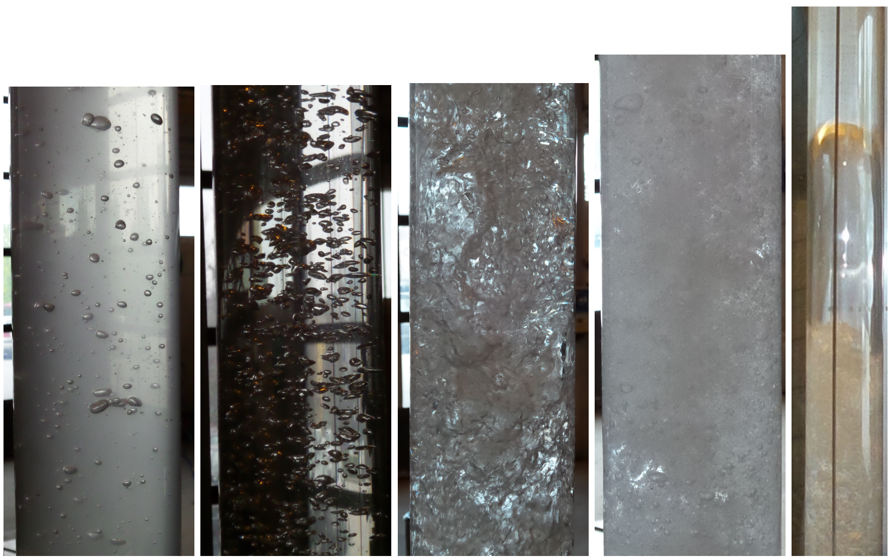
1. Connect hose to the manifold through connectors #1 and #2.

2. Turn on water and gas supply.

3. Open valve #5 to allow water to fill in the tube up to the desired level. This level is determined by safety conditions described by Ziebel's instructions. The plastic tube between the top end of Z-line and yellow cable must not be submerged in the water. For this reason, it is important to fill the tube with water only until 3/4 of the tube length to ensure liquid droplets will not reach plastic tube on the top of Z-line.

4. Close valve #5 and start using pressure gauge #3 to obtain the necessary size of bubbles from gas supply.

Using variuos gas flowrates, different multiphase flow conditions where created. The flow regimes mostly consisted of bubble flows with different bubble conditions, i.e. bubble flows with low gas rates and high gas rates. Another flow regime was a slug flow that was generated whose data was also used in the process of generating neural networks. Figure 3.5 illustrates some of the various types of flow generated.

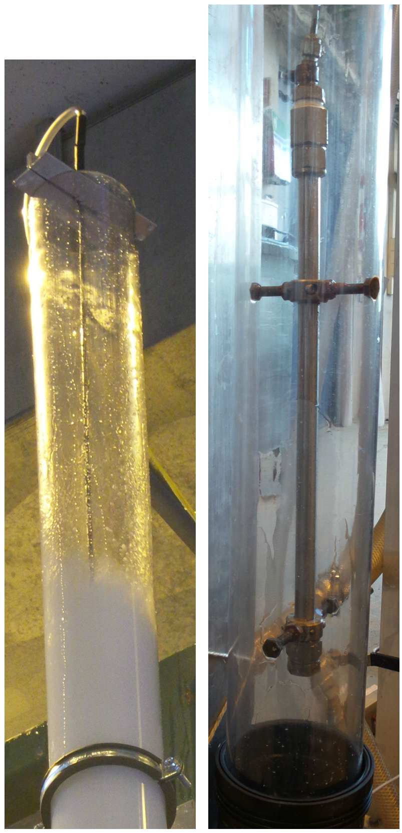


**(a)** **(b)** **(c)** **(d)** **(e)**

**Figure 3.5:** Different types of generated multiphase flows. (a) bubble flow with low gas rate, (b)bubble flow with medium gas rate, (c) bubble flow with high gas rate, (d) bubble flow with pine oil, (e) slug flow.

In the second experiment, where pine oil is one of the liquids in the system, a few millilitres of pine oil is placed inside the water hose before starting the water to fill the tube. This guarantees good mixing of pine oil with water solution and equal distribution throughout the height of the water column. The purpose for pine oil addition is to decrease the size of the bubble that will form.

Another important aspect of experimental setup is the tensioned or relaxed condition of Z-line. Figure 3.6 illustrates additional equipment used to change the Z-line condition from relaxed to tensioned. It could be seen that Z-line was hanged from the top part and fixed in the bottom part in order prevent movements by centralizing it. Prevention of excess movements of Z-line helps to reduce the unnecessary noise while acquiring data.



**(a)** Top section **(b)** Bottom section

**Figure 3.6:** Equipment setup at the top and bottom parts of the pipe

Chapter 4

# Artificial Neural Network

## 4.1 Introduction

Artificial neural network (Beale and Jackson, 1969; Mohaghegh, 2000; Shokir, 2001; Zurada, 1995) is the technology that started development from the challenge to obtain a full understanding of some ideas and aspects about how biological systems work, especially the human brain. A Neural system consists of a basic element called the artificial neuron, or simply the neuron. This neuron receives some input signals from other neurons, each signal is multiplied by a certain value called weight, and then the resulting sum of the weighted signals is activated through a non-linear function to determine the neuron output. This basic element, with its features, repeats itself vertically designing the layer, which in turn designs the whole network as it is repeated horizontally many times with only three types: input layer (only one layer), hidden layer (could be more than one layer), and finally output layer (only one layer).

The vast majority of applications performed by artificial neural network have been trained by supervised training technique. In this technique, both input data and corresponding desired output data are given to the network. As the network starts training, the input layer receives the input signals, then processing the data through the hidden layers until reaching the output layer yielding the resulted outputs. These outputs are then compared with the desired outputs to compute the error, which is back-propagated through the system causing it to adjust the weights, which control the network. The weights are randomly given small values at the beginning of training the network. The process of training is repeated, stopping only when the system has attained the desired accuracy.

One of the problems that occurs during neural network training is called “overfitting”. In this case, the error on the training set gets to a very small value, but when the network is exposed to new data, leads to unacceptably large errors. In other words, the network has memorized the training examples, but it has not learned to generalize. In order to let the network to get trained with sufficient generalizability, the available data should be divided into three subsets. The first subset is the training set, which is used to train the network (i.e., determination of the optimum values of synaptic weight and biases). The second subset is the validation set; the error on the validation is monitored during the training process. The validation error will normally decrease during the initial phase of training and so does the error corresponding to training set. However, when the network begins to overfit the data, the error on the validation set will typically begin to rise. When the validation error increases for specified number of iterations, the training is stopped, and the weights and biases at which the validation error and training error were minimum are considered as the optimum values of the synaptic weights and biases. The third subset is the testing set; this set of data, which is not used during the training, is used to obtain the overall accuracy of the network and compare performance of various network structures.

## 4.2 Setting Up a Neural Network within MATLAB

This section is intended to illustrate the steps for setting up a neural network using MATLAB, with the purpose of predicting the type of fluid flow in a vertical pipe. Neural network models attempt to simulate the information processing that occurs in the brain and are widely used in a variety of applications, including automated pattern recognition.

Pattern recognition is nearly synonymous with machine learning (Bishop, 2006). This branch of artificial intelligence focuses on the recognition of patterns and regularities in data. In many cases, these patterns are learned from labeled "training" data (supervised learning), but when no labeled data are available other algorithms can be used to discover previously unknown patterns (unsupervised learning).

We will build a supervised neural network to learn the structural pattern of one third octave data throughout a pipe in a given flow condition, based on the structural patterns observed during a training phase.

### 4.2.1 Defining the Network Architecture

For the current problem we define a neural network with one input layer, one hidden layer and one output layer. The input layer encodes the one third octave band data for 37 bands (from band #0 to band #36) on the discretized length of the pipe. For our problem the length of the pipe has been discretized into a grid of 35 nodes. Therefore, each input sample is a vector of $37 \times 35 = 1295$ elements.

The number of samples in the input layer depends on the length of time at which the data for each flow condition was acquired. For this problem, data was obtained for each flow type for approximately 15 minutes. Since the temporal resolution of the measurement system was 3.3 seconds, this amounts to 273 samples per flow condition. All the samples from different flow types were put together in a matrix of 1295 rows whose number of columns is equal to the sum of number of samples for all flow types.

The output layer of our neural network consists of eleven units, one for each of the considered flow states (or classes). Of the eleven units, five correspond to the experiments with pure water, and the remaining six pertain to the experiments where pine oil was added to water. The output units are encoded using a binary scheme. To create the target matrix for the neural network, we transform each flow class using the following binary encoding:

1 0 0 0 0 0 0 0 0 0 0    for flow class #1
0 1 0 0 0 0 0 0 0 0 0    for flow class #2
⋮
0 0 0 0 0 0 0 0 0 0 1    for flow class #11

Thus, each flow class is described by a vector of 11 elements. For each sample in the input layer, one such output vector is used. All these vectors are put together as the columns of a matrix. This matrix will have 11 rows, and its number of columns is the same as the number of samples.

### 4.2.2 Creating the Neural Network

The problem of flow condition prediction can be thought of as a pattern recognition problem, where the network is trained to recognize the flow class most likely to occur when specific one third octave band data are observed. We create a pattern recognition neural network using the input and target matrices defined above and specifying a hidden layer of size 20. A schematic of the structure of the network is illustrated in Figure 4.1.

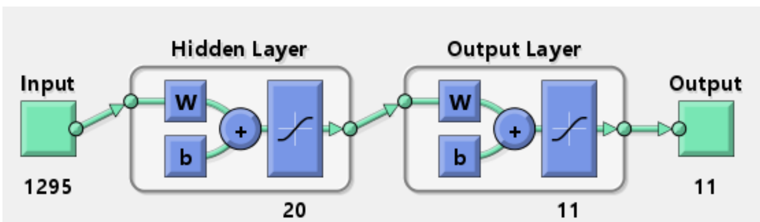



**Figure 4.1:** The structure of the resulting neural network. Letters “W” and “b” represent “weights” and “biases”, respectively.

### 4.2.3 Training the Neural Network

The pattern recognition network uses the default Scaled Conjugate Gradient algorithm for training. At each training cycle, the training sequences are presented to the network, one sample at a time. Each hidden unit transforms the signals received from the input layer by using a transfer function logsig to produce an output signal that is between and close to either 0 or 1. Weights are adjusted so that the error between the observed output from each unit and the desired output specified by the target matrix is minimized.

When using the MATLAB function `train` we divide the data randomly so that 70% of the samples are assigned to the training set, 15% to the validation set, and 15% to the test set. The training process stops when one of several conditions is met. For example, in the training considered, the training process stops when the validation error increases for a specified number of iterations (6) or the maximum number of allowed iterations is reached (1000). The MATLAB code used to generate and train the network is included in the Appendix.

Chapter 5

# Results and Discussion

Neural nets were trained to classify flow states with 3 sets of data. The first set was the one third octave band data acquired from experiments with pure water. The second set was the data from experiments with water plus pine oil. The third set included all data from the first and second sets. The different classes of flow generated and experimented on are listed in Table 5.1.

| No. | Liquid Phase | Flow Regime | Description |
|---|---|---|---|
| 1 | water | single phase | Water filling up the pipe (no air inflow) |
| 2 | water | bubble flow | air flow rate: 0.07 $m^3$/hour |
| 3 | water | bubble flow | air flow rate: 1.34 $m^3$/hour |
| 4 | water | bubble flow | air flow rate: 4.39 $m^3$/hour |
| 5 | water | bubble flow | air flow rate: 9.16 $m^3$/hour |
| 6 | water+pine oil | bubble flow | air flow rate: 0.05 $m^3$/hour |
| 7 | water+pine oil | bubble flow | air flow rate: 0.81 $m^3$/hour |
| 8 | water+pine oil | bubble flow | air flow rate: 2.67 $m^3$/hour |
| 9 | water+pine oil | bubble flow | air flow rate: 5.52 $m^3$/hour |
| 10 | water+pine oil | bubble flow | air flow rate: 10.23 $m^3$/hour |
| 11 | water+pine oil | slug flow | – |

**Table 5.1:** List of conducted experiments.

As seen in Table 5.1, the main flow regime considered in the experiments were bubble flow. Thus, the primary objective is to find out whether neural networks are able to classify bubbleflows of different air flow rates. Nevertheless, one slug flow experiment was also carried out in order to enhance the versatility of the trained neural nets to various flow regimes.

The first, second and third neural networks were trained with experiments (1 to 5), (6 to 11), and (1 to 11), respectively (see Table 5.1).

## 5.1 One Third Octave Band Results

The trained neural networks could correctly identify the flow class in almost all the cases. This performance implies that neural networks can be used with a high certainty to distinguish between different states of flow in the pipe. The results are presented through a few types of plots.

### 5.1.1 Confusion Plots

A confusion matrix in the area of machine learning is referred to a specific table system that illustrates the performance of a supervised learning algorithm. The columns of this matrix represent the instances of the predicted outcomes (in the case of our neural network system, the outputs). The rows of the matrix, on the other hand, represent the instances of the actual outcomes (the targets).

The confusion matrices are plotted for the three neural networks and illustrated in Figures 5.1 through 5.3.

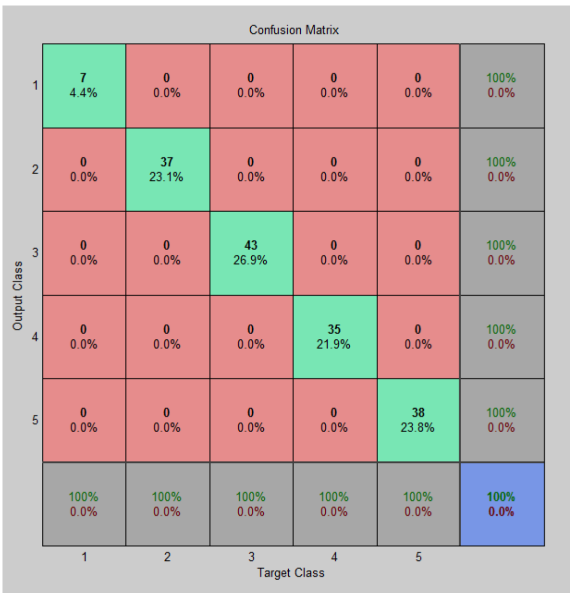



**Figure 5.1:** Confusion plot for neural network trained with water experiments. Experiments 1 through 5 in Table 5.1 are included.

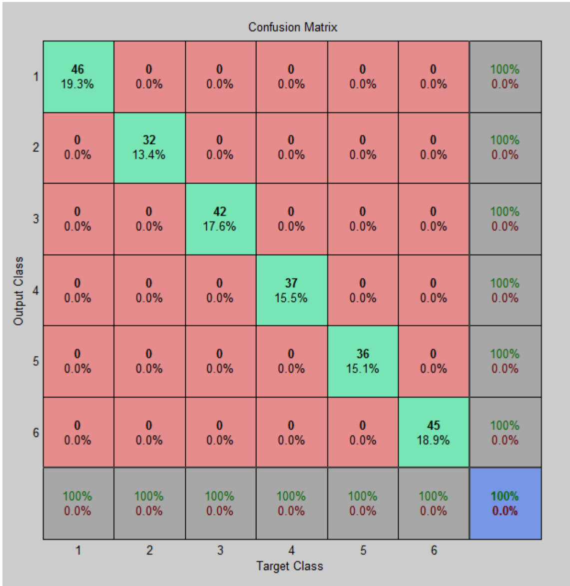



**Figure 5.2:** Confusion plot for neural network trained with water plus pine oil experiments. Experiments 6 through 11 in Table 5.1 are included.

The confusion plots show how many flow conditions were classified correctly in the green squares. It also shows how many flow conditions were classified incorrectly in the red squares. The total percentage of the correct and incorrect classifications are shown in the blue square. Also the total percentages for each row and column are shown in grey squares.

Figures 5.1 through 5.3 illustrate the confusion matrix for the Test set, a subset of the data which was not used during the training of the network. The plots clearly show the high efficiency of the trained neural networks in classifying the flow types. In the case of the first two networks (Figures 5.1 and 5.2), the networks perform the classification flawlessly.

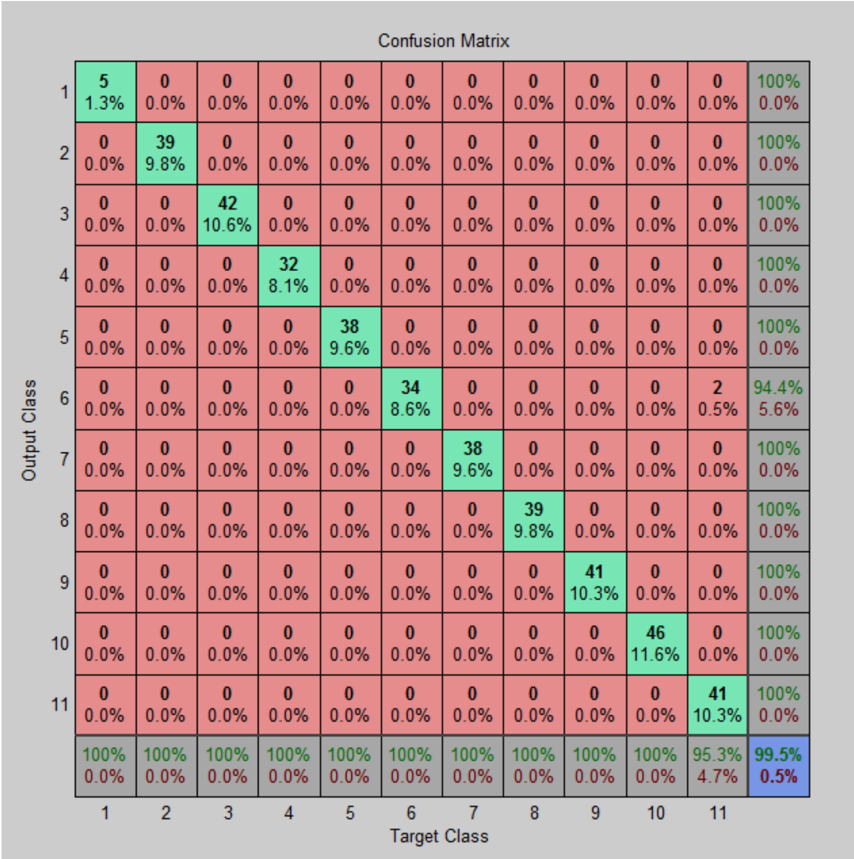



**Figure 5.3:** Confusion plot for neural network trained with all experiments. Experiments 1 through 11 in Table 5.1 are included.

The third network (Figure 5.3), however, showed some incorrect classifications. The reason can be the fact that the data used for training this network was based on two different fluids, namely pure water and water plus pine oil.

### 5.1.2 Performance Plots

The performance plot shows how the network converged on a lower error solution. As shown in Figures 5.4 through 5.6, these plots show the profile of mean squared error, which has a deacreasing trend while training the network.

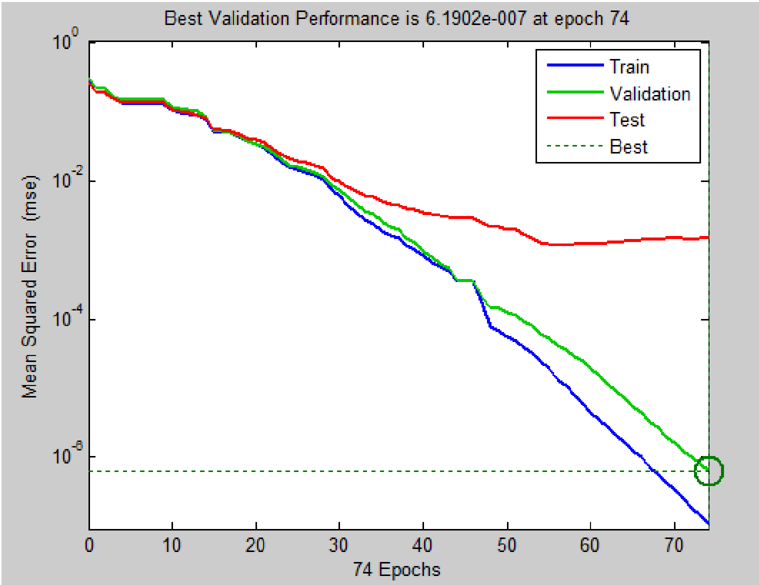



**Figure 5.4:** Performance plot for neural network trained with water experiments. Experiments 1 through 5 in Table 5.1 are included.

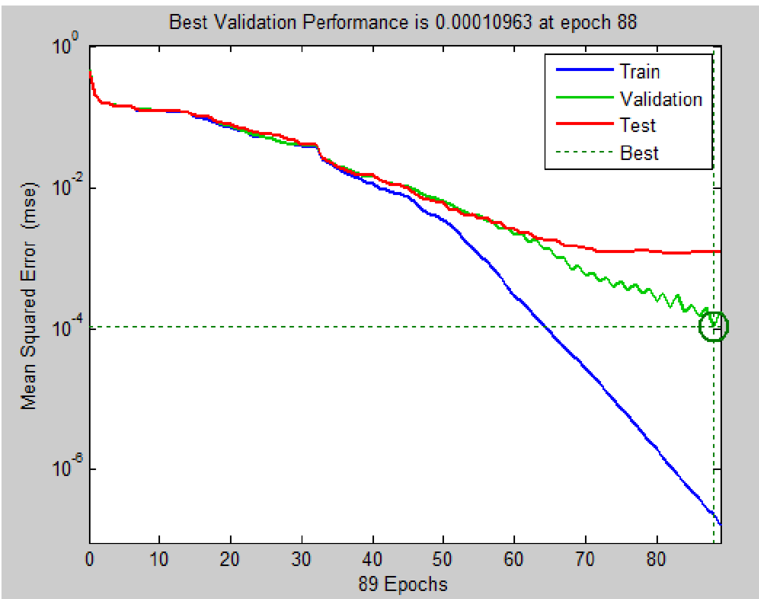



**Figure 5.5:** Performance plot for neural network trained with water plus pine oil experiments. Experiments 6 through 11 in Table 5.1 are included.

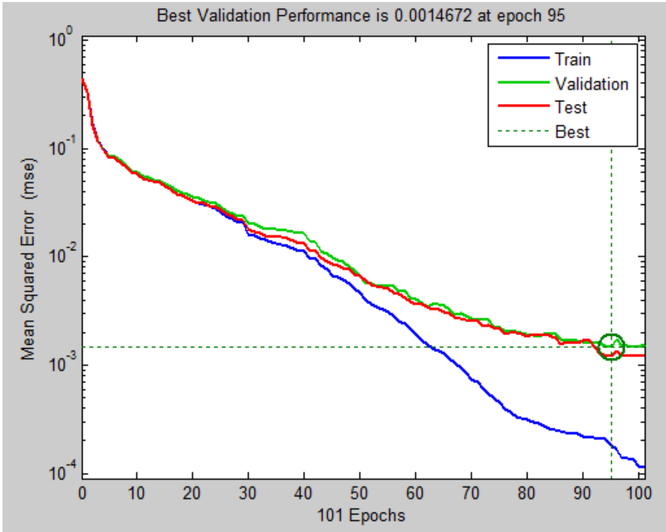



**Figure 5.6:** Performance plot for neural network trained with all experiments. Experiments 1 through 11 in Table 5.1 are included.

The overall errors for the first two networks (Figures 5.4 and 5.5) are of lower orders than the errors for the last neural network (Figure 5.6). This can also be owing to the fact that training of the last network is more complex due to data coming from experiments with various fluids.

### 5.1.3 Receiver Operating Characteristic Plots

The Receiver Operating Characteristic (ROC) plot shows the percentage of true positive class predictions we get as a function of how many false positive classifications we are willing to accept. The closer the lines follow the left and top sides of the plot, the better.

The ROC plots for the three neural networks are presented in Figures 5.7 through 5.9. All the plots show satisfactory profiles. This, again, confirms high the capability of neural networks to classify flow conditions in the pipe.

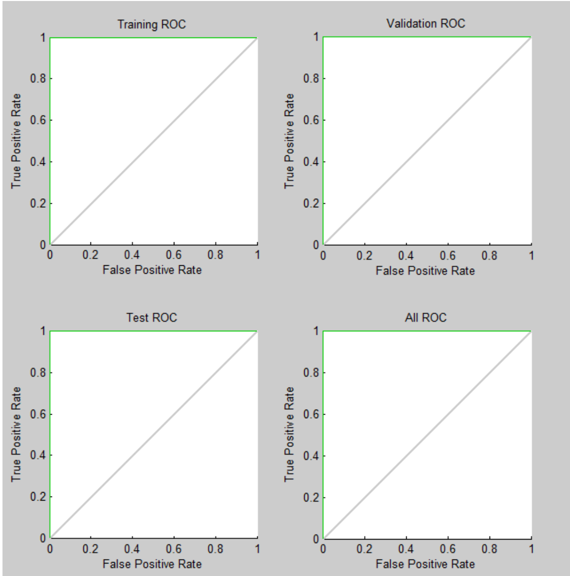



**Figure 5.7:** ROC plot for neural network trained with water experiments. Experiments 1 through 5 in Table 5.1 are included.

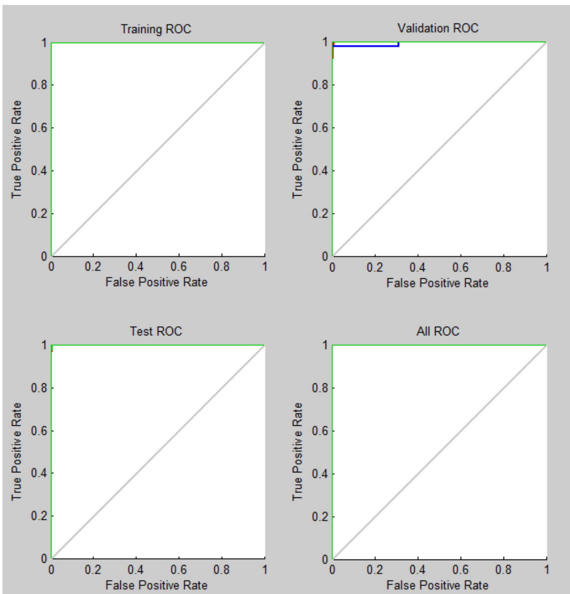



**Figure 5.8:** ROC plot for neural network trained with water plus pine oil experiments. Experiments 6 through 11 in Table 5.1 are included.

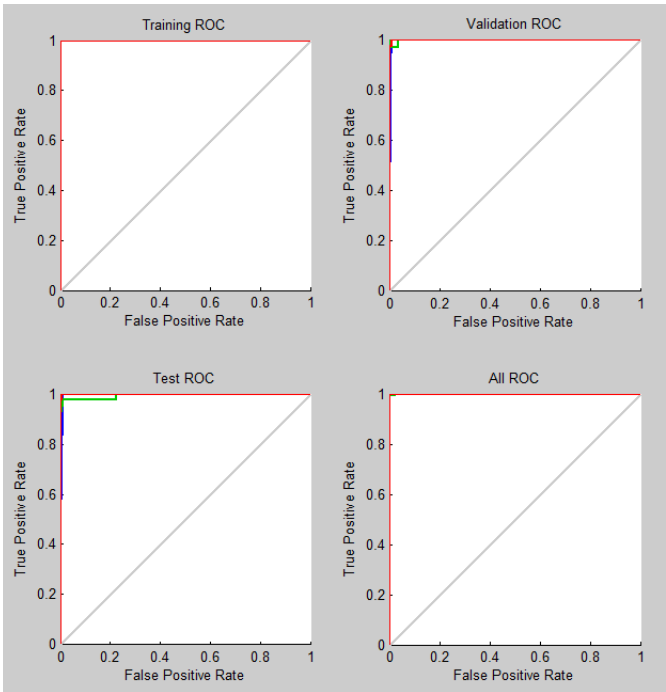



**Figure 5.9:** ROC plot for neural network trained with all experiments. Experiments 1 through 11 in Table 5.1 are included.

Chapter 6

# Conclusions and Recommendations

This work consisted of a series of experiments, processing the data from the experiments and interpreting the processed data using artificial neural networks. The objective was to interpret the one third octave band data obtained from experiments to classify flow conditions/regimes in a reasonable way. The follwoing are the conclusions drawn from this study.

- The generated and obtained neural networks could correctly identify the flow conditions with almost 100% accuracy. The only inaccuracy was caused during the training of the network with data from all experiments which included pure water and water plus pine oil.
- The generated neural networks not only classify flow regimes, but also different flow rates within the same flow regime. This property of the networks give them the ability to outperform human being if asked to classify the flow conditions/regimes.
- From the confusion plots, it is concluded that neural networks can classify flow conditions without a bias toward any one particular condition.
- It remains to be proven that neural networks trained in the laboratory conditions (low pressure, specific fluids, etc.) can actually be used to classify data from downhole conditions.

Further work can be done by using more flow regimes other than bubble and slug flow to develop a neural network. This will require modifications in the current experimental setup. Moreover, other types of fluids can be used to simulate the well conditions more precisely. Also, in order to find out whether the neural networks created in the laboratory conditions will work in the field conditions, data from real fields can be used to test the accuracy of the neural networks.

# Bibliography


Beale, R., Jackson, T., 1969. Neural Computing: An Introduction. Adam Hilger Company.

Bishop, C. M., 2006. Pattern Recognition and Machine Learning. Springer.

Boone, K., Ridge, A., Crickmore, R., Onen, D., January 2014. Detecting leaks in abandoned gas wells with fibre-optic distributed acoustic sensing. In: International Petroleum Technology Conference. No. IPTC 17530. Doha, Qatar.

Brown, G., Carvalho, V., Wray, A., Sanchez, A., Gutierrez, G., June 2005. Slickline with fiber-optic distributed temperature monitoring for water-injection and gas lift systems optimization in mexico. In: SPE Latin American and Caribbean Petroleum Engineering Conference. No. SPE 94989. Rio de Janeiro, Brazil.

Brown, G. A., Kennedy, B., Meling, T., October 2000. Using fibre-optic distributed temperature measurements to provide real-time reservoir surveillance data on wytch farm field horizontal extended-reach wells. In: SPE Annual Technical Conference and Exhibition. No. SPE 62952. Dallas, Texas.

Carnahan, B., Clanton, R., Koehle, K., Harkins, G., Williams, G., May 1999. Fiber optic temperature monitoring technology. In: SPE Western Regional Meeting. No. SPE 54599. Anchorage, Alaska.

Clanton, R., Haney, J., Pruett, Goiffon, J., Gualtieri, D., May 2006. Real-time monitoring of acid stimulation using a fiber-optic dts system. In: SPE Western Regional/AAPG Pacific Section/GSA Cordilleran Section Joint Meeting. No. SPE 100617. Anchorage, Alaska, U.S.A.

Dria, D., March 2014. Distributed fiber optic sensing: An overview of well monitoring with dts and das. SPE Webinar.

Fryer, V., Shuxing, D., Otsubo, Y., Guilfoyle, P., April 2005. Monitoring of real-time temperature profiles across multizone reservoirs during production and shut-in periods using permanent fiber-optic distributed temperature systems. In: SPE Asia Pacific Oil & Gas Conference and Exhibition. No. SPE 92962. Jakarta, Indonesia.

Johannessen, K., Drakeley, B., March 2012. Distributed acoustic sensing - a new way of listening to your well/reservoir. In: SPE Intelligent Energy International. No. SPE 149602. Utrecht, The Netherlands.

J.Y. Julian and, G. K., Cismoski, D., Younger, R., Brown, D., Brown, G., Richards, K., Meyer, C., Sierra, J., Leckband, W., Sack, J., Julian, F., November 2007. Downhole leak determination using fiber-optic distributed-temperature surveys at prudhoe bay, alaska. In: SPE Annual Technical Conference and Exhibition. No. SPE 107070. Anaheim, California, U.S.A.

Mateeva, A., Mestayer, J., Cox, B., Kiyashchenko, D., Wills, P., Lopez, J., Grandi, S., Hornman, K., Lumens, P., Franzen, A., Hill, D., Roy, J., 2012. Advances in distributed acoustic sensing (das) for vsp. In: SEG Las Vegas Annual Meeting. No. SEG-2012-0739. Las Vegas.

Mohaghegh, M., 2000. Virtual-intelligence application in petroleum engineering: Prat 2-artificial neural network. Jounal of Petroleum Techology.

Molenaar, M., Hill, D., Webster, P., Fidan, E., Birch, B., January 2011. First downhole application of distributed acoustic sensing (das) for hydraulic fracturing monitoring and diagnostics. In: SPE Hydraulic Fracturing Technology Conference and Exhibition. No. SPE 140561. The Woodlands, Texas, USA.

Rahman, M., Zannitto, P. J., Reed, D. A., Allan, M. E., 2011. Application of fiber-optic distributed temperature sensing technology for monitoring injection profile in belridge field, diatomite reservoir. In: 2011 SPE Digital Energy Conference and Exhibitio. No. SPE 144116. The Woodlands, Texas.

Shokir, E. M. E.-M., 2001. Neural network determines shaly-sand hydrocarbon saturation. Oil and Gas Journal Vol. 99, 17.

van der Horst, J., den Boer, H., in 't panhuis, P., Wyker, B., Kusters, R., Mustafina, D., Groen, L., Bulushi, N., Mjeni, R., Awan, K., Rajhi, S., Molenaar, M., Reynolds, A., Paleja, R., Randell, D., Bartlett, R., Green, K., January 2014. Fiber optic sensing for improved wellbore production surveillance. In: International Petroleum Technology Conference. No. IPTC 17528. Doha, Qatar.

Ziebel, 2014. website.
URL `www.ziebel.no`

Zurada, J., 1995. Introduction to Artificial Neural System. PWS Publishing Company.

# Appendix

## MATLAB Code for Generating the Neural Network

```
function net = create_pr_net(inputs,targets)
%CREATE_PR_NET Creates and trains a pattern recognition neural network.
%
%  NET = CREATE_PR_NET(INPUTS,TARGETS) takes these arguments:
%    INPUTS - RxQ matrix of Q R-element input samples
%    TARGETS - SxQ matrix of Q S-element associated target samples, where
%      each column contains a single 1, with all other elements set to 0.
%  and returns these results:
%    NET - The trained neural network
%
%  For example, to solve the Iris dataset problem with this function:
%
%    load iris_dataset
%    net = create_pr_net(irisInputs,irisTargets);
%    irisOutputs = sim(net,irisInputs);
%
%  To reproduce the results you obtained in NPRTOOL:
%
%    net = create_pr_net(Pw',Tw');

% Create Network
numHiddenNeurons = 20;  % Adjust as desired
net = newpr(inputs,targets,numHiddenNeurons);
net.divideParam.trainRatio = 70/100;  % Adjust as desired
net.divideParam.valRatio = 15/100;  % Adjust as desired
net.divideParam.testRatio = 15/100;  % Adjust as desired

% Train and Apply Network
[net,tr] = train(net,inputs,targets);
outputs = sim(net,inputs);

% Plot
plotperf(tr)
plotconfusion(targets,outputs)
```

code/neural.m