NON-CONTACT MEASUREMENT
AND CHARACTERISATION OF
ARMOUR CERAMICS

by

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A thesis submitted to the Swinburne University of Technology in fulfilment of the
requirements to the degree of Doctor of Philosophy
Hawthorn, Melbourne, Australia
July 2014.
DECLARATION

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

Manasa Kesharaju

31/10/2014
ACKNOWLEDGEMENTS

The author wishes to express her gratitude to Defence Materials Technology Centre (DMTC) for their financial support and Dr. Ian Crouch, Australian Defence Apparel (ADA) for his support, interest and involvement in this research.

The author is grateful for the support obtained from both her supervisors, Prof. Romesh Nagarajah and Dr. Tonghua Zhang at Swinburne University, all the way through her project. In particular, Prof. Romesh Nagarajah provided constant guidance and encouragement with my research.

The author wishes to acknowledge the support received from the Non-Contact Inspection research group and technicians, particularly (Mr. Brian Dempster) at IRIS. The author also wishes to thank her research colleague, Mr. Tim Barry for his constant encouragement especially in difficult times. She also would like to thank Mr. David Thomas from Melbourne University for providing assistance in using micro-CT scan equipment.

The author has benefited greatly from discussions with Susan Bowles at the Defence Science and Technology Organisation, Melbourne.

Finally, the author would like to express her gratitude to her mother Mrs. K. Ratnamala and father Mr. K. Jayasimha Rao, and constant encouragement from her husband Mr. M. Rajendra Prasad and also other family members for their support, patience and endurance, which have enabled her to accomplish her goal.
This thesis documents a Doctoral research program undertaken at Swinburne University of Technology (SUT), during the period 2010 to 2014. This research is a subset of an overall research program titled “Personnel Survivability” undertaken by the Defence Materials Technology Centre (DMTC) for the defence industry. This thesis reports on the investigation of using an ultrasonic sensing-based non-destructive testing method to detect, locate and classify various defects in reaction-sintered silicon carbide ceramics. The motivation for this research is to ultimately develop a real time on-line inspection system that would be far more reliable and cost effective than currently used X-ray methods and assist manufacturers in identifying the location of high density areas and defects.

Ultrasonic inspection of reaction-sintered silicon carbide (RSSC) ceramics is difficult due to their high density, variations in grain boundary compositions, thickness variation and influence of microstructure variations. Hence, proper care was taken in developing a suitable experimental inspection procedure. An A-scan ultrasonic inspection approach was adopted. An investigation was carried out to select an appropriate ultrasonic inspection technique (immersion and contact type) on selected representative components. In this research, a calibration methodology was developed and implemented for both immersion and contact testing for obtaining accurate ultrasonic signals repeatedly from the selected ceramic components being inspected.
One of the conclusions of this research was that, it was difficult to classify the raw ultrasonic signals using only the neural network approach. Hence, the use of Discrete Wavelet Transform (DWT) in pre-processing of signals prior to input to the neural network for signal classification was investigated. ‘Signal enhancement’ and ‘Extraction of local features’ was performed on raw ultrasonic signals. The MATLAB toolbox was used for signal pre-processing and neural network analysis. Use of a neural network approach to defect detection in combination with the DWT technique assisted in achieving a classification percentage of 91%. Further, to improve the classification performance of Principal Component Analysis (PCA) and Genetic Algorithm (GA) were investigated. The results showed that PCA identified features yielded the highest classification percentage of 96% followed by GA (94%). The results obtained using ultrasonic inspection were validated against results obtained from X-ray and micro-CT scan images. This results obtained from this research demonstrates that ultrasonic sensing combined with artificial intelligence based signals processing techniques are effective in identifying the location of high porosity areas, and other defects in armour ceramics and has the potential to replace currently used inspection techniques.
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<td>AI</td>
<td>Artificial Intelligence</td>
</tr>
<tr>
<td>ANN</td>
<td>Artificial Neural Networks</td>
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<tr>
<td>ADA</td>
<td>Australian Defence Apparel</td>
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<td>ART</td>
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<td>Back Wall Echo</td>
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<td>CFRP</td>
<td>Carbon-Fiber Reinforced Plastic</td>
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<td>Feed Forward</td>
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<td>Multi Dimensional Scaling</td>
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<td>RF</td>
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<td>$\lambda$</td>
<td>Wavelength of the Signal</td>
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<td>$\rho$</td>
<td>Density of Material</td>
<td>g/cm$^3$</td>
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<td>Young's Modulus</td>
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<td>Acoustic Impedance</td>
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</tr>
<tr>
<td>$c$</td>
<td>Ultrasonic Velocity</td>
<td>m/s</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>Attenuation Coefficient</td>
<td>dB/m</td>
</tr>
<tr>
<td>$D$</td>
<td>Diameter of Transducer</td>
<td>mm</td>
</tr>
<tr>
<td>$f_c$</td>
<td>Central Frequency</td>
<td>Hz</td>
</tr>
<tr>
<td>$f$</td>
<td>Transfer Function</td>
<td></td>
</tr>
<tr>
<td>$F$</td>
<td>Focal Length of Transducer</td>
<td>mm</td>
</tr>
<tr>
<td>$G$</td>
<td>Receiver Gain</td>
<td>dB</td>
</tr>
<tr>
<td>$f_q$</td>
<td>Sampling Frequency</td>
<td>Hz</td>
</tr>
<tr>
<td>$V_w$</td>
<td>Velocity of Ultrasound in Water</td>
<td>m/s</td>
</tr>
<tr>
<td>$p$</td>
<td>Inputs for Neural Network</td>
<td></td>
</tr>
<tr>
<td>$t$</td>
<td>Target Output in Neural Network</td>
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<tr>
<td>$b$</td>
<td>Neural Network Bias</td>
<td></td>
</tr>
<tr>
<td>$N$</td>
<td>Near Field Length</td>
<td>mm</td>
</tr>
</tbody>
</table>
CHAPTER 1.

INTRODUCTION

1.1 OVERVIEW

This thesis documents a Doctoral research program undertaken at Swinburne University of Technology (SUT), during the period 2010 to 2014. The research was funded by the Defence Materials Technology Centre (DMTC) at the Industrial Research Institute Swinburne (IRIS), a research centre attached to SUT. The research was undertaken with the co-operation of Australian Defence Apparel (ADA). This research was a subset of an overall research program titled “Personnel Survivability” undertaken by DMTC for the defence industry.

The specific objective of this research project is the investigation and development of an ultrasonic sensor-based defect detection and characterization system for armour ceramics. The motivation of this research is to develop an on-line inspection system that would be far more reliable and cost effective than currently used X-ray methods and enable identification of the location of high density areas and defects. In addition, the motivation is also to enable real time quality control, including the implementation of accept/reject criteria.

The aim of this chapter is to provide a background to the research project and an overview of problems encountered using current inspection methods for armour ceramics. This chapter also describes the objectives of the project and provides an outline of the whole thesis.
1.2 BACKGROUND

The quality and integrity of engineering ceramics, especially those used in high-performance body armour systems, is of paramount importance and a number of material characteristics affect the service life of the finished product. Some of these relate to microstructure, mechanical properties, physical properties and elemental distribution [9]. One of the most commonly used armour ceramic materials is silicon carbide (SiC), which exhibits suitable properties and ballistic performance while having a low density compared to other armour ceramic materials. Silicon carbide ceramics have been prepared by various methods like sintering, hot pressing [10], hot-isostatic processing and gas pressure sintering [11]. Recent developments have lead to the creation of reaction-sintered silicon carbide ceramics [12-17].

In this research, the reaction-sintered silicon carbide ceramic material is investigated. The reaction sintering process typically involves the infiltration of liquid silicon into a porous ceramic preform containing silicon carbide and carbon. An in situ reaction occurs between silicon and carbon to produce a secondary silicon carbide (SiC) phase, which then bonds with the original SiC particles. The residual pores and space not occupied by silicon carbide are filled with liquid silicon. This can lead to a number of characteristic defects such as islands of free silicon metal, closed areas of un-sintered material, as well as conventional porosity. Most of these casting-like defects occur during the high temperature process as the liquid silicon infiltrates the green compact. Some of other common defects found in SiC include isolated pores, low density regions, large grains, inclusions and variations in grain boundary compositions due to non-uniform distribution of impurities.
The role of the ceramic armour manufacturer Australian Defence Apparel (ADA) is to deliver high quality ceramic components in the form of tiles to the defence industry and in this case, the responsibility to provide a reliable product is even more vital as the end users are soldiers in the field. Therefore, the manufacturer performs defect detection on each product prior to delivery to the customers. At present, these ceramic components are inspected offline using an X-ray technique. This involves considerable time and expensive equipment. Also, identification of defect types depends solely on the experience and knowledge of the operator. Hence, there is a requirement to develop a new automated inspection system that would be far more accurate and cost effective with a built-in set of accept/reject criteria.

1.3 RESEARCH OBJECTIVES

The overall aim of this research is to develop an ultrasonic sensor based inspection technique to detect, locate and classify various defects in reaction-sintered silicon carbide (RSSC) armour ceramic components. Specifically, the research objectives include:

- To investigate and evaluate common defects that occur in armour ceramic components using ultrasonic NDT testing.

- To determine density and thickness variation across armour ceramic components previously subjected to X-ray inspection.

- To develop an intelligent inspection system for rapid and robust ultrasonic non-destructive testing incorporating artificial intelligence based signal processing and data interpretation techniques.
1.4 REQUIREMENT FOR DEFECT DETECTION IN ARMOUR CERAMICS

At present, the most common method for evaluating armour ceramic ballistic integrity is destructive testing. Destructive testing of a few armour plates from a production lot is not necessarily indicative of the performance of the remaining untested plates. Microstructural defects that could prove detrimental to the performance of armour ceramic components could be present, but these flaws cannot be detected without proper testing of individual plates. Moreover, destructive testing also incurs additional cost to the manufacturer [18].

As previously discussed in Section 1.2, the non-destructive testing of ceramic components is usually carried out offline using X-radiography. This involves considerable time, effort and expensive equipment. Identification of defect types depends exclusively on the experience and knowledge of the operator. Furthermore, X-radiography is not able to distinguish microstructural differences in areas of similar bulk density. Hence, the motivation for this research stems from a need for providing a non-destructive testing method capable of detecting and locating any defects and microstructural variations within armour ceramic components before issuing them to the soldiers who rely on them for their survival.

The development of an automated ultrasonic inspection method would make possible the checking of each ceramic component and immediately alert the operator about the presence of defects. It eliminates the requirement for a quality control inspector as the decision maker in the ultrasonic inspection of armour ceramic components. This inspection system will offer advantages in terms of cost effectiveness...
and reliability to manufacturers. Moreover, the mapping of density variation across the ceramic components assists manufacturers in identifying the regions of high porosity and enable concurrent quality control including implementation of accept/reject criteria.

1.5 OVERVIEW OF METHODOLOGY

To achieve the research objectives, a methodology is developed to conduct ultrasonic inspection of selected armour ceramic components. This methodology includes:

- Determining ultrasonic velocity in ceramic components.
- Collecting and acquiring the ultrasonic A-scan signals from different types of defects present in ceramic components.
- Applying suitable signal pre-processing techniques to de-noise, compress the data and extract features.
- Performing feature selection to choose a significant feature subset to train an artificial neural network.
- Training the neural network to classify defects.
- Testing the trained network.

The starting point for ultrasonic NDT testing is to select and study several samples containing the various types of defects. In this research, three representative ceramic components previously subjected to X-ray inspection are investigated. An investigation was carried out to select an appropriate ultrasonic inspection technique (immersion and contact type) on the selected samples. One among these three components has no defects; however several experiments are conducted to determine the local density variation across the ceramic components using the ultrasonic
immersion testing method. The inspection process is automated by means of moving a focused transducer attached to a robotic arm along the surface of the ceramic component.

The other two ceramic components being investigated have curved surfaces and are manually inspected using ultrasonic contact testing. The immersion testing rig is not suitable for these components as the focusing point will be different at various locations on the curved surface and this generates difficulty in obtaining accurate ultrasonic signals. Several experiments are carried out to determine the actual velocity of ultrasound energy in the selected material and a suitable frequency for the investigation. Then, the signals are obtained through ultrasonic contact testing of ceramic components to determine the presence of defects.

The next step in the process of ultrasonic defect identification is pre-processing and analysis of the ultrasonic signals obtained from the ceramic components. Signal processing and classification are carried out using the neural network toolbox in MATLAB software. Furthermore, a series of tests are done to check the repeatability of the ultrasonic signals obtained from the defect and defect-free regions. Thereafter, a substantial number of inspection trials are conducted on both defect and defect-free regions of the ceramic samples to provide sufficient ultrasonic signals for training and testing the neural network component of the inspection system. Finally, X-ray and micro-CT scan results are used to validate the results obtained from ultrasonic inspection.
1.6 PERCEIVED CONTRIBUTIONS OF THIS RESEARCH

This research has made a number of specific contributions to the field of ultrasonic non-destructive inspection in general and inspection of SiC armour ceramics in particular. These contributions are summarized below:

- Calibration of experimental devices

  Various calibration methods are used in ultrasonic inspection of armour ceramic components. In this research, a specific methodology is developed and implemented for both immersion and contact testing for obtaining accurate ultrasonic signals repeatedly from the selected ceramic components being inspected. In ultrasonic immersion testing, importance is given to the apparatus, namely robotic and ultrasonic testing unit. In contact testing, a grid surface is drawn across the surface of each ceramic component and each grid intersection has been used as a testing point. Repeated inspection trials are then carried out to determine the reproducibility of the measurement. This calibration process is carried out continually throughout the experimental phase of the project. The calibration results are presented in Chapter 6. The implementation of a calibration methodology for the experimental devices reduces the amount of uncertainty and increases the accuracy associated with the experimental results significantly.

- Classification of ultrasonic signals

  In this research, a combination of signal processing techniques for feature extraction and feature selection are investigated for the purpose of maximising ultrasonic signal classification performance. The signal processing techniques investigated included Wavelet Transform (WT), Principal Component Analysis (PCA) and Genetic
Algorithm (GA). In this research, signal pre-processing using the Discrete Wavelet Transform (DWT) for feature extraction is carried out prior to passing the ultrasonic signal features into the neural network for defect classification. Subsequently, an approach to feature subset selection using PCA and GA not published previously has been investigated in this research. This approach is investigated to determine the possibility of achieving improved signal classification. The results demonstrate that this approach increases the defect classification percentage significantly to 98% compared to 91% classification with features used initially for analysis.

1.7 OUTLINE OF THE THESIS

This thesis is divided into nine chapters as described below:

Chapter 1 presents a brief introduction to the background of the research and the problem to be investigated. This research confines itself to the use of ultrasonic inspection techniques for the detection of defects in armour ceramics. Hence, the objectives emphasise the need to obtain an understanding of the history of armour ceramics, fundamental principles, and relevant concepts of armour ceramics and ultrasound testing techniques.

Chapter 2 outlines the history of armour ceramics followed by the manufacturing process for SiC armour ceramics and its use in industrial applications. It also deals with silicon carbide armour ceramics processing, properties along with sintering additives, densification and related defects.

Chapter 3 describes the background theory and different methods of ultrasonic inspection, and provide details on ultrasonic transducers and different couplant types used in the ultrasonic inspection of ceramic components.
Chapter 4 details the potential neural network topologies to be used in this research along with the feature extraction and feature selection methods used to detect various defects from the ultrasonic signals obtained from the ceramic components. This chapter is also a major building block of the thesis as it highlights signal pre-processing techniques together with feature selection methods for statistical learning in the context of defect classification.

Chapter 5 contains an extensive literature review on ultrasonic testing of metals, composites and ceramics. It also details the application of artificial intelligence techniques in ultrasonic NDT; in particular, the application of neural network based signal processing techniques for defect classification.

Chapter 6 presents the experimental program that is designed and implemented to inspect representative armour ceramic components obtained from Australian Defence Apparel, Australia. This chapter also details the calibration process relating to the test equipment.

Chapter 7 presents the results of the inspection carried out on representative armour ceramic components, including the results obtained from neural network classification of the ultrasonic signals from defective and defect-free regions of the ceramic components. The classification performance obtained by using different feature selection methods is compared. The results obtained from ultrasonic inspection are validated against X-ray and micro-CT scan results.

Chapter 8 compares the results obtained using different signal processing approaches with neural networks for defect classification. In addition, it evaluates the effectiveness of the developed inspection methodology in relation to approaches described by other researchers.
Finally, Chapter 9 summarises the findings of the research program, and identifies areas for further research.
CHAPTER 2.

ARMOUR CERAMICS

2.1 OVERVIEW

As emphasised in the previous chapter, a deeper understanding of armour ceramics is essential for this research. Hence, this chapter describes the history of armour ceramics followed by the manufacturing process for SiC armour ceramics and its use in industrial applications. An overview of the physical and mechanical properties of SiC ceramics is presented in Section 2.7. The subsequent sections discuss ceramic processing and common defects that occur in SiC ceramics and significance of detecting these defects. Finally, a review of current inspection methods in the context of armour ceramics is presented.
2.2 Armour Ceramics

2.2.1 Overview

A brief history of armour is followed by a description of key armour ceramic properties. The processing methodology for ceramic materials and properties and critical defects common in silicon carbide armour are described in detail. This is followed by a description of methods currently used for inspection.

2.2.2 History of Armour

Armour is a shielding that is used to protect an object, individual, or a vehicle from direct contact with weapons or projectiles, usually during combat, or from a dangerous environment. Throughout history, humans have used various forms of armour for shielding themselves against threats [19]. The evolution of armour materials has progressively improved from animal hides and leather to metals such as bronze, steel and eventually aluminium, to recent use of ceramic materials [18].

The use of armour is believed to have extended back beyond historical records, when native warriors protected themselves with leather helmets and skins[19]. In 1500 B.C, first documented use of armour was by Egyptians, who used bronze plates that were sewed into garments [20]. Later ancient Greeks and Romans used bronze breast plates, back plates and helmets for protection [20]. Around 1250 AD, armour made of rigid plates, similar to those of used by ancient Greeks and Romans reappeared in Europe. The use of steel in plate armour had become prevalent in the 14th century in European Middle Ages [20]. But, during 16th and 17th centuries in Western Europe, body armour was losing its popularity as it was not set to meet the challenge of firearms
and other weapons that were utilizing gunpowder [19]. It was not until the Civil War in the US that body armour regained popularity. Despite the fact that many military authorities supported the use of body armour during World War I, it only reached a preliminary testing stage before it was eventually rejected [19]. Finally, during World War II, the next generation of ballistic vests known as flak jackets were introduced. These flak jackets made of heavy steel plates sewn into cloth, were issued to Air Force pilots in 1942 [19]. During the Korean War, the M12 vest made up of aluminium plates and nylon cloth was issued [19]. The improvement of flak jackets and vests made them lighter and better, and they were used in Vietnam, but although they were capable of stopping shrapnel, they could not stop bullets efficiently. It was not until 1960's, that the modern form of bulletproof vests were developed with the emergence of Kevlar and armour ceramic materials [18, 19].

2.3 ARMOUR CERAMIC PROPERTIES

Armour ceramics was initially developed in 1960's for personnel safety in the form of bulletproof vests to improve the limitations of normally used steel armour [19, 21]. Whilst the bulk of traditional metallic armour materials such as steel plates were employed for protection against threats due to their high hardness and strength properties, the primary disadvantages of using steel metallic armour was its weight, which constrains the utilization for a given application. The main drive to develop armour ceramics was based on the need for lighter materials with analogous mechanical properties to steel metallic armour as the armour used in combat was required to be mobile [18].
Advanced ceramic materials, that in general have densities of \(4 \text{g/cm}^3\) or less, have a distinct advantage over steel, which had a density of approximately 7 to 8 \(\text{g/cm}^3\). By replacing metal armour with armour ceramics, the overall weight of personal armour was reduced by as much as 60-70 %. Besides reduction in weight, it was also essential for armour ceramics to meet requirements in terms of ballistic threats [18].

2.3.1 Mechanical properties

The mechanical properties that make ceramic materials ideal for armour applications include low density, high hardness, high Young's modulus (E), high shear modulus, high bulk modulus, good abrasion and high compressive strength[18]. Besides, the advantages of ceramic materials, they are brittle and typically possess low tensile strength, which limits their ballistic performance as compared to traditional steel armour [22]. Therefore, the ceramic armour component is generally integrated into a multi-layered armour system which exploits the high compressive strength of ceramic materials whilst compensating for the effect of low tensile strength [22]. The integration of armour ceramics into an armour ceramic system along with armour ceramic processing will be discussed in detail in later sections.

2.4 Armour Ceramic System Components

An armour ceramic system is composed of five layers that include a cover layer, a ceramic ballistic layer, a bonding layer, a backing layer and a protective layer [23]. The cover layer is the outermost layer, that provides scrape protection and limits debris through the front face after a ballistic impact event occurs. The armour ceramic ballistic layer is the main component for defeating the projectile [23]. The bonding layer is
often a rubber material that is used to reduce shock wave reflections through the ceramic system. The backing layer is either a soft material such as a polymer composite or a hard material such as a metal that absorbs any additional kinetic energy that is not dissipated by the armour ceramic layer [23]. The most important layers are the armour ceramic ballistic layer and the backing layer, as the others are secondary layers used for additional support [23].

### 2.5 Armour Ceramic Materials

Common ceramic materials used for armour applications include aluminum nitride (AlN), aluminum oxide (Al₂O₃), aluminum oxynitride (ALON), boron carbide (B₄C), silicon carbide (SiC), silicon nitride (Si₃N₄) and titanium diboride (TiB₂). All of the listed materials are usually utilized for personnel, vehicular armour, helicopter, structural applications and their ballistic performance [21] [24]. They have densities less than 4.5 g/cm³, high hardness values, high compressive and tensile strengths, good abrasive properties, high material velocities and good elastic properties[18]. A list comparing properties of common armour ceramic materials against steel is presented in Table 2.1. Boron carbide and hot-pressed silicon carbide are commonly chosen for personnel protection in the form of plate inserts, armoured land vehicle seats in addition to protection against high-caliber threats such as heavy machine guns and medium cannons [25].
<table>
<thead>
<tr>
<th>Material (sintered)</th>
<th>Density (g/cm³)</th>
<th>Hardness (GPa)</th>
<th>Tensile Strength (N/m²)</th>
<th>Fracture Toughness (MPa·m¹/₂)</th>
<th>Velocity (m/s)</th>
<th>E (GPa)</th>
<th>Poisson's Ratio</th>
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<tr>
<td>Sic</td>
<td>3.16</td>
<td>19.1</td>
<td>525</td>
<td>3.1</td>
<td>11820</td>
<td>415</td>
<td>0.16</td>
</tr>
<tr>
<td>Sic (hot-pressed)</td>
<td>3.21</td>
<td>24.5</td>
<td>600</td>
<td>5.2</td>
<td>12100</td>
<td>430</td>
<td>0.17</td>
</tr>
<tr>
<td>Al₂O₃</td>
<td>3.98</td>
<td>15.2</td>
<td>510</td>
<td>3.5</td>
<td>11000</td>
<td>416</td>
<td>0.23</td>
</tr>
<tr>
<td>AlN</td>
<td>3.25</td>
<td>13.5</td>
<td>325</td>
<td>4.5</td>
<td>10700</td>
<td>320</td>
<td>0.23</td>
</tr>
<tr>
<td>B₄C</td>
<td>2.51</td>
<td>28.4</td>
<td>470</td>
<td>3.5</td>
<td>14090</td>
<td>456</td>
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<td>TiB₂</td>
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<td>26.5</td>
<td>285</td>
<td>6.2</td>
<td>11400</td>
<td>565</td>
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</tr>
<tr>
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<td>14.7</td>
<td>720</td>
<td>6.1</td>
<td>11000</td>
<td>290</td>
<td>0.27</td>
</tr>
<tr>
<td>Steel</td>
<td>7.80</td>
<td>6.0</td>
<td>1800</td>
<td>50.0</td>
<td>5850</td>
<td>200</td>
<td>0.28</td>
</tr>
</tbody>
</table>

Table 2.1 Average physical, mechanical and acoustic property comparison of common armour ceramic materials to properties of steel [5-8].

2.6 ARMOUR CERAMIC PROCESSING AND RELATED DEFECTS

2.6.1 Overview

This section details general ceramic processing phases utilized for fabrication of armour ceramic materials. The process can be divided into four distinct stages that include powder processing, mixing, forming and densification. The presence of defects in armour ceramic materials is discussed in terms of its detrimental effects on ballistic performance. It is important to investigate the cause of defects such as pores, inclusions, large grains and cracks, so that improvements can be made to the specific processing phases to minimize their occurrence and improve the final product.
2.6.2 Ceramic Processing and Related Defects

The first stage of powder processing involves the preparation of the starting powders, where the initial particle size and particle size distribution are chosen. During this stage, the likely issues that can arise include contamination and poor particle size distribution, which can soon lead to defects such as pores and inclusions [18]. If a smaller particle size is used for ceramic manufacturing, a fine-crystalline microstructure can be achieved for higher densification [5]. In addition, high hardness, elastic modulus and other material properties can be attained by having a smaller particle size, good particle distribution and higher powder content of the starting powder [5].

The second stage of mixing encompasses the consistent addition of processing aids and sintering aids to the starting powders. Potential issues that can occur include poor mixture and excess second phase addition which can later lead to defects such as inclusions, unwanted second phases and forming of cluster of particles. Materials with a higher content of processing or sintering aids are likely to have a larger particle size and less micro-structural uniformity [5, 18].

The third stage of forming involves processing the starting powders or slurry into sample of desired shape and dimensions. Common forming methods include pressing, slip casting or extrusion and injection moulding [21, 24]. Potential issues that may occur during this stage include poor mixing or powder distribution causing density variation. This can later lead to defects such as cracks, laminations and voids [18].
The fourth stage involves densification or sintering, which can either be pressure-less or pressure-assisted. Pressure-less sintering can be divided into categories of solid state sintering, liquid phase sintering and reaction bonding technique. During this stage, variations in the percentage of second phase or non-uniform density distributions can result in defects such as open or closed pores, large grains, or uncontrolled phase generation. During the cool-down period from exposure to high temperature, each individual grain wants to contract, nevertheless there is resistance from neighbouring grains, which results in the build-up of residual stresses at grain boundaries and junctions of multiple intersecting grains [22]. As the amount of residual stresses increases with grain size, micro-cracking might occur with large grain size [18].

2.7 Silicon Carbide Armour Ceramics

2.7.1 Overview

One of the most commonly used armour ceramic materials is silicon carbide (SiC), which exhibits suitable properties and ballistic performance while having a low density compared to other armour ceramic materials. In this research, reaction-sintered silicon carbide ceramic components were investigated and therefore this section discusses the processing methods for reaction-formed silicon carbide ceramics, its properties and common defects.

2.7.2 Silicon Carbide Processing and Properties

Silicon carbide is derived from a powder or grain prepared by the carbon reduction of silica, and the technique by which it is produced has altered very little
from its original preparation by E.G. Acheson in 1891 [26]. SiC is manufactured commonly by using the Acheson method, where two electrodes are connected with graphite powder and a mixture of silica and coke is packed in the adjoining areas. This gathering is electrically heated at 2700°C [26]. The carbothermal reaction of silica (SiO$_2$) is accomplished by the reaction in Equation (1).

$$\text{SiO}_2 + 3\text{C} \rightarrow \text{SiC} + 2\text{CO}$$  \hspace{1cm} (1)

Silicon carbide is used mainly in applications that require low density, high strength, low thermal expansion, high hardness, high elastic properties, high thermal shock resistance, good abrasion and high chemical inertness. Some commonly reported values of hot-pressed SiC include its high hardness value of 1870 – 2020 kgmm$^{-2}$ [8, 21], tensile strength ~ 600MPa, a compressive strength ~ 2480MPa, a fracture toughness of ~ 5.2 MPam$^{1/2}$, an elastic modulus between ~430 GPa and ~500 GPa and a longitudinal acoustic velocity between ~ 11000 m/s and 12000 m/s [8, 18, 21]. In contrast to other materials with high strength and hardness, SiC has a low density value of ~ 3.16 g/cm$^3$ for sintered SiC and ~ 3.20 g/cm$^3$ for hot-pressed SiC. The theoretical density of SiC reported in literature is ~ 3.22 g/cm$^3$ [8].

2.7.3 Silicon Carbide Sintering Additives

Silicon Carbide is difficult to densify without additives because of the covalent nature of Si-C bonding and a low diffusion coefficient [16]. The two most common sintering additives for SiC processing are boron and carbon and are commonly used for solid state sintering. Generally, the purpose of adding boron is to create atomic
vacancies and enhance sintering kinetics, while addition of carbon reduces the densification hindering silica layer, which is an important requirement for sintering [27]. Solid state sintering, with addition of boron and carbon, at temperatures around 2100° C has become a routine process for densification of silicon carbide. Besides, liquid-phase sintering has the potential to become an alternative, commercially attractive method, with sintering temperatures (1700° C -2000° C) [16]. As proposed by Sciti [16], addition of metal oxides results in liquid phase formation at high temperatures, which acts as a mass transportation medium during sintering. The major requirements of the liquid phase sintering medium are a sufficient volume fraction of liquid showing thorough moistening of solid phase and a considerable solubility of solid in the liquid. The transport properties of liquid phase depend on its volume fraction, selected additives and densification parameters[16]. Hence, these sintering additives are critical for achieving full density for SiC armour ceramics.

2.7.4 Silicon Carbide Densification

In conjunction with the addition of sintering additives, high sintering temperatures between 1800° C and 2000° C are also used to enhance densification[28]. Densification is a critical stage in which the final microstructure and therefore the presence of microstructural defects will be determined [18]. Densification methods for preparation of SiC ceramics can be divided into pressure-less sintering and hot pressing techniques.

Hot pressing can be described as sintering under the application of external pressure [29]. The applied mechanical pressure can increase the driving pressure for
densification by acting against the internal pore pressure without increasing the driving force for grain growth [29]. Hence, SiC armour ceramics are typically hot-pressed to obtain full density without increasing the grain size. Hot pressing SiC between 1900° C and 2300° C with pressures ranging from 100-400 MPa was demonstrated by Kriegesman et al.[30] in 1986, and dense SiC parts were fabricated without the use of sintering aids [31].

While the majority of high performance SiC materials for armour applications have traditionally been fabricated using hot pressing, pressureless sintering is more desirable from a manufacturing perspective because it allows production of large, complex-shaped parts, offers good mass productivity and its more cost effective [25]. However, unlike the hot pressing demonstrated by Kriegesman et al [30], in which dense SiC was manufactured without the use of sintering additives, boron and carbon sintering aids are required for fabricating high density SiC via solid state pressureless sintering. The addition of boron and carbon promotes sintering by enhancing grain boundary diffusion while reducing surface diffusion [30]. Liquid phase sintering is another form of pressureless sintering in which metal and metal oxide sintering aids such as aluminium are used [32]. The sintering aids can react with each other or SiO₂ in the SiC powder to form a liquid phase that promotes densification by dissolving and re-precipitating SiC onto undissolved grains. Liquid that does not dissolve into SiC forms a grain boundary phase that dictates the mechanical properties [16, 32].

2.8 REACTION SINTERING SILICON CARBIDE

Silicon carbide ceramics have been prepared by various methods like sintering, hot pressing[10], hot isostatic processing, gas pressure sintering[33] or self-propagating
combustion synthesis [11] and the recent developments involve the reaction-sintering silicon carbide ceramics [12-17]. The reaction-sintering process typically involves the infiltration of liquid silicon into a porous ceramic preform containing silicon carbide and carbon. An in situ reaction occurs between silicon and carbon to produce a secondary SiC phase, which then bonds the original SiC particles. The residual pores and space not occupied by silicon carbide are filled with liquid silicon. It was reported in [13] that employing reaction sintering process lowers the processing temperatures to 1425 - 1500°C. Moreover, other advantages of the reaction-sintering technique include good shape capability, low cost, production of dense structure and high purity.

2.8.1 Reaction-Sintered Silicon Carbide Defects

Although SiC is one of the strongest ceramic materials, its high strength can be limited by the presence of a variety of defects. There are various likely causes of microstructural defects during processing of SiC, which can occur during the general powder processing, mixing, forming and densification steps described in Section 2.6.2. Common defects found in SiC include isolated pores, low density regions, large grains, inclusions and variations in grain boundary compositions due to non-uniform distribution of impurities.

Currently used inspection methods do not lend themselves to differentiating between defects in many regions of the reaction-sintered silicon carbide (RSSC) ceramic material. Moreover, discontinuities can be so microscopic, numerous and widely dispersed that it is impractical to resolve them individually. Porosity, density variation, presence of free silicon metal and fatigue in ceramics are examples of such
defects. In RSSC ceramic components a number of characteristic defects such as islands of free silicon metal, closed areas of un-sintered material, cracks, isolated pores, as well as conventional porosity are found. Most of these casting-like defects occur at the forming and densification stages, during the high temperature process as the liquid silicon infiltrates the green compact. Therefore, the forming process for SiC is important since defects are often introduced during this stage and may remain in the product even after successful sintering. Also, improper mixing in the mixing stage leads to pore clusters that later form cracks at the cluster-matrix interface due to differential sintering. These clusters generally originate in the dry-pressing process that was reported by Hurst et al [34]. These critical defects found in SiC are not easily detectable in bulk ceramic samples using current inspection methods and could prove to be detrimental to the performance of SiC armour ceramics.

2.9 Inspection Methods

2.9.1 Destructive Testing

Presently, the most common method for evaluating armour ceramic ballistic integrity is destructive testing. Destructive testing of a few armour plates from a production lot is not necessarily indicative of the performance of the remaining untested plates. Microstructural defects that could prove detrimental to the performance of the armour ceramics could be present, but these flaws cannot be detected without proper testing of individual plates. Moreover, destructive testing also incurs additional cost to the manufacturer. Armour ceramic materials that undergo ballistic or static testing are destroyed, leading to the eradication of potentially usable products. For that
reason, the development of a non-destructive method for manufactured part inspection is particularly important for personnel and vehicular armour [18].

2.9.2 X-ray Inspection

At present, the non-destructive testing of armour ceramic components is carried out offline using x-radiography. This involves considerable time and expensive equipment. Identification of defect types depends exclusively on the experience and knowledge of the operator. Along with this, x-radiography is not able to distinguish microstructural differences in areas of similar bulk density. Therefore, there is a requirement to develop a new more reliable on-line inspection system to detect, locate and identify any defects and microstructural variations within armour ceramic components before utilizing them in the field.
CHAPTER 3.

ULTRASONIC INSPECTION

3.1 OVERVIEW

The requirement for an online non-destructive inspection method for quality control that is cost-effective and more reliable than current inspection methods (such as X-ray) has been emphasized in Chapter 2. The literature review indicates that ultrasonic techniques have the potential to be used to detect defects in armour ceramics. Ultrasonic techniques have also got the potential for online implementation. This chapter describes the theoretical background in the context of ultrasonic non-destructive inspection. This includes the history of ultrasound, its fundamentals and ultrasonic applications. Following this, the importance of selecting suitable ultrasonic equipment and appropriate transducers is highlighted. A brief description of different ultrasonic inspection methods and couplant types is provided in Section 3.6.
3.2 THEORETICAL BACKGROUND

3.2.1 Overview

Ultrasound is defined as sound generated above the human audible range. As the audible range falls between frequencies of 20 Hz and 20 kHz, ultrasound includes the sound waves with a frequency greater than 20 kHz. Ultrasound has a short wavelength[35] and therefore can be reflected off very small surfaces. Ultrasonic testing is based on time-varying deformations or vibrations in materials[35, 36]. In order to effectively describe the fundamentals and principles of ultrasound a brief history is provided.

3.2.2 History of Ultrasound

The philosophy of ultrasound dates back as far as the 6th century BC, when Pythagoras performed experiments on vibrating strings, which led to a tuning system known as the Sonometer [37]. Aristotle, in 4th Century BC, added to the philosophy by correctly assuming that sound waves resonate in air through motion of the air itself [37]. Between 1564-1642, Galileo Galilei elevated the study of vibrations and the correlation between pitch and frequency of the sound source to scientific standards[37]. Galileo discovered the general principles of sympathetic vibrations, or resonance by conducting experiments with a pendulum and relating the frequency of vibrations to the length of the pendulum [38]. In 1822, Swiss physicist Daniel Colladen used an underwater bell to successfully estimate the speed of sound in waters off Lake Geneva [37]. In late 1800’s, physicists were also working towards defining the fundamental physics of the transmission, propagation and reflection of sound vibrations or waves. One of the most notable was Lord Rayleigh in England, whose "Theory of Sound" published in 1877, first described the sound wave as a mathematical equation[39].
Another breakthrough in high frequency echo-sounding techniques came in 1880, when Pierre and Jacques discovered the piezoelectric effect in which an electrical potential was produced when mechanical pressure was exerted on a quartz crystal, and reciprocally, mechanical stress could be achieved in response to a difference in voltage[39]. This has made it possible for the generation and reception of ultrasound in the frequency range of megahertz (MHz) or millions of cycles per second, and its use in echo-sounding devices[39].

With the development of ultrasound principles and early devices, practical applications of the technology were soon to follow. This started with the use of acoustic waves for determining distance[39]. Colladen's use of underwater devices had pioneered the idea of measuring distance underwater using sound waves, which brought about the term SONAR, or Sound Navigation and Ranging[39]. The first functioning echo ranging device as patented in the US in 1914 by Reginald Fessenden was capable of detecting an iceberg from two miles away, but could not precisely determine its direction[37].

Thereafter, the theory of Sonography was further applied to flaw detection in solids. In 1928, Sergei Sokolov proposed a technique for detecting irregularities in metals[37]. His work utilized a transmission technique for detecting metal flaws by varying ultrasonic energy across a medium. However due to poor resolution, he recommended a more practical idea of a reflection method, nevertheless the equipment for implementing this was not available until the 1940's [37]. It was in the 1940's that the use of ultrasound expanded to its most common modern application in the field of medicine, which initially started with uses in therapy rather than diagnostics[37]. Jerome Gersten applied high intensity ultrasound in the treatment of patients with rheumatic arthritis[37]. In the mid to late 1940's, lower intensity medical ultrasound
began to take off as a diagnostic tool. Karl Dussik began experimentation on echo imaging of the brain, in which the first attempt at combining ultrasound with scanning and mapping was attempted[39]. These developments led to extensive studies of ultrasonic medical imaging in the United States and Japan starting in 1948 [39]. In the late 1950's and early 1960's the work of Ian Donald in Scotland determined that clear ultrasonic echoes could be obtained from the fetal head, and with further experimentation, the diagnostic study of pregnancy from beginning to end became possible[37, 39]. In the early 1970's several technological improvements led to major changes in the field. The first was the advancement in high frequency ultrasound technology that led to the ability to detect small flaws, which caused more parts to be rejected despite that fact that the probability of component failure had not changed [2]. In addition to detection, obtaining quantitative information about flaw properties became important for predicting and determining the differences between components [2]. All these underlying principles of ultrasound serve as the basis for the current work that involves inspecting SiC armour ceramics.

3.2.3 Ultrasonic Wave Propagation

Transmission of an acoustic wave through a material results in particle motion and interaction between the wave and the material[35]. These are considered as the basis for ultrasound testing from which acoustic and elastic properties can be determined. The acoustic impedance of material, refraction and attenuation of sound waves as they interact with the material are significant phenomena that are discussed in detail in the following sections. Ultrasonic vibrations travel in the form of waves, similar to the way light travels[1]. However, unlike optical waves which can travel in a vacuum, ultrasound requires an elastic medium, such as a liquid or a solid, to transmit[1].
There are several important parameters that characterize the behaviour and properties of an acoustic wave. The time required to complete a full wave cycle is known as the period, $T$, and is measured in seconds[1]. The frequency of the wave, $f$, is defined as the number of oscillations of a given particle per second and is measured in inverse seconds, or Hertz. Within a given wave it is the same for all particles[35]. The wavelength is the distance between two planes in which the particles are in the same state of motion, and is typically measured in microseconds, $\mu$s. The velocity of wave propagation is represented by the speed of sound over a given condition, and is measured in meters per second. Velocity is a characteristic of the material and is constant for a given material with a specified frequency and wavelength [35]. The wavelength is directly proportional to the velocity and the period of the wave and inversely proportional to the frequency of the wave, as given in the equation (1) below[1].

$$\lambda = \frac{c}{f}$$  \hspace{1cm} (1)

In solids, several types of wave propagation can occur and are based on the way the particles oscillate[1]. Longitudinal and shear waves are the two modes of propagation most widely used in ultrasonic testing. In longitudinal waves, the oscillations occur in the direction of wave propagation. Since compressional and dilational forces are active in these waves, they are called pressure or compressional waves. They are also sometimes called density waves because their particle density fluctuates as they move. Compression waves can be generated in liquids as well as solids because the energy travels through the atomic structure by a series of compression and expansion movements[40]. In the transverse or shear wave, the particles oscillate at right angles or transverse to the direction of propagation. Shear
waves require an acoustically solid material for effective propagation and, therefore, are not effectively propagated in materials such as liquids or gasses\cite{2}. Shear waves are relatively weak when compared to longitudinal waves\cite{2, 41}. The particle movement responsible for the propagation of longitudinal and shear waves is shown in Figure 3.1

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{fig31.png}
\caption{Direction of particle movement in longitudinal and shear waves \cite{1}}
\end{figure}

### 3.2.3.1 Acoustic Impedance

The acoustic impedance or sound resistance denoted by $Z$, is a material property defined as the product of its density ($\rho$) and sound velocity ($c$) according to the equation (2) \cite{35}.

$$Z = \rho \cdot c$$ \quad (2)

Acoustic impedance determines the passage of sound between two different materials \cite{35} by describing its reflection and transmission characteristics\cite{7}. Acoustic waves are reflected at boundaries where there is a difference in acoustic impedance between materials on each side of the boundary and this difference in $Z$ is commonly referred to the impedance mismatch \cite{2}. The greater the impedance mismatch, the
higher the percentage of energy that will be reflected at the interface or boundary between one medium and another[2].

3.2.3.2 Refraction

Refraction occurs when the ultrasonic wave changes direction and velocity as it crosses a boundary between different materials[7]. The velocity of sound in each material is directly dependent on the composition and physical characteristics or density and elastic properties of each medium[42]. The ratio between wave speed in one material and wave speed in a second material is called the index of refraction[7]. The relationship between the angles and the waves can be described by Snell's law, given by equation (3).

\[
\frac{\sin \theta_1}{c_1} = \frac{\sin \theta_2}{c_2}
\]

(3)

where \( \theta_1 \) = angle of incidence, \( \theta_2 \) = angle of refraction, \( c_1 \) = velocity of sound in the first material and \( c_2 \) = velocity of sound in the second material[2, 7].

3.2.3.3 Attenuation of Ultrasonic wave

When sound travels through a medium, its intensity decreases with distance[2]. In an ideal material, the sound pressure, which is indicated by the signal amplitude, is only reduced by spreading of the sound wave[2]. The factors like scattering and absorption, and their combined effect is referred to as attenuation[35]. Attenuation is generally defined as the reduction in strength of a signal. Ultrasonically, it can be described as the loss in acoustic energy that occurs between two points of travel. Hence, ultrasonic attenuation is in particular defined as the rate of decay of an acoustic wave as it propagates through a material[2].
Absorption is the conversion of sound energy to other forms of energy [2]. This energy is permanently lost, and therefore is of little consequence to the inspection of the material since it provides no additional information about the material itself [43]. Scattering is the reflection of sound in directions other than its original direction of propagation [2]. This is caused by material not being homogeneous, and the material containing acoustic interfaces in which there are different densities or sound velocities [35]. Scattering can result from reflection at grain boundaries, small cracks, and other material inhomogeneities [43]. These inhomogeneities can be material flaws that are added unintentionally during processing and forming. Along with this, grain scattering losses occur on a micro-structural level because small crystalline grains in a material such as ceramics scatter incident waves in many directions resulting in net loss of amplitude with distance in the propagation direction [35]. Attenuation is generally expressed in terms of sound pressure of an acoustic wave in the form of the exponential function [35, 43] as shown in equation (4).

\[ P = P_0 e^{-\alpha L} \]  

(4)

where \( P_0 \) is the initial sound pressure level at a reference location, \( P \) is the sound pressure level at a second reference location, \( \alpha \) is the attenuation coefficient in Nepers/length and \( L \) is the distance of travel from the original source to second reference location [43].

Ultrasound attenuation is typically expressed in units of decibels (dB) and the conversion is obtained by applying the logarithm to base 10 and multiplying by 20 [2, 35, 43] to obtain the equation shown in (5).

\[ \alpha \cdot L = 20 \ln\left(\frac{P_0}{P}\right) \text{ dB} \]  

(5)
This equation provides a more comparable scale for expressing acoustic loss in a material and can be expressed in dB/m.

3.3 ULTRASONIC EQUIPMENT

In ultrasonic equipment, electrical energy is transformed into mechanical energy in the form of sound pressure waves through an ultrasonic transducer. All the information is presented in one of four presentation styles: A-scan, B-scan, C-scan and digital numeric[2]. In an A-scan presentation as shown in Figure 3.2, the amount of received ultrasonic energy is displayed as a function of time[44]. Most instruments with an A-scan display allow the signal to be displayed in its natural radio frequency form (RF), as a fully rectified RF signal. In the A-scan presentation, relative discontinuity size can be estimated by comparing the signal amplitude obtained from an unknown reflector to that from a known reflector[44]. In a B-scan, the ultrasonic testing equipment displays the material being inspected as a cross-sectional view. In the B-scan, the time-of-flight (travel time) of the sound energy is displayed along the vertical axis and the linear position of the transducer is displayed along the horizontal axis[44]. In a C-scan, the ultrasonic testing equipment displays the ceramic tile in a topographical perspective[44]. This presentation is useful when plotting thickness of material over a given area. The C-scan presentation provides a plan-type view of the location and size of test specimen features[44]. With digital numeric presentation the ultrasonic testing equipment calculates the “flight time” of the ultrasonic pulse from the transmitter until it is received back at the receiver[41].
A detailed understanding of the sound beam, material and geometry of the part is required prior to development of an ultrasonic based inspection system. Once the appropriate equipment type is selected, the next step involves selecting the right ultrasonic transducer, which allows for the best penetration of the ultrasound. Additional information on the ultrasonic equipment used in this research is provided in Chapter 6.

### 3.4 Ultrasound Transducer

The ultrasonic transducer converts electrical energy into mechanical energy in the form of sound and again mechanical energy back into electrical energy [2, 35]. Krautkramer [35] and other authors [1, 2, 41] have emphasized that the transducer is one of the most essential components of an ultrasonic testing system. The achievement of sensitivity and resolution of the system depends on the selection of a proper transducer [1]. Transducers are available in a range of frequencies and sizes and are selected depending on their application[1]. It has been emphasized by various authors [18, 35, 41, 45] that selection of a transducer also depends on the type of material being investigated. Another important criteria is the type of inspection method that is being
used [18]. According to Bhardwaj [42] and Silk [46], the frequency of a transducer is a significant determining parameter in its application. The ultrasonic pulse emitted depends on the particular transducer characteristics such as crystal size and diameter. The selection of a suitable ultrasonic transducer for any given ultrasonic NDT problem is critical [46].

Sensitivity and resolution are two terms that are used in ultrasonic inspection to describe the ability of a technique to locate defects and flaws[2]. Sensitivity is a term that is used to describe defect detectability or the ability to locate small discontinuities[2]. Resolution is a term that is used to describe the ability of a system to locate discontinuities that are either in close proximity to each other within the material or located near the surface of the test specimen[2]. The smallest defect size that can be detected or the resolution of the transducer is half the wavelength ($\lambda/2$) of the transducer[41]. Therefore, smaller the defect, the higher is the frequency of ultrasound required for detecting it. Using a higher ultrasonic frequency results in a higher rate of signal damping in the material. The lower frequency probes are therefore preferred to reduce the damping of ultrasound within the test material. On the other hand, the testing capability of the probe is compromised if the frequency of the ultrasound is too low (1 - 2 MHz). Further, in order to obtain a satisfactory amplitude of the ultrasound signal, the probe diameter should not be less than 5 mm [35]. Therefore, there is a need to correlate the sensitivity and other characteristics of the ultrasonic transducer along with the quality requirement of the armour ceramics to be inspected in this research.

One of the most critical parameters for determining sensitivity and resolution is the frequency of the transducer that is being used for ultrasonic testing, as it indicates the wavelength for the acoustic waves that are transmitted into the sample [7].
According to the literature, most ultrasonic NDT inspection tasks are carried out at frequencies between 0.2 to 25 MHz [1, 2, 35, 47]. The higher the frequency of a transducer, the straighter the sound beam, and the greater the sensitivity, measurement resolution, and attenuation. Moreover, for any given frequency, the larger the transducer, the more directional the sound beam and lower the sensitivity [41]. While increasing the transducer frequency improves sensitivity and resolution, there are also adverse effects[18]. As the wave frequency increases, attenuation or loss of signal due to wave scattering also increases[48]. Highly dense materials are acoustically transparent over a wide range of frequencies, while porous and granular materials attenuate more rapidly at higher frequencies. Hence the type of material being examined and the type of inhomogeneities present will also have a direct influence on attenuation[49, 50]. For that reason, the frequency must be optimised to strike a balance between the degree of tolerable attenuation and the desired sensitivity to flaws. Another factor that must be considered for determining sensitivity is the acoustic impedance coupling between the bulk material and defect[18]. While the relationship among frequency, wavelength and attenuation can also affect the defect resolution of a system, there are some transducer parameters that have a unique effect depending on the type of resolution under consideration[18]. Brennan [18]in his research proposed that both lateral and axial resolution are dictated by beam diameter and pulse width respectively.

3.4.1 Near Field and Far Field Regions

The ultrasonic waves generated by a transducer will emerge initially as a parallel beam that diverges later[51]. That is, the waves propagate out from the transducer face with a circular wave front and where these waves interact, there are areas of destructive or constructive interference, referred to as nodes[2]. The acoustic waves break up into
high and low energy bands and the resulting ultrasonic beam can be divided into two fields: the near field and the far field[2] that are shown in Figure 3.3.

Near the face of the transducer, there are extensive fluctuations in which the sound field is very uneven[7]. This region is known as near field[2]. If a flaw is positioned in the near field region it can be difficult to detect due to non-uniform sound intensity [18]. Away from the transducer, the sound field is more uniform in the region known as the far field[2]. In the far field, the beams spread out in a pattern originating from the centre of the transducer and this region is important given that this is where the sound wave is well behaved and at its maximum strength[41]. So, this is the region in which best possible detection occurs.

![Figure 3.3 Sound fields of a ultrasonic transducer](image)

**Figure 3.3** Sound fields of a ultrasonic transducer [1]

### 3.4.2 Ultrasonic Beam and Beam Spread

An ultrasonic transducer does not transmit a single acoustic wave, but rather a multitude of acoustic waves, which are collectively referred to as an ultrasound beam[2]. It is the interaction of this beam with the material under inspection that determines the ultrasound results and is important for the evaluation of defect size[41]. A sound wave transmitted from a transducer spreads out in one direction within a given
angular range. The cross-section of the sound beam expands with increasing distance and the energy is distributed over a greater area. With this, the intensity of sound energy per unit area becomes smaller. This phenomenon is identified as beam divergence[2] as shown in Figure 3.4. The beam angle is the angle between the beam axis of a refracted wave and the angle to the refracting interface[2]. The refraction when passing through the interface changes the direction of propagation of the sound wave according to Snell's reflection law [36] as presented in Section 3.2.3.2.

![Figure 3.4 Beam divergences with beam angle spread (α) and near field area (N) for the diameter of the transducer (D) [1]](image)

**3.5 Inspection Methods**

There are three main categories of ultrasonic transducer configurations that are commonly used for testing [52]. The first configuration involves a single transducer that is used as both the transmitting and receiving transducer and this is referred to as the pulse-echo technique[52]. In this technique, an ultrasonic sound beam generated by the transducer travels perpendicular to the testing sample and the reflected ultrasonic wave is used for evaluating the defects[53]. This is one of the most commonly used methods for inspecting materials[18, 41]. The second configuration known as through transmission requires two transducers directly facing each other. The sample is placed between the transducers and the presence of defects is detected by the signal obtained by the receiving transducer[52]. This technique is normally used when the test parts are
easily accessible on both sides[47]. The third configuration known as pitch-catch method, also involves two transducers, however they are not directly across each other. This technique is used specifically for test samples, where either the top or bottom surface is inaccessible. In this situation, the receiving transducer is placed in an accessible location to collect the signal[52]. The pulse-echo technique is used in this research and is described in Chapter 6.

3.6 COUPLANT METHODS

3.6.1 Overview

A couplant is generally a liquid or a semi-liquid that is placed between the transducer and test sample that allows or improves the transmission of ultrasonic energy[54]. In general, thick gel, oil or water is used as a coupling agents in ultrasonic testing [1]. In this research, both contact and immersion testing methods are investigated. This section provides a brief description of both contact and immersion methods.

3.6.2 Contact Method

For contact testing, a thin layer of coupling agent is applied to the face of the transducer in order to provide acoustic impedance matching between the transducer and the sample. This ensures that the maximum ultrasonic energy enters the material, when the transducer is placed in contact with the part; however, some pressure is manually applied to ensure good acoustic contact with the test piece. The reflected signals are collected over a single point at a fixed transducer position. The major advantage of the pulse echo contact technique is its adaptability to large and irregularly shaped objects.

This technique offers high sensitivity to small discontinuities and permits accurate determinations of discontinuity depth beneath the entry surface. The major
disadvantage of the pulse echo contact technique is reduced near surface resolution caused by ringdown interference that is caused by direct contact of the transducer face and test object and the presence of a large excitation pulse. A delay line can be attached to the face of the transducer to improve the near surface resolution which separates the excitation pulse from the incident surface response and to better match the acoustic impedance of test material. The length of the delay line should be such that multiple reflections from the delay line fall well outside the back surface reflection. It is required to place a thin layer of gel between the transducer face and the delay line for good coupling[1].

3.6.3 Immersion Method

Immersion coupling uses a long fluid delay line. In immersion testing both the transducer and test sample are immersed in the coupling medium of water, that is more likely to be used in an on-line production inspection system[1, 55]. The distance between the transducer and the test object is large enough to separate in the time domain the reflections from the test object front surface and the transducer's excitation signal [9]. In this case, an immersion tank is set up in order to contain the test sample and the transducer in water as shown in Figure 3.5. The transducer is mounted on a robotic arm, so that its position can be controlled in x, y, and z directions. When the transducer is positioned at its optimum focal length, completely perpendicular to the sample surface, the signal amplitude is maximized[18]. Immersion testing provides significant coupling uniformity and is ideal for automated testing.
The velocity of ultrasound in SiC ceramic components is 12000 m/s[18], but varies in different ceramic components depending on the sintering and manufacturing process used. The ceramic components being investigated in this research are manufactured using the reaction-sintering technique as presented in Section 2.8. The simplest method of measuring the velocity of ultrasound in a part of known thickness, is to measure the time-of-flight (TOF) between the front surface echo and the first back-wall echo. The velocity of the ultrasound in the material can be calculated from the equation (1) shown in Section 3.2.3. However, the thickness of the reaction-sintered silicon carbide (RSSC) ceramic components investigated in this research was not known initially. Hence, a methodology was followed where a grid surface with 0.5 mm step has been drawn on the surface, and every intersection of the grid is considered as one test point. The thickness of the sample at each test point is calculated using a coordinate measuring machine (CMM) to a tolerance of ±0.5 μm. It is observed that the variation in thickness across the ceramic components is less than 0.01%. Thereafter, the
TOF at a few locations is recorded and longitudinal velocity calculated from equation(1) as proposed above. The longitudinal velocity in the tested ceramic components is found to be between 11750m/s to 11800m/s.
CHAPTER 4

ULTRASONIC SIGNAL ANALYSIS FOR DEFECT DETECTION

4.1 OVERVIEW

The previous chapter described the selection of parameters for ultrasonic testing of armour ceramics. However, the processing of ultrasonic raw signals and classification of defective signals obtained from the investigated ceramic components is a complex task. The aim of this chapter is to report and discuss the processing of ultrasonic signals for purposes of defect detection and characterisation of armour ceramics. Wavelet Transforms (WT), Principal Component Analysis (PCA) and Genetic Algorithms (GAs) are described. These artificial intelligence approaches are used to identify and select signal features, that are then used in a Neural Networks (NN) based signal classification system to classify ultrasonic signals and identify defects within the armour ceramic components. The theoretical background to Neural Networks is also presented here.
4.2 SIGNAL PRE-PROCESSING AND FEATURE EXTRACTION

4.2.1 Overview

Signals are a popular means of representing information and signal processing has significance in many applications. A received signal can be directly applied to a neural network, thereby forcing the neural network to discover the intrinsic features characterising the signal and perform the desired detection. A practical drawback of this approach is that it can be very slow, particularly in the context of a large-scale problems such as the one addressed in this research. Hence, pre-processing of raw signals in the initial phase and extracting suitable features from the pre-processed signals have become important in most signal classification problems. Also, pre-processing is essential to remove redundant information, thereby enabling more effective classification of data. The Wavelet Transform (WT) is investigated in this research, in the context of removal of signal noise and feature extraction. The following section explains, in detail, the ultrasonic signal pre-processing methods applied in this research.

4.2.2 Wavelet Transform

In this section, the transformation of time-based signals using the Wavelet Transform (WT) is described. The objective of using this transform is to de-noise and compress the ultrasonic signals in term of features selection prior to their input to the Artificial Neural Network (ANN) for classification. Due to the high density of SiC ceramics, the defect features embedded close to the front and back wall echoes in the ultrasonic raw signals are hard to detect. Hence, the WT is applied on all ultrasonic signals to extract further information from those signals relating to defects not readily available in the raw signals.
In practice, most of the signals obtained from experiments are time-domain signals in their raw format. This representation is not always the best representation of the signal for most signal processing related applications. In many cases, the required information is hidden in the frequency content of the signal. The frequency spectrum of a signal generally shows the frequency components that exist in the signal[3]. The Fourier Transform (FT) provides the frequency content of the signal. However, there is no frequency information available in the time-domain signal, and vice versa in the frequency domain. Nevertheless, FT is not suitable for non-stationary signals, where the frequency representation together with the related time information is required. The Wavelet Transform is capable of providing the time and frequency information of the signal simultaneously[3]. In comparison to the Short-Time Fourier Transform (STFT), wavelet analysis makes it possible to perform a multi-resolution analysis[56]. In addition, higher frequencies are better resolved in time and lower frequencies are better resolved in frequency[3].

Wavelet Analysis involves breaking up of a signal using a shifted and scaled version of the original wavelet or “mother wavelet”[41]. The similarity between the signal and the mother wavelet function is computed separately for different time intervals, resulting in a two dimensional representation. The central frequency of the mother wavelet is chosen close to that of the ultrasonic pulse. There are various of wavelet types to choose from for a mother wavelet. The wavelet contains both the analysing shape and the window. The Continuous Wavelet Transform (CWT) is defined as shown in equation (6)

\[
X_{WT}(\tau, s) = \frac{1}{\sqrt{|s|}} \int_{-\infty}^{\infty} x(t) \psi^* \left( \frac{t-\tau}{s} \right) dt.
\]
The transformed signal $X_{WT}(\tau, s)$ is a function of the translation parameter $\tau$ and the scale parameter $s$. The mother wavelet is denoted by $\Psi$, the * indicates that the complex conjugate is used in case of a complex wavelet. The mother wavelet is contracted and dilated by changing the scale parameter $s$. The variation in scale $s$ changes not only the central frequency $f_c$ of the wavelet, but also the window length. Therefore, the scale $s$ is used instead of the frequency for representing the results of the wavelet analysis. The translation parameter $\tau$ specifies the location of wavelet in time, by changing $\tau$ the wavelet can be shifted over the signal. For constant scale $s$ and varying translation $\tau$ constant fills the columns of the time-scale plane. The elements in $X_{WT}(\tau, s)$ are called wavelet coefficients, where each wavelet coefficient is associated with a scale (frequency) and a point in the time domain[56].

The drawback in the use of the Continuous Wavelet Transform (CWT) for signal analysis is that it increases the complexity and memory required to calculate a large number of coefficients. It is not necessary to use all the wavelet coefficients obtained as inputs to a neural network for signal classification that in turn increases the memory requirements [41]. Another drawback of CWT is that the representation of the signal often contains redundant components[3]. Therefore, another function called the Discrete Wavelet Transform (DWT) is applied to the signal which enables the specification of the scale and position of the signal[3].

The main feature of DWT is that a time-scale representation of a digital signal can be obtained using digital filtering techniques. The signal is passed through a series of high pass filters to analyse the high frequencies and it is passed through a series of low pass filters to analyse the low frequencies. The DWT analyses the signal at different frequency bands with different resolutions by decomposing the signal into approximation and detail coefficients[3]. The resolution of the signal, which is a
measure of the amount of detail information in the signal, is changed by filtering operations, and the scale is changed by up sampling and down sampling operations. This method is known as sub sampling that corresponds to reducing the sampling rate or removing some of the samples of the signal[3]. Figure 4.1 illustrates this procedure for a frequency band of 0 to π rad/s, where x[n] is the original signal to be decomposed and h[n] and g[n] are low pass and high pass filter respectively.

![Figure 4.1 A Sub-band Coding Algorithm [3]](image)

### 4.3 Feature Selection

#### 4.3.1 Overview

Feature extraction and feature selection are two different approaches for the reduction of dimensionality. Dimensionality reduction (feature transformation) and feature subset selection are two techniques for reducing the attribute space of feature set, which is an important component of both supervised and unsupervised
classification approaches. Feature extraction involves linear or non-linear transformation from the original feature space to a new one of lower dimensionality. Although it does reduce the dimensionality of the vectors fed to a classifier, the number of features that must be measured remains the same. Feature selection, on the other hand, directly reduces the number of original features by selecting a subset of them that still retains sufficient information for classification and thereby reduces the computational complexity and improves the classifier's generalization ability. The first motivation is quite obvious, as smaller number of features require less run time to train and to apply to the classifier. The second motivation is a low dimensional representation reducing the risk of “over fitting” [57].

The following section provides an introduction to Principal Component Analysis (PCA); a variable-reduction procedure similar to factor analysis and genetic algorithms: a type of randomized population-based stochastic search technique.

4.3.2 Principal Component Analysis

Feature transformation or dimensionality reduction refers to a technique that creates new variables as combinations of the original high-dimensional variables in order to reduce the dimensionality of a data set. The idea behind using Principal Component Analysis (PCA) is to reduce the dimensionality of a data set consisting of a large number of interrelated variables, while retaining as much as possible of the variation present in the data set[58]. This is based on consideration that a large number of inputs, while increasing the computational load, do not inevitably contribute to improving the effectiveness of defect classification. In general, the PCA technique transforms n vectors \((x_1, \ldots, x_n)\) from a d-dimensional space to n vectors \((x'_1, \ldots, x'_n)\) in a new, d’-dimensional space as shown in equation (7)
\[ x'_i = \sum_{k=1}^{d'} a_{k,i} e_k, \quad d' \leq d \]  

Where \( e_k \) are the eigenvectors corresponding to the \( d' \) largest eigenvalues for the scatter matrix and \( a_{k,i} \) are the projections of the original vectors \( x_i \) on the eigenvectors \( e_k \). These projections are called the Principal Components of the original data set and these are linear combinations of \( x \) [59]. The Principal Components are orthogonal to each other and capture the maximum amount of variation in the data. Often the variability of the data can be captured by a relatively small number of Principal Components and as a result, PCA can achieve high dimensionality reduction [58, 60].

### 4.3.3 Genetic Algorithms

Genetic Algorithms (GAs), are a type of randomized population-based stochastic search technique that offer an effective approach in finding near optimal solutions to complicated optimization problems [61]. In the current research, GA is used as a feature selection method.

The literature indicates that Genetic Algorithms have been used in conjunction with Neural Networks in three major ways [61, 62]. First, they have been used to set the weights in fixed architectures where GA has been used to set the learning rates. Second, GA has been used to investigate Neural Network topologies that include the difficulty of specifying number of hidden layers and connectivity of nodes. A third major application of GA is to select the input features and to interpret the output behavior of Neural Networks [63].

The motivation for GAs comes from biological evolution, where the best individuals have a higher possibility of survival. In GA terminology, the solution vectors (binary strings) are usually called chromosomes and a set of chromosomes is called a population. The better a chromosome is, the higher is its probability of being
selected in the new population, or as a parent in a genetic operation. A new population is typically formed by retaining some of the chromosomes in the old population and composing new chromosomes by applying three genetic operators (Selection, Crossover and Mutation) on the old chromosomes[64]. A population size of 100 individuals and 200 generations is used in this research.

*Selection*- Similar to biological systems, parents are selected according to their fitness. The better the chromosomes are, the more chances they have to be selected. Among a variety of selection operators that can be selected *Tournament* and *Roulette Wheel* are popular. In this work, the independent variables to be optimized are the set of original features selected as listed in Table I.

*Crossover*- The crossover operation is performed in each generation to generate a better solution from available solutions. This is performed by interchanging genetic material of chromosomes in order to create individuals that can benefit from their parent’s fitness.

*Mutation*- Mutation is responsible for maintaining diversity in the population by randomly “flipping” bits of the chromosome, based on some probability.

In addition to the above mentioned genetic operators, ‘elitism’ has been used that guarantees the best string individual to survive until the last generation.

To conveniently implement the genetic operators of GA, individual chromosomes of a population are represented as a binary string and parameters are coded into a binary string. In this research, for the feature selection, each bit of the chromosome is associated with an input parameter (input features) and interpreted in a way that if the $k^{th}$ bit of the chromosome equals 1, then the corresponding $k^{th}$ parameter is counted in
as a feature for classification; the other way around if the bit is 0. Each obtained feature subset is assessed according to its fitness value and is then sent to a classifier for fitness evaluation. The error rate obtained from the classifier is then returned to GA as a measure of quality of the chromosome used to obtain the corresponding set of transformed feature matrices, (i.e. based on the measure of classification performance, fitness values are assigned).

4.4. ARTIFICIAL NEURAL NETWORKS

4.4.1 Overview

This section presents background information on neurons and neural network configurations. The purpose of a neural network (NN) is to map an input into a desired output. A brief description of the feed-forward network and the back propagation training method is also presented in Sections 4.4.6 and 4.4.7 respectively. The neural network toolbox from MATLAB software is used for training and testing ultrasonic signals in this research.

4.4.2 A Biological Model

The human body is made up of a large number of living cells. Certain cells in the human nervous system are interconnected in a manner and communicate with the brain that they are experiencing a number of sensations. These specialized communication cells are called neurons. It was the observation of these interconnected neurones that gave rise to the name neural networks[4, 65].

The neuron has a central cell body, or soma, with some special attachments, dendrites and axons. The dendrites are special nodes and fibers that receive electrochemical stimulation from other neurons. The axon allows the neuron to
communicate with other neighbouring neurons. The axon connects to a dendrite fiber through an electrochemical junction known as a synapse. For simplicity, the neuron is depicted with a handful of connections to other cells. In reality, there can be from tens to thousands of interconnections between neurons. The key concept to remember is that neurons receive inputs from other neurons and send outputs to different neurons and cells[4].

4.4.3 Neuron Model

Artificial Neural Networks (ANN’s) came into being after McCulloch and Pitts[66] introduced a set of simplified neurons in 1943. ANN's grew out of research into artificial intelligence and were designed to mimic the biological neural networks found in the brain. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurones, which is also true for ANN's[4]. ANN's offer advantages over conventional computing in fields such as pattern recognition, generalisation and data classification. ANN can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other techniques[4]. A trained neural network can be thought of as an expert in the categorisation of information it has been given to analyse. With a sufficient number of hidden neurons, neural networks can be trained to produce any continues multivariate function with any desired level of precision [4].

Generally, neural networks are trained so that a particular input leads to a specific target output. That is, ANNs communicate by sending signals to each other through a large number of biased or weighted connections. A simple artificial neuron model with weighted inputs is shown in Figure 4.2. Each input \((x_1, x_2, \ldots, x_i)\) has a corresponding weight value \((w_1, w_2, \ldots, w_i)\) where \(i\) is a number of inputs to the neuron and \(x_0 = 1\). The
sum of the weighted inputs and the bias $w_0$, forms the input to the transfer function $f$. Neurons may use any differentiable transfer function $f$ to generate their output $z$ from input, which is equal to the sum of $w_i x_i$ and $w_0$ or $z = f(w_i x_i + w_0)$ [4].

Lingvall [67] in his research recommended a few guidelines that can be used in deciding the number of inputs to a network for an inspection application. They are listed below:

- The inputs should have sufficient data to distinguish between defect and non-defective signals.
- The inputs should represent the defect type and preserve the information necessary for successful classification.
- The number of representative training examples must be sufficient [67].

![Figure 4.2 A simple neuron model [4]](image)

4.4.4 Transfer Function

The sum of the weighted inputs and the bias forms the input to the transfer function ($f$). Neurons can use any differentiable transfer function to generate their output [68]. The behaviour of an ANN depends on the transfer function ($f$) and this function typically falls into one of the following three categories:
- **Linear Transfer Function** - the output activity is proportional to the total weighted input. It is referred in MATLAB as *purelin* function.

- **Threshold Transfer Function** - the output is set at one of two levels, depending on whether the total input is greater than or less than some threshold value and it is known as *hard limit* or *hardlim* function in MATLAB.

- **Sigmoid Transfer Function** - 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 [41, 68]. Multilayer networks often use the log-sigmoid or tan-sigmoid transfer functions and known as *logsig* and *tansig* in MATLAB. In this research, both log-sigmoid and tan-sigmoid transfer functions are used as they generate outputs between 0 and 1.

**4.4.5 Learning Methods**

Neural networks possess particular properties such as an ability to learn or adapt to changes, to generalise using incomplete data, and to cluster and organise data [41]. Learning in neural networks is highly significant and during the process of learning, the network adjusts its parameters and the synaptic weights, in response to an input stimulus so that its actual output response converges to the desired output response[69]. The weights are changed at every epoch. During training and testing of a neural network, an *Epoch* is defined as processing of a single set of input signals of the network[41]. Paradigms observe learning rules described by mathematical expression called learning equations[69]. The two major paradigms of learning are supervised and unsupervised learning.
4.4.5.1 Supervised Learning

During the supervised training session, an input stimulus is applied that results in an output response. This response is compared with an a priori desired output signal, i.e. the target response. If the actual response differs from the target response, the neural network generates an error signal. This error signal is then used to calculate the adjustment that should be made to the network's synaptic weights so that the actual output matches the target output [69].

4.4.5.2 Unsupervised / Self-organised Learning

In contrast to supervised learning, unsupervised learning does not require a target output. During the training session, the neural network receives at its input many different input patterns or salient features and it arbitrarily organizes the patterns into categories. When a stimulus is later applied, the neural network provides an output response indicating the class to which the stimulus belongs. Although unsupervised learning does not require a teacher, it requires guidelines to determine how it forms groups. Hence, if no guidelines have been provided as to what type of features should be used for grouping the objects, the grouping may or may not be successful [69].

4.4.6 Feed-forward Neural Networks

Researchers have discovered that combining neurons into layers permits artificial neural networks to solve highly complex classification problems [41]. This section briefly describes the feed-forward neural network that is composed of layers of neurons. Feed-forward networks allow signals to travel in one direction, from input to output and also associate inputs with outputs. Amongst the numerous Artificial Neural Network (ANN) architectures described in the literature [4, 41, 65, 69], the feed-
forward network is the most commonly used. Based on the topologies, the layer that accepts the data values to be interpreted via the input nodes is known as the input layer and the output response is obtained from the output layer. Intermediate layers are called hidden layers as their outputs are not readily observable. Figure 4.3 illustrates a three layer feed-forward neural network topology. The circles represent the neurons and the arrows represent the communication paths between neurons. Each arrow is also associated with a weight value.

![Three layer feed-forward neural network](image)

**Figure 4.3** Three layer feed-forward neural network with inputs [4]

The feed forward neural network with one or more hidden layers is generally used for defect classification in the context of Non-Destructive Testing (NDT). The training process of the feed-forward network requires a set of examples consisting of network inputs and target outputs[69]. During training, weights and biases of the network are iteratively adjusted to minimise the network performance function which is the mean square error (\(mse\))[68]. In MATLAB, this function is defined by `net.performFcn`. The mean square error value is the average squared error between the network outputs and the target outputs. There are several training algorithms for feed-
forward networks such as Levenberg-Marquardt, variable learning rate, conjugate gradient and scaled conjugate gradient algorithms [68]. All of these algorithms use the gradient of the performance function to adjust the weights to maximise performance. The gradient is determined using a technique called back propagation, which involves performing computations backwards through the network [68].

4.4.7 Back Propagation Learning Algorithm

The Back Propagation (BP) network training algorithm is an iterative gradient algorithm designed to minimise the mean square error between the actual output of a feed-forward network and the desired output [68]. During the training session, the process starts by applying the first input pattern along with the corresponding target output. The input then causes a response to the neurons of the first layer, which in turn cause a response to the neurons of the next layer, and so on, until a response is obtained at the output layer [68]. That response is then compared with the target response, and the error is calculated. From the difference in error value at the output neurons, the algorithm computes the rate at which the error changes as the activity level of neuron changes. To this point, the calculations are computed in a forward direction (input layer to output layer). Later the algorithm continues calculating the error and computing new weight values, moving layer by layer backward, towards the input. When the input is reached and the weights do not change, the algorithm then selects the next pair of input-target patterns and repeats the process [69].

There are two different ways in which gradient descent algorithm can be implemented: incremental mode and batch mode. In the incremental mode, the gradient is computed and the weights are updated after each input is applied to the network. In
the batch mode all of the inputs are applied to the network before the weights are updated[68].

It is very difficult to know, which training algorithm will be the best for a given problem. It will depend on many factors, including the complexity of the problem, the number of data points in the training set, the number of weights and biases in the network, the error goal and analysis type the network is being used for (discriminant analysis or regression) [68]. In this research, both back propagation learning algorithms "Levenberg-Marquardt" and "Scaled Conjugate Gradient" methods are investigated.

4.4.8 Levenberg-Marquardt (LM)

One of the most popular supervised learning algorithms is the Levenberg-Marquardt (LM) mechanism. The LM algorithm is an iterative technique that locates the minimum of a multivariate function that is expressed as the sum of squares of non-linear real-valued functions[70]. This algorithm appears to be the fastest method for training moderate-sized feed-forward neural networks. However, it requires a large amount of memory[68].

The training parameters used for trainlm (MATLAB functions for LM) are epochs, show, goal, time, min_grad, max_fail, mu, mu_max, and mem_reduc [68]. The training status is displayed for every show iterations described in the network. The other parameters determine when the training stops in the neural network. The training stops when any of the following conditions are met while training the network[68].

- When the number of iterations exceeds a given number of epochs.
- If the performance function drops below a certain goal value.
- If the magnitude of the gradient value is less than min_grad function.
• The maximum amount of time is exceeded.

• Validation performance has increased more than max_fail times since the last time it decreased (when using validation)[68].

The function max_fail is associated with the early stopping technique during the network training process. The functions mu and mu_max are the initial value and maximum values for μ respectively. The parameter mem_reduc is used to control the amount of memory used by the algorithm[68].

4.4.9 Scaled Conjugate Gradient (SCG)

The scaled conjugate gradient algorithm developed by Moller[71], was designed to avoid the time-consuming line search. This algorithm requires only a little storage, so it is often a good choice for networks with a large number of weights[71].

The training parameters used for trainscg (MATLAB functions for SCG) are epochs, show, goal, time, min_grad, max_fai, sigma, lambda and lr. The first six parameters and training stopping criteria are same as discussed previously in section 4.4.8. The parameter sigma determines the change in the weights for the second derivative approximation. The parameter lambda regulates the indefiniteness of the Hessian [71]. The function lr corresponds to the learning rate. The learning rate lr is multiplied times the negative of the gradient to determine the changes to the weights and biases. The larger the learning rate, the bigger the step. If the learning rate is made too large, the algorithm becomes unstable. If the learning rate is set too small, the algorithm takes a long time to converge[68].
4.5 Artificial Neural Network Architecture

4.5.1 Overview

The architecture of a network describes how many layers a network has, the number of neurons in each layer, each layers transfer function and how the layers connect to each other [68]. The first step in training a feed-forward network is to create the network object. The next step is to initialise the weights and biases of the network; then the network is ready for training. There are circumstances when the weights have to be re-initialised. Both theoretical analysis and simulations indicate that large networks tend to overfill the training data and thus have a poor generalisation, while networks that are too small have difficulty in learning through the training samples[68].

4.5.2 Creating a Network

The first step in training a feed forward network is to create the network object. It basically requires four inputs and returns the network object. The first input is a matrix of minimum and maximum values of the input vector. The second input is an array containing the sizes of each layer. The third input is a cell array containing the names of the transfer functions to be used in each layer. The final input contains the name of the training function to be used[68]. In MATLAB, the function newff creates a feed-forward network. This command creates the network object and also initializes the weights and biases of the network and the network is ready for training. There will be times when one is required to reinitialize the weights[68].

4.5.3 Initialising Weights

Before training a feed-forward network, the weights and biases have to be initialised. In general, each separate weight value is set to a random value. An
automatic initialisation of the weights has to be carried out before each new training set is used. The initialisation function takes a network object as input and returns a new network object with all weights and biases initialised[68].

### 4.5.4 Simulation and Training of Network

Once the weights and biases are initialised, the network is ready for simulation and training. The simulation of the network takes the network input and the network object defined during the initialisation process and returns a network output. The network can be trained for function approximation or pattern classification. The training process requires a set of examples of proper network behaviour; network inputs ($p$) and target outputs ($t$). The weights are adjusted for each neuron in three layers as shown in Figure 4.2 depending on the mean square error ($mse$) and the desired target ($t$)[68].

The learning rate is used in Feed-forward neural networks during Back Propagation (BP) to adjust the weights between neurons in connecting layers. Selecting the learning rate for a non-linear network is a challenge. As with linear networks, a learning rate that is too large leads to unstable learning[68]. A learning rate that is too small results in the training time being lengthy. The rate of change of weights during the BP phase where the weights and bias are being adjusted to reduce the prediction errors are controlled by the learning rate[68]. Further, the use of momentum rate allows the network to skip through possible local minima. The momentum parameter controls the amount of error adjustment with each iteration during training the neural network for signal processing[41]. Both the learning rate and momentum parameter affect the speed and quality of the learning process, and error values deliver information on which a decision is taken as when to stop training[41].
4.5.5 **Normalization**

Neural network training can be made more efficient when normalization or a pre-processing step is performed on the network inputs and targets. Data normalization can also speed up training time by starting the training process for each feature within the same scale. If the number of inputs are very large, then the weight must be very small in order to prevent the transfer function from becoming saturated [68]. It is standard practice to normalize the inputs before applying them to the network. Generally, the normalization step is applied to both the input vectors and the target vectors in the data set. In this way, the network output always falls into a normalized range. The network output can then be reverse transformed back (post-processing) into the units of the original target data when the network is put to use in the field [68].
CHAPTER 5

LITERATURE REVIEW

5.1 OVERVIEW

The objective of this review is to acquire an understanding of the context of the research and provide a background to the research in the field of ultrasonic Non-destructive testing (NDT) of armour ceramics. Sources used included books, journal articles, conference publications, International and Australian Standards on NDT, patent applications and NDT&E related websites.

As proposed in Chapter 1, a deeper understanding of ultrasonic testing of metals, composites and ceramics is required along with an understanding of different signal processing techniques that can be used for defect classification. The literature review covers the following areas and this chapter is divided into three major sections, namely:

1. Non-destructive defect detection in ceramics
2. Ultrasonic inspection of metals, composites and ceramics
3. An artificial intelligence approach to ultrasonic signal processing.

The subsequent sections focus on the use of high frequency ultrasound in the inspection of metals, composites and ceramics. Finally, a review of automated inspection systems is presented. The current and emerging applications in this research area are also discussed.
5.2 Non-Destructive Defect Detection in Ceramics

Non-destructive techniques have generally been used for the detection of macroscopic defects in structures after they have been in service for some time. At present, it has become increasingly evident that it is also practical and cost effective to expand the role of non-destructive evaluation to include all aspects of materials production and application. Therefore, current efforts are directed at developing and perfecting this technique in the controlling and monitoring of the materials production process[72].

As discussed in Section 2.6.2, detection of defects is almost exclusively concerned with manufacturing defects rather than with in-service inspection. Therefore, there is a requirement for the non-destructive quality inspection that dictates the service life of ceramic components. The need of non-destructive testing techniques varies depending on the processing stage, fabrication method and the nature of the finished product. Manufacturing industries will have certain specifications and thus follow accept/reject criteria for each type of product manufactured. The following section describes several Non-destructive testing and evaluation (NDT&E) techniques as described in the literature to inspect ceramics.

In a research study, Vary [72] compared the advantages and disadvantages of four types of acoustic microscopy techniques for flaw detection and imaging in monolithic ceramics. The techniques include scanning laser acoustic microscopy (SLAM), scanning acoustic microscopy (SAM), photo-acoustic microscopy (PAM) and scanning electron acoustic microscopy (SEAM). Vary stated that although SAM produced high resolution results (30µm or less) in detecting flaws, it was found to be time-consuming and highly dependent on factors like surface roughness[72].
Sanders et al. [73] used conventional radiography to characterize the porosity in silicon nitride test bars with different mean bulk densities. The results obtained from the radiographs assisted in improving sintering methods in producing samples with uniform densities, i.e. close to theoretical and a sixty percent increase in strength[73].

Meitzler et al.[74] used direct- digital projection X-ray imaging systems with a large area flat panel for crack detection in armour ceramics. The authors stated that X-ray imaging systems offered the most time and cost effective NDE technology for inspection of multi-layer ceramic composite armour[74].

Sun et al.[75] used through-thickness thermal imaging, air-coupled ultrasound and X-ray CT scan to measure density/porosity. The authors proposed that through-thickness thermal imaging directly measures thermal diffusivity, which is a function of density[75]. In addition, density is also related to ultrasonic attenuation and X-ray attenuation [76].

X-ray computed tomography (CT) is another NDE method that has a number of engineering applications along with medical applications. In general, the CT scan provides the ability to map the relative X-ray linear attenuation of the materials throughout a component, permitting the extraction of dimensional and material characteristics of features[77]. Infrared thermography (IR) is another NDE method used for characterisation of ceramic composites. This technique is based on the concept that after applying a uniform heat pulse to the sample surface, a localized disruption of the heat flow will occur when defects or flaws are present in the material[77]. The change in the heat flow translates into temperature differences on the material surface. The temperature variations on the surface of a sample were used to create thermographic images in terms of either temperature differences or thermal diffusivity[77].
Adam et al. [78] reviewed various non-destructive techniques used to identify defects including voids, porosity, matrix cracks, delaminations, stacking, winding and in service defects in composites. Ultrasonic testing was found to be sensitive compared to other NDT techniques such as radiography[78].

Radiography has been the preferred method for inspecting ceramics. However radiography has inherent dangers because the radiation produced can have a detrimental effect on operators if they are exposed to it. The other problem with the X-ray image or the radiography approach is related to the reliance on human operators to interpret the images produced. Human error in identifying defects in armour ceramics may occur due to operator fatigue, distraction and lack of sufficient experience. Along with this, multiple defects are sometimes misinterpreted as single defects from the grey-scale image of the X-ray[41].

5.3 ULTRASONIC TESTING OF VARIOUS MATERIALS

5.3.1 Overview

The usual objective in ultrasonic NDT is to detect and characterise a variety of discrete hidden discontinuities that can impair the integrity and reduce the service life of a structure. Such discontinuities include cracks in metals, delaminations in composites and inclusions and other type of defects in ceramics. Although a structure may be free of distinct identifiable discontinuities, it may still be susceptible to failure because of inadequate or degraded mechanical properties. This can arise from faulty material processing, over aging and degradation in aggressive service environments. For these reasons, it is important to have non-destructive methods for characterising anomalies in microstructures and their associated mechanical property deficiencies. The
literature review documented in the following sections focusses on the ultrasonic inspection of metals, composites and ceramics.

5.3.2 Ultrasonic Testing of Metals

Ultrasonic testing is the most effective non-destructive method of detecting subsurface discontinuities commonly found in bar, plate and tubes[79].

Blessing et al [79] inspected steel samples at a frequency range of 1 to 20 MHz to study the effects of surface roughness on ultrasonic signal echo amplitude. They observed multiple back wall echoes in the ultrasonic signal for surfaces with roughness up to 23 microns[79].

Silk et al [80] investigated the propagation of ultrasound in small diameter metal tubes along with simulated defects. Ensminger [81] observed major limitations in using ultrasound to inspect metal castings due to the sensitivity of ultrasound to grain size and surface roughness.

Lowe et al [82] studied the propagation of the ultrasonic waves and their sensitivity to detect defects using guided waves. The significant issues highlighted in this work were the selection of the optimum guided wave modes and establishment of relationships between the defect size and the strength of wave reflection[82].

Palanisamy [83] carried out research on ultrasonic inspection of gas porosity defects in aluminium die castings. In this work, it was demonstrated that the loss of ultrasonic signal echo due to grain size variations was reasonably small in relation to loss of signal echo caused by variations in surface roughness of aluminium castings. In addition, it was found that using a hybrid signal processing approach of Fast Fourier Transforms and Wavelet Transforms with Artificial Neural Networks lead to the detection of gas porosity of diameter 0.7 mm for casting with surface roughness of 100 microns[83].
Ambarder et al [84] investigated the effects of grain size and porosity levels on the velocity of ultrasound. One significant finding of their work was that velocity of ultrasound was independent of the size of porosity in castings[84].

5.3.3 Ultrasonic Testing of Composites

This section reviews the literature on the ultrasonic inspection of multi-layered composites published over the last decade.

A large number of multi-layered composite structures exist in practice. These include fiber-reinforced composite materials, aircraft structures, biological tissues, thin films, modern electronic systems and semiconductors[9]. In contrast to metals, early damage in composites is usually distributed over an extended region in the material and thus, for any technique to be useful, it must be capable of global monitoring or inspecting the composite structure[85]. The inspection of multi-layered structures using ultrasound is a challenging task. The detection of variations in composition; the determination of the material’s configuration, including its ply-layup sequence, thickness and its porosity; the detection of fibre/matrix disbonds or other failures, fibre or matrix cracking, voids and inclusions and the determination of residual stresses and stress gradients are of particular interest in non-destructive evaluation (NDE)[85]. In addition, another problem is high attenuation of the ultrasonic signal due to scattering and multiple reflections inside the material caused by different acoustic impedance of the layers or resin placed between the layers [9].

Potel et al. [86] used ultrasonic methods to detect and characterize defects caused by damage in composite materials. A two-dimensional ultrasonic cartography was performed section by section in pulse-echo mode, at different positions from the impact.
point. Moreover, a three-dimensional cartography has been presented[86]. The results provide a good visualization of the delaminations and a very close agreement was obtained between the C-scan damage localization maps and destructive testing observations[86].

Aymerich et al. [87] studied delaminations and matrix cracking caused by low-energy impacts on quasi-isotropic carbon/PEEK laminated composite plates by means of pulse-echo techniques: conventional time-of-flight and amplitude C-scans in normal incidence [87]. In addition, backscattering C-scans were employed (in which the transducer is set at an angle to the laminate plane) that allows the detection of matrix cracks through the laminate thickness. Selected results from full waveform ultrasonic analysis of impacted carbon/PEEK laminates were then compared with X-ray data in order to demonstrate the efficiency of the proposed inspection technique[87].

Steiner et al.[88] used acoustic emission, ultrasonic C-scans, and ultrasonic polar backscattering methods for the evaluation of matrix cracks and delaminations in composite laminates. It was observed that the traditional C-scans were sensitive to delaminations but not to matrix cracks in the specimen[88]. Consequently, polar backscattering scans were evaluated for the detection of crack initiation, location, evolution, as well as crack density. The results were compared with the results obtained from acoustic emission techniques and through optical microscopy[88].

In the investigation of damage tolerance of composites, Hull et al.[89] proposed an ultrasonic B-scan technique, specially designed to yield quasi-three-dimensional images of impact damage and stated that X-radiography to a certain degree is capable of
revealing delaminations and matrix cracks in composite structures, however it fails to provide three-dimensional information[89].

Teti et al. [90] investigated ultrasonic non-destructive evaluation (NDE) of defects in carbon fiber reinforced plastic (CFRP) laminates, displaying different quality levels according to their fabrication cycle. Ultrasonic (UT) testing, mechanical testing, and structural examinations were carried out to quantitatively characterize the CFRP laminates and their quality[90].

D' Orazio et al. [91] addressed the problem of automatic inspection of composite materials using an ultrasonic technique. The authors developed a normalization procedure to suppress with a uniform step the samples which are under a selected threshold value[91]. Consequently an evaluation is made of the number of signal points that have to be eliminated to reduce the signal length to that obtained from a minimum ply thickness. The reduced signal maintains the same shape and peak as the original signal[91].

The two most prevalent fabrication defects in solid laminates are porosity and foreign objects. Porosity is detectable because it contains solid-air interfaces that transmit very little and reflect large amounts of sound. Inclusions, or foreign objects, are detectable if the acoustic impedance of the foreign object is sufficiently different from that of the composite material[92]. Radiography is occasionally used for composite parts that maybe subject to micro-cracking. Bonded honeycomb assemblies are inspected with both ultrasonics and radiography. Radiography is capable of finding
many types of defects in honeycomb core that would go undetected with ultrasonics alone[92].

5.3.4 Ultrasonic Testing of Ceramics

Singh et al [93] investigated the microstructure problems that generally occurs in reaction-formed silicon carbide ceramics which includes micro-structural coarsening, silicon lake formation and incomplete reaction of carbon[93]. Margetan et al [94] have investigated the feasibility of using ultrasonic pulse/echo time-of-flight (TOF) to determine porosity levels in silicon carbide ceramic tiles. In this work, they related the TOF values to local longitudinal velocity values. The relationship was then used to translate the ultrasonic TOF C-scan images into porosity images [94].

Richter et al [95] performed ultrasonic inspections on multi-layer armour panels and have studied how disbonds on either side of the rubber layer would affect armour performance. About ninety panels were investigated of which few of them have artificial disbonds of three different sizes[95].

Portune et al [96] presented a study of micro structural differences between high and low amplitude regions of ultrasonic bottom surface reflections in silicon carbide (SiC) tiles [96]. The frequency based attenuation relationship has been used to study bottom surface signal amplitude of a sintered SiC tile. The results showed that examination of the attenuation coefficient as a function of frequency via Fast Fourier Transform (FFT) enabled a better understanding of the microstructure present in the sample. However, the strong dependence of bottom surface amplitude values on the top surface quality (i.e., the influence of surface roughness and flaws) reduced the
confidence in conclusions drawn from the bottom surface amplitude data [96]. A similar approach adopted by Kunerth [97], where a ultrasonic backscatter energy technique was used to map the overall porosity distribution of SiC sample[97].

Brennan et al [98] analysed isolated bulk defects and inhomogeneities in SiC fabricated by hot pressing and chemical vapor deposition using high frequency ultrasound (75 MHz). With the results obtained, Brennan et al [98] pointed out that the reflected signal amplitude in the C-scan image showed more variation related to the thickness, while the TOF data highlighted significant differences due to uneven polishing that was not a factor in the amplitude data.

Revel [99] has proposed a measurement method of determining apparent density of green ceramic tiles. The method uses a non-contact ultrasonic through transmission technique where the time-of-flight is measured during the transmission through the tile[99]. The conversion factor between velocity and apparent density is determined by a calibration procedure with a reference method of known uncertainty, which is based on a hydrostatic weighing in a mercury bath [99].

Eren et al [100] used an ultrasonic non-destructive approach to characterize porosity and identify defects in porcelain ceramic tiles. A contact ultrasound technique, based on the A-scan, and measurement of the material frequency response were found to be useful for the characterization of porosity in porcelain tiles[100]. The authors also investigated ceramic specimens with two types of simulated defects (a piece of paper and aluminum foil)[100]. Through experimentation it was determined that a 5% change in porosity in ceramic tiles resulted in a 20% reduction in ultrasonic wave velocity.
They also found that the ratio of signal reflected by a defect to the back-wall echo provided a good measure of the severity of the defect[100].

Romagnoli et al [101] investigated delamination cracks of green and sintered ceramic tiles by using ultrasonic pulse velocity measurement. It was assumed by the authors that an increase in travel time for a given thickness indicated the presence of delaminations, as there will be a decrease in travel velocity when sound wave travels around the pore[101].

A matrix specimen and SiC/SiC composites specimen were studied by Nam et al [102] using the ultrasonic method to detect surface micro cracks. Authors reported that the cracks were accurately detected on both the top and side because of the flat polished surface, however the crack detection for unidirectional composite specimens was difficult due to the uneven surface[102].

5.4 AN ARTIFICIAL INTELLIGENCE APPROACH TO ULTRASONIC SIGNAL PROCESSING

5.4.1 Overview

Automated signal classification is becoming increasingly popular in many commercial applications, including non-destructive evaluation (NDE). Inspiration for the use of such systems derives from the need for accurate interpretation of large volumes of inspection data, and minimization of errors due to human factors[103]. Automated signal classification systems have the potential for detecting flaws and interpreting ultrasonic signals accurately [27]. Rose [104] reported a novel project relating to use of pattern recognition methods for automated characterization of
ultrasonic signals using a set of features chosen from time, frequency and spatial domains[104]. Over the past few decades, a substantial interest in the development of feature extraction techniques has been kindled largely by the requirement for addressing pattern recognition, defect detection and image processing problems, where features constitute inputs to a classifier. Selecting features that can effectively classify patterns is often a nontrivial task in many applications[105]. Once a set of optimal features are chosen, a suitable classifier is used to classify the signals. A number of supervised and unsupervised classification algorithms are proposed that includes Fisher’s Linear Discriminant, K-Nearest Neighbours, Neural Networks (NN), Neuro-Fuzzy classifiers, Tree Classifiers and Support Vector Machines (SVM) [103]. This section aims to highlight the need for signal analysis, and describes different methods used in the automation of defect detection and signal classification in various applications. Furthermore, a review of the application of Artificial Intelligence (AI) and signal processing techniques is presented in relation to ultrasonic inspection.

5.4.2 Signal Pre-Processing

5.4.2.1 Overview

Signal pre-processing is the first step in ultrasonic signal interpretation. There is a requirement for signal pre-processing to be applied on the input signals to achieve better classification[41]. Human expertise, which is often required to convert ‘raw’ data into a set of useful features, can be accompanied by automatic feature extraction methods. In some approaches, feature extraction is integrated with the modelling process similar to artificial neural networks [64]. In other approaches, feature extraction is a pre-processing method. In general, pre-processing methods may include:
• Standardization- Features can have different scales although they refer to comparable objects[64].

• Signal enhancement- The signal-to-noise ratio may be improved by applying signal or image processing filters. These operations include de-noising, smoothing, background removal or sharpening. The Fourier transform and wavelet transforms are popular methods[64].

• Extraction of local features- for sequential, spatial or other structured data, convolutional methods using hand crafted kernels are used to encode problem specific knowledge into the features[64].

• Feature discretization- Some algorithms discretise continuous values into finite discrete sets that may simplify the data description and improve data understanding[64].

• Linear and non-linear space embedding methods- when the dimensionality of the data is very high, techniques such as Principal Component Analysis (PCA) and Multidimensional Scaling (MDS) are used to project the data into a lower dimensional space while retaining as much information as possible. The coordinates of the data points in the lower dimension space might be used as features[64].

A commonly used signal pre-processing signal enhancement method is discussed briefly in the following section.

5.4.2.2 Discrete Wavelet Transform

Due to its excellent properties of time-frequency localization and adaptive multi-scale decomposition, the discrete wavelet transform (DWT) has been applied extensively for feature extraction in many applications [105]. Yu et al [105] proposed a cluster based approach for extracting features from the coefficients of a two-dimensional discrete wavelet transform. The wavelet coefficients from the matrix of
each frequency channel are segregated into non-overlapping clusters in an unsupervised mode. The energy of each of these clusters is treated as a feature that contains useful information about the image\[105\]. The feature vector of an image thus computed was used as an input pattern to a neural network for image classification. The results show that the performance obtained with the cluster-based method is superior to that obtained using the energies from standard matrices of 2-D wavelet coefficients\[105\].

Sambath et al \[106\] in their research presented a signal processing technique based on a wavelet transform, which enhanced the ability to characterize defects. An artificial neural network (ANN) combined with discrete wavelet transform (DWT) coefficients as input to the ANN, have been applied to interpret ultrasonic signals during weld bead inspection \[106\].

Martin et al \[107\] developed an artificial neural network model for the ultrasonic pulse echo technique to classify resistance spot welds into four classes. They used a back propagation multi-layer feed forward ANN training algorithm for the classification of spot welds. Feature inputs to the ANN consisted of ten component vectors that contained information on relative heights of the echoes and the distance between consecutive echoes. A success rate of 100% was achieved\[107\].

Obaidat et al \[108\] in their research developed a methodology to detect defects using ultrasonic-based NDT using multilayer perceptrons. The authors found that results obtained by using the discrete wavelet transform and neural networks were superior to those obtained using neural networks on their own\[108\].
Lee [109] has addressed important issues in signal feature extraction approaches and provided evidence of the superiority of the discrete wavelet transform (DWT) to Fast Fourier Transform (FFT) as a feature extraction method[109].

Polikar et al [103] developed an ultrasonic sensor based inspection system for weld inspection of piping in boiling water reactors. The Discrete Wavelet Transform (DWT) was employed and the features extracted were used as inputs to neural networks that were used to classify defects into three categories of defects namely, crack, counterbore and rootweld [103].

**5.4.3 Feature Selection**

**5.4.3.1 Overview**

Feature extraction and feature selection are two different approaches for the reduction of dimensionality[64]. The research on feature selection dates back to the early sixties, where Narendra and Fukunaga [110] used probabilistic separability measures as the constraint while Foroutan and Sklansky [111] used the error rate of the piecewise linear classifier. Ideally, the feature selection process should select an optimum subset of features from the set of available features which is necessary and sufficient for solving the problem. Feature selection is important as all available features may not be useful. Some of the features may be redundant, while others may cause confusion during the learning phase. In addition, these features unreasonably increase the complexity of the feature space which in turn demands more computation time for learning or finding a solution to the given problem [112]. Although feature selection is predominantly performed to select relevant and informative features, it can have other motivations, including:
- General data reduction, i.e. to limit storage requirements and increase algorithm speed.
- Feature set reduction to save resources in the next round of data collection or during utilization.
- Performance improvement.
- To gain knowledge about the process of generating the data [64].

The feature subset selection approaches can be grouped into following categories; filter wrapper and embedded methods that perform the feature selection process as an essential part of a machine learning algorithm. A brief overview on each of these methods is presented below.

i. **Filter Methods**

This method uses statistical properties of the features to filter out features poor in information content. This is done prior to applying any classification algorithm. The filter method acquires no feedback from classifiers, but estimates the classification performance by some indirect assessments, such as distance measures which reflect how well the defect classes separate from each other [57]. The Fisher criterion is such a filter method, which compares the importance of each feature independently of other features by comparing the feature's correlation to the output labels [113]. Some of the existing filter based algorithms includes FOCUS algorithm, RELIEF algorithm and Decision trees [114].

ii. **Wrapper Methods**

The second approach is computationally challenging, but often provides more accurate results than filter methods. A wrapper algorithm explores the feature space to score feature subsets according to their predictive power, optimizing the subsequent induction algorithm that uses the respective subset for classification [113].
Wrapper methods in contrast to filter methods are classifier-dependent. Based on the accuracy of the classification, the methods evaluate the ‘goodness’ of the selected feature subset directly, which should instinctively yield better performance. In spite of good performance, wrapper methods have limited application due to the high computational complexity involved and it has been proved to be true especially in the context of Support Vector Machines, a classifier that has found success in a variety of areas[57, 115].

iii. Embedded Methods

The third approach performs feature selection in the process of model building i.e. an extra term is added that affects the size of the selected feature subsets and optimizes the new objective function to select features. This approach is however limited to linear kernels[113, 115].

Another approach for feature selection is known as concave feature selection, which is based on the minimization of the "zero norm". This embedded method can be used to establish a feature ranking in order to compare its feature selection performance with other wrapper methods[113].

In summary, Wrapper methods tend to give better results, however filter methods are usually computationally less expensive than wrappers.

Maldonado and Weber [113] proposed a wrapper based feature selection algorithm using Support Vector Machines with kernel functions. This method performs a sequential backward selection which uses errors occurring in a validation subset as a measure in selecting the features. The important characteristic of the proposed method is that different runs of the algorithm may select different features due to the random
data split in each iteration. In comparison with other feature selection methods the authors have suggested that the proposed method outperforms other filter and wrapper methods, however an unfortunate split of the data set may remove an important feature that affects the classifier's performance [113].

Liu et al.[57] developed a filter based feature selection method (SFS) in the context of Support Vector Machines that takes into account the class separability of individual features as well as the correlation between features. Class separability involves calculating the normalized distance between classes and then eliminating the features that yield low separability values. SFS method starts with an empty set and iteratively selects one feature at a time and adds it to the current feature set[57].

Sanchez-Marono et al [116] investigated the effectiveness of four filter methods under different situations like increasing number of relevant features and samples, the level of noise and interaction between features. With a reduced set of features, all the four methods were found to work better, and got worse when the number of features increased. Among the four filter methods the Correlation based Feature Selection method (CFS) performed best [116].

Liu et al [117] reviewed feature selection algorithms for classification and clustering. Talavera[118] presented the forward selection mechanism for feature selection using clustering of categorical data. However, the forward selection method used in this work was not sufficiently reliable [118].
5.4.3.2 Principal Component Analysis

Malhi et al [59] studied a Principal Component Analysis (PCA) based approach to select the most representative features for the classification of defective components and defect severity in three types of rolling bearings, where no prior knowledge on the defect conditions was available. The unsupervised classification scheme was investigated and the proposed scheme has been shown to provide more accurate results for defect classification with few feature inputs when compared to using all features initially considered relevant [59].

Tamilarasan et al [119] presented different feature selection methods for intrusion detection. Backward elimination and forward elimination experiments were performed using neural networks and the features ranked based on their influence on the final classification [119].

Howley et al [120] have investigated the effect of PCA on machine learning accuracy with high dimensional spectral data based on different pre-processing steps. Their results show that using the PCA method in combination with classification improves classification accuracy when dealing with high dimensional data [120].

Janecek et al [121] investigated the relationship between various feature reduction methods (feature subset selection and dimensionality reduction) and the resulting classification performance. In particular, feature subsets determined with a wrapper method were compared to sets of linear combinations of the original features computed with three variants of Principal Component Analysis. The authors concluded that the
classification accuracy achieved with a reduced feature sets is often significantly better than with the full feature set used as input to the classifier [121].

Palanisamy et al [83] have proposed a hybrid signal pre-processing technique utilizing various combinations of PCA, Wavelet transform and Fast Fourier transform in order to identify defects in rough surface castings.

5.4.3.3 Genetic Algorithms

For many classification problems, the possible inputs to neural networks can be quite large. Hence there may be some redundancy among different inputs. The problem of finding a near-optimal set of input features to an artificial neural network (ANN) can be formulated as a search problem. Given a large set of inputs, a near optimal subset is to be chosen which has the fewest number of features; yet, the performance of the ANN using this subset must be superior to that of the ANN using the large input set [61]. Genetic algorithms (GAs) are wrapper based random search methods that have also been used for feature selection. Normally, in a genetic algorithm based feature selection approach, each chromosome of the population represents a feature subset. A classifier is used to evaluate each chromosome (feature subset) based on the classification accuracy and the dimension of the feature subset[112].

Muni et al [112] presented an online feature selection algorithm using genetic programming. The proposed methodology determines the size of the feature subset by assigning higher probabilities to smaller sizes. The classifiers that are more accurate using smaller number of features are given higher possibility to pass through the
genetic program operations. Thus, a good classifier using a small feature subset is selected[112].

Casillas et al [122] devised a genetic feature selection scheme for a fuzzy rule based classification system. Pal and Chintalapudi [123] proposed a new method of selecting the appropriate features online while training a neural network. In this approach, selection of features and construction of the classifier are done simultaneously producing a good results for a given problem[123].

The innovative work of Siedlecki and Sklansky [124] validated the evidence for GAs advantage compared to classical search algorithms. Siedlecki et al [124] introduced a form of GA for selecting a small subset from an initially large set of coordinates of the feature space in the design of a pattern classifier.

Kudo et al [125] provided a comparative study of algorithms for large-scale feature selection using methods including leave-one-out, k-nearest-neighbour and genetic algorithms. The authors concluded that GAs are more suitable as feature selection method for large-scale problems[125].

Sherrah et al [126, 127] presented an automatic evolutionary pre-processing (EPrep) method for feature extraction/selection. However, the main disadvantage of this method was the computation time and complexity[127]. Subsequently, many studies demonstrating the advantages of using GA as a feature selection technique have been published [128-131].
5.4.4 Applications of Neural Networks

Liu et al [132] developed an A-scan ultrasonic non-destructive testing method for detecting cracks by means of back propagation neural networks. The trained neural networks were then utilized for the identification and classification of cracks in the medium to determine the type, location and length of the crack. The root mean square error of the outputs of the training set was found to be 10.43%, while the testing set error was 11.58 % [132].

Margrave et al [133] reviewed three types of neural network configurations developed for the purpose of accurate interpretation of flaws in steel plates. The defect varieties investigated include side-drilled holes, inclusions, porosity, smooth and rough cracks and non-defective plates. The signals obtained from the defects were directly used as inputs to the neural network without using any pre-processing technique. Amongst three types of neural network configurations investigated, Multi-layer perception architecture using a back propagation training algorithm performed better than the Learning Vector Quantisation (LVQ) and Kohonen networks[133].

Iyer et al [134] considered an automated signal classification system to process ultrasonic signals acquired from a region of interest in concrete pipes. A feature extraction scheme based on the discrete wavelet transform and unsupervised clustering to extract signal features for classification by the multi-layer perceptron (MLP) classifier was proposed. The MLP classifier was compared to the statistical classifier, Linear Discriminant Analysis (LDA), to demonstrate that the MLP classifier was superior in its ability to ‘learn’ from training patterns. However, non-linear regression analysis of the data yielded the lowest classification accuracy[134].
Selvakumar et al [135] investigated the deformation characteristics of sintered aluminium preforms using neural networks (NN). The model was based on a four-layered neural network architecture with back propagation learning algorithm. The results in a comparative study between the regression analysis and the NN revealed that the NN could predict the material characteristics of sintered aluminium preform better than regression polynomials[135].

Solis et al [136] investigated learning parameters for flaw detection within a block of aluminium. The detected echoes were pre-processed applying the Hilbert transform to produce the signal envelopes and then normalised to be fed as inputs to a neural network. The Wavelet Transform (WT) was applied to the ultrasonic signals to obtain time-frequency data. The Adaptive Resonance Theory class two (ART2) architecture was used. The results demonstrated that discrimination between echoes coming from flaws and other echoes was possible (comers, second-time around echoes or noise)[136].

Several other researches [106] [107-109, 137] [41, 119, 128, 138] have also applied artificial neural networks for classifying various defects in the fields of metals, composites, ceramics, food products and health monitoring. The most frequently used neural network architectures used are Feed-forward neural network (FF), Multi-layer Perceptrons (MLP), Adaptive Resonance theory (ART) and Learning Vector Quantization (LVQ) networks[133, 134].
5.5 CONCLUSIONS

The research findings presented by each of the authors cited in the literature review were critically studied to set up a sound foundation for this research project and to provide a basis for measuring its contribution to knowledge. The literature review indicate that non-destructive techniques like X-ray's have the potential to be used to detect defects like porosity and cracks in ceramic components. However, with this technique multiple defects are sometimes misinterpreted as single defects and also has failed in distinguishing between high density and low density regions in ceramic components. On the other hand, an extensive search of the literature has indicated that ultrasonic techniques were not been successfully used to detect various defects like un-sintered silicon, black spots, silicon rich areas and density variation especially in armour ceramics to-date. Hence, this is the topic of research addressed in this thesis. This literature search was focused on obtaining information on ultrasonic inspection of ceramics components with various common defects and containing irregular porosities. However, it was found that there was no published research addressing these issues in particular with density variation and defects like un-sintered silicon, black spots, silicon rich areas.

From the different research contributions relating to the application of artificial intelligence techniques in the field of non-destructive testing, it was observed that artificial neural network (ANN) has been the approach of choice in ultrasonic signal classification. However, this approach has not been sufficiently explored for classification of ultrasonic signals obtained from armour ceramic components. Therefore, the development of an effective classification methodology for the ultrasonic
signals obtained from these ceramic components through a neural network approach is investigated as part of this research program.

The possibility of applying various signal processing techniques like FFT and Wavelet analysis to ultrasonic signals has been studied by several researchers as described in the literature review. However, the use of techniques such as PCA and GA in relation to feature selection has yet to be explored. The research documented in this thesis addresses the feature extraction using Discrete wavelet transform (DWT) and feature selection using PCA and GA in detail.
CHAPTER 6.

EXPERIMENTAL DESIGN

6.1 OVERVIEW

This chapter is divided into two parts. The first part discusses the methodology used to carry out ultrasonic immersion testing on selected armour ceramic components to determine local density variation through time-of-flight (TOF) measurements. Further, the experimental set-up used for the research, the calibration process for the ultrasonic equipment and the process of identification of suitable experimental parameters for the ultrasonic immersion testing of ceramic components are also described.

The second part of the chapter details the ultrasonic contact testing of SiC armour ceramic components along with the experimental set-up used. An extensive experimentation program is carried out on selected SiC ceramic components to determine suitable ultrasonic parameters. Thereafter, ultrasonic contact testing of armour ceramic components is carried out and the ultrasonic signals analysed using artificial intelligence based signal processing techniques for the purpose of identifying various defects. The subsections of the chapter also detail the methodology used along with the data acquisition and gating techniques.
PART ONE

6.2 EXPERIMENTAL METHODOLOGY

In this section, the experimental methodology used to carry out ultrasonic immersion testing is explained. This is illustrated in Figure 6.1.

The SiC armour ceramic components were obtained from Australian Defence Apparel, Australia. Initially, X-ray inspection was carried out on selected ceramic components to determine their characteristics including defective and non-defective areas. Types of defects were identified based on human expert interpretation. These X-ray results were stored in an image file format. Later, testing was carried out on the same ceramic components using ultrasonic inspection methods (i.e contact and

Figure 6.1 Overview of the experimental methodology for ultrasonic immersion testing
immersion techniques). Ultrasonic sensor and component parameters such as longitudinal velocity, frequency of the transducer, thickness of ceramic component and water path distance were determined by carrying out a series of ultrasonic inspection trials. The thickness of the selected components at each test point was calculated using a coordinate measuring machine (CMM) to a tolerance of ±0.5 µm. Finally, the results obtained from ultrasonic testing and neural network based signal classification were validated against previously obtained X-ray results and Micro-CT scans of the ceramic components.

6.3 SAMPLE PARTS

6.3.1 Overview

The Reaction Sintered Silicon Carbide (RSSC) armour ceramic components used in the current research were supplied by Australian Defence Apparel (Melbourne, Australia). The percentage composition of SiC is 88%, with approximately 12% of residual silicone in these products. The dimensions of the SiC samples used in immersion testing are 150 ×150 mm with a thickness of 8.7 mm. The thickness difference across the tile was less than 0.01%. A grid pattern was drawn on the ceramic components being investigated with accurate increments of 0.5 mm, and the ultrasonic transducer was focused on each of these grid points using a robotic arm. This is illustrated in Figure 6.2.

The armour ceramic components were manufactured using a reaction bonding process which involves the infusion of liquid silicon into a porous ceramic preform. This can lead to a number of characteristic defects such as islands of free silicon metal, closed areas of un-sintered material, as well as conventional
porosity. Moreover, discontinuities can be so microscopic, numerous and widely dispersed that it is impractical to resolve them individually. Porosity, density variation, presence of free silicon metal and fatigue in ceramics are examples of such defects [9, 139].

![Figure 6.2 A ceramic sample with a grid surface](image)

### 6.4 IMMERSION TESTING

#### 6.4.1 Overview

In this research, the objective was to detect defects of size 0.5 mm or smaller in diameter in high density SiC armour ceramics. Nevertheless, to detect defects of this size in highly dense SiC ceramics, a frequency greater than 2 MHz is normally required as the acoustic wavelength must be sufficiently short to apply acoustic waves to the interactions between bulk material and any heterogeneities present within the material [140]. In addition, authors [94, 141-144] those who performed experiments on SiC ceramic components recommends over a frequency range between 5-12MHz. Initial experiments were carried out using immersion testing using several probes with different frequencies. Section 6.4.2 describes the immersion testing rig developed for this research for determining density variation across square shaped ceramic components. Subsequently, contact testing was performed on selected curved ceramic
components that contained various defects. The following section describes the experimental set-up details of immersion testing.

### 6.4.2 Immersion Testing Inspection Rig

The experimental set-up for ultrasonic immersion testing consisted of an ultrasonic flaw detector, a focused immersion probe, an immersion water tank, calibration blocks, supporting blocks and a probe handling device. An image of the experimental set-up used to carry out ultrasonic immersion scanning is shown in Figure 6.3. This consisted of a robotic arm with a repeatability of 0.1 mm used to affect the X, Y, and Z directional movement. An immersion tank of $20 \times 30 \times 15$ cm was filled with water that provides constant coupling, in which the square shaped ceramic component of 150 mm in dimension was placed at a fixed location using supporting blocks. A focused immersion transducer of 7.5 MHz frequency, 12.7 mm element diameter and 5.5” focal length was selected for the experiments. A beam of ultrasound was transmitted into the material and the reflected ultrasonic energy data was recorded and transferred to a computer for analysis. Water was used as a coupling agent and the ultrasonic velocity in the coupling agent was determined as 1480m/s [2]. The longitudinal velocity inside the ceramic component was found to be between 11750m/s. The details on measurement of longitudinal velocity are provided in Chapter 3 under Section 3.7.

### 6.4.2.1 Immersion Transducers

An immersion transducer is a single element longitudinal wave transducer. It is specially designed to transmit ultrasound in situations where the test part is partially or wholly immersed in water. The types of probes used in this research are listed in Table 6.1.
<table>
<thead>
<tr>
<th>Frequency (MHz)</th>
<th>Manufacturer</th>
<th>Diameter of Probe (mm)</th>
<th>Focal Length (mm)</th>
<th>Probe Length (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>Panametrics (V308)</td>
<td>19.05</td>
<td>101.6</td>
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<td>Panametrics (V321)</td>
<td>12.7</td>
<td>139.7</td>
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<td>25.4</td>
<td>30</td>
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<td>25.4</td>
<td>30</td>
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<td>Panametrics (V316-NSU)</td>
<td>3.5</td>
<td>25.4</td>
<td>64</td>
</tr>
</tbody>
</table>

Table 6.1 Immersion probes

**Figure 6.3** Experimental set-up of ultrasonic immersion testing.
6.5 EXPERIMENTAL EQUIPMENT

6.5.1 OMNISCAN MX

The OMNISCAN MX digital ultrasonic flaw detector, supplied by Olympus, Australia, as shown in Figure 6.4, is a microprocessor-based instrument that incorporates an internal alphanumeric data logger (a type of memory storage) that stores A-Scan waveforms with set-up information and flaw detection readings. A-scans stored in the OMNISCAN MX are converted from analogue to digital signals and then transferred to the signal processing unit (Intel Core 2.53 GHz processing speed computer) via compact flash drive. Before acquiring the data from the sample, selectable configuration parameters are used to optimize the pulser and receiver sections of the ultrasonic flaw detector. These parameters are described:

6.5.1.1 Longitudinal Velocity

The longitudinal velocity is the primary parameter that is required to be set in the ultrasonic flaw detector. The velocity of ultrasound as determined by experiments in this research is 11750m/s as described in section 6.4.

6.5.1.2 Frequency of the Transducer

The selection of frequency of the transducer is another important characteristic of ultrasonic testing as the selected frequency has to accommodate the varying properties of the material being inspected. The frequency of transducer used in immersion testing was 7.5MHz, 12.7mm element diameter and 5.5" focal length was selected after investigation of various other transducers of higher frequencies, namely 10, 15, and 20MHz. It was observed that using these high frequencies caused higher signal damping within the ceramic material.
6.5.1.3 Receiver Gain (G)

The receiver gain needs to be adjusted over a broad dynamic range to account for the wide variation in received signal amplitude among typical tests. In this research, the receiver gain was set as 40 dB [1].

6.5.1.4 Pulse Repetition Frequency (PRF)

The pulse repetition frequency controls the rate at which the pulser fires, typically at rates from 10 Hz to 1000 Hz. A high PRF permits faster scanning and data acquisition, while a low PRF limits wrap around noise when working with a very long sound paths[1]. Hence, in order to obtain a faster scanning speed, a PRF of 60 Hz was set up in the experiments.

6.5.1.5 Pulse Width (PW)

A pulse width of 30ns was used as higher resolution results were required in this research[1].

6.5.1.6 Mode of Operation

From the available modes of ultrasonic testing techniques (i.e. Pulse/echo, Dual, and through transmission) pulse/echo mode is the most commonly used ultrasonic method to investigate the quality of materials. In this research, the pulse/echo method was used where a single element transducer acts as both transmitter and receiver.

Figure.6.4 OMNISCAN MX ultrasonic flaw detector equipment
6.5.2 Probe Handling Device

A four axis robotic arm was used to effect the X, Y and Z directional movement. A special probe holding apparatus was designed and fabricated for this research. It consisted of two holders, one for the transducer and another for a LED-fibre optic pointer. It was then attached to the end of the robotic arm. The main factors considered in the design were the ease of handling the probe and the degree of positioning required the LED-fibre optic pointer. The Figure.6.5 illustrates the probe handling apparatus with a 7.5MHz ultrasonic transducer attached. A LED-fibre optic pointer was attached at an angle of 51° to the device for tracing the path of the ultrasonic transducer across the surface of the ceramic sample. Ultrasonic focus effect of sound path in the sample is illustrated in Appendix A.

Figure.6.5 Probe handling device with 7.5MHz immersion probe
6.6 CALIBRATION AND REPEATABILITY TESTS

6.6.1 Overview

The calibration of instruments is an important factor in the overall preparation for ultrasonic inspection. The ultrasonic instrument set-up requires a range of calibration and sensitivity settings to be made according to given standards, using defined calibration blocks. The calibration of the ultrasonic equipment has to be carried out prior to commencing both immersion and contact testing. For immersion testing, calibration of the robotic arm and placement of the immersion tank is also essential before commencing the experiments. These calibrations confirm the accuracy and repeatability of the test results.

6.6.2 Robotic Arm

A grid surface with 5mm step has been drawn on the surface of the ceramic component and every intersection of the grid is considered as one test point. The calibration of the robotic arm was carried out in immersion testing by moving it repeatedly to a particular point after programming of every single test point. A repeatability of $\pm 0.1\text{mm}$ at a particular position in the three directions (X, Y and Z directional movement) was observed. The positional variation of the robotic arm at a particular location is substantially smaller than the smallest defect size (0.5 mm) to be detected in this research. Hence, from these experiments it could be concluded that the repeatability of the robotic arm is within the limits for carrying out ultrasonic immersion testing.
6.6.3 Immersion Testing

A calibration sheet as shown in Figure 6.6 below is placed under the immersion tank. This enables the repeatability of placement of the immersion tank as well as the ceramic sample at a fixed location using the supporting blocks to be determined.

Figure 6.6  Calibration sheet used for immersion testing
PART TWO

6.7 EXPERIMENTAL METHODOLOGY

In this section, the experimental methodology used to detect various defects in the investigated ceramic components is described. This is illustrated in Figure 6.7.

Figure 6.7 Overview of the experimental methodology for defect detection in ceramic components
6.8 SAMPLE COMPONENTS

6.8.1 Overview

Currently, Australia Defence Apparel (ADA), Melbourne, Australia, uses X-radiography to inspect armour ceramic components offline as a part of their quality control regime. This involves considerable time and use of expensive equipment. Identification of porosity and other defect types depends exclusively on the experience and skill of the X-ray equipment operator. Along with this, multiple defects are also misinterpreted as single defects in X-radiography as it is a greyscale image and X-radiography is not able to distinguish microstructural differences in areas of similar bulk density. As such, there is a requirement for an automated inspection system possibly based on an ultrasonic approach that would enable industry to preferably carry out online inspection of the ceramic components. An automated inspection system would and cost effective with a built-in set of accept / reject criteria.

6.8.2 Selection of Ceramic Components

Two different ceramic components which were previously subject to X-ray analysis and contained various defects were scanned to create a data base of ultrasonic A-scan signals that were used in training the defect classification system. These defects were categorized as "Cracks", "Un-sintered Silicon", "Black spots" and "Porosity or Density variation". Along with these a different dataset has been created for "Defect free" signals.
6.8.3 X-ray Inspection of Selected Ceramic Components

**Figure 6.8** X-ray of a ceramic tile (Tile no-55)

**Figure 6.9** X-ray of a ceramic tile (Tile no-3)
6.9 CONTACT INSPECTION

6.9.1 Contact Testing Experimental Set-up

The pulse echo contact technique has been used to inspect two double-curved, ceramic components of 300mm in length and 7.5±0.5mm in thickness. Krautkramer [35] and other researchers [46, 145] have emphasised that the transducer is one of the most essential components of the ultrasonic system and its selection depends on the material type that is being inspected. Contact probes of 5MHz, 10MHz and 20MHz frequencies were investigated in ultrasonic contact testing. According to the proposed literature [14, 18], the velocity of the ultrasonic beam in silicon carbide ceramics is 11800m/s.

In these experiments, a grid pattern with accurate increments of 10mm was drawn across the surface of ceramic components and a contact probe was placed manually on each of these grid points. Each of these grid points was considered a test points and numbered accordingly. Due to the rough curved surface as well as presence of high density areas in ceramic components, the direct contact transducers with frequencies (5MHz and 10MHz) were unable to find small flaws, porosity and provide better resolution. Therefore, a delay line contact transducer of 10 MHz frequency with 6.3mm element diameter has been chosen for scanning the defective ceramic components as it provides excellent near surface resolution compared to the normal contact transducers. Another advantage is that delay line transducer improves the ability to find small flaws in thin objects [1]. The experimental set-up for contact testing is shown in Figure.6.10. The air gap between the specimen and probe was eliminated by applying thick lubricant on the surface of the specimen.
ultrasonic instrument used in this application was an OMNISCAN from Olympus, Australia.

Figure 6.10 Contact testing of a ceramic tile using a delay line transducer

6.9.2 Contact Transducers

<table>
<thead>
<tr>
<th>Transducer</th>
<th>Frequency (MHz)</th>
<th>Diameter of transducer (mm)</th>
<th>Nearfield (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>V109</td>
<td>5</td>
<td>6</td>
<td>6.4</td>
</tr>
<tr>
<td>V202</td>
<td>10</td>
<td>6.3</td>
<td>10</td>
</tr>
<tr>
<td>(Delay line)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>V116</td>
<td>20</td>
<td>3</td>
<td>7.9</td>
</tr>
</tbody>
</table>

Table 6.2 Contact transducers

6.10 Data Acquisition and Gating

6.10.1 Overview

In the process of developing a suitable ultrasonic contact technique for inspecting silicon carbide ceramic components, many issues had to be considered. One among
them is data reduction and the other is extracting features that provide information about a defect, its size and orientation. This section describes the acquisition of signals along with a gating technique for discontinuity discrimination. Section 6.10.3 provides details on the “Amplitude gating technique” that has been applied on individual signals for feature extraction.

6.10.2 Acquisition and Gating of Signals

The acquired analogue signals produced while scanning the ceramic components were converted to digital signals by using an A/D converter and stored on a computer system. Ultrasonic signals were acquired at a sampling frequency of 100 MHz and each of the A-scan signals consisted of 2000 data points that incorporate ultrasonic pulse recurrences. As existing practice in industry involves classifying each captured A-scan ultrasonic signal, gating is necessary for reducing the size of the data. Hence, a gating technique has been applied to each of the signals, that checks and positions the time-gating on a digitally captured A-scan image as shown in Figure.6.11.a. A signal segment of interest that contains 300 data points is then singled out as shown in Figure.6.11.b This is a type of dimension reduction, which has first two back wall echoes and makes it feasible to classify each echo.
6.10.3 Amplitude Gating Technique

In this technique, three different gates are set on the acquired signal that monitors the amplitude of the reflected energy from the transducer. Two of these gates are typically set on first and second back surface echoes and the third gate is set between the two back surface reflection signals. In this method, any signal that appears in the gate above a predetermined amplitude level activates an indication of defect or discontinuity. Figure 6.12 shows the ultrasound signal reflected from a region of interest across a ceramic components using a delay line probe.
Figure 6.12 Ultrasound signal reflected from a region of interest across a ceramic tile.

6.11 CALIBRATION AND REPEATABILITY TESTS

6.11.1 Contact Testing

A grid surface with 10mm step has been drawn on the surface of the tile as shown in Figure 6.10 in Section 6.9.1 and every intersection of the grid is considered as one test point. While performing contact testing, the transducer is positioned at the centre of these grid points ensuring the repeatability of the results in extracting the ultrasonic signals.

6.11.2 A-scan Display Repeatability Tests

The A-scan signal amplitude of the back wall echo is acquired to evaluate the repeatability of the signals obtained by means of ultrasonic equipment. The amplitude of the back wall echo signal is measured with reference to the full screen height of the display. It is necessary to set an appropriate common signal gain of 40 dB for the amplification of the probe output signals[1]. A series of experiments are conducted in
extracting the ultrasonic signals at a number of test points from both defect and non-defect regions. As illustrated in Figure 6.13, the back wall echo signal amplitude is observed as constant after continuously repeating the experiments thrice (3 series) at the same test locations. The maximum deviation of the signal amplitude is 5%. This small variation that has caused reduction in signal amplitude at a few test points is mainly due to the movement of the transducer out of the couplant medium or due to the variation in pressure applied on the contact transducer (i.e., Contact testing as shown in Figure 6.9).

![Figure 6.13](image)

**Figure 6.13** Repeatability test on the ultrasonic signals with defects and without defects.

### 6.12 Summary

The methodology developed to carry out this research is based on the requirement for detecting various defects in SiC armour ceramic components. After selecting the ceramic components with defects which have been previously inspected using the X-ray technique, the initial calibration of apparatus and equipment was carried out. The experimental set-up for contact testing consists of an ultrasonic flaw
detector, ultrasonic contact transducer and calibration blocks. Likewise, the experimental set-up for ultrasonic immersion testing consists of an ultrasonic flaw detector, immersion probes with different focal lengths in water, an immersion water tank, calibration blocks, supporting blocks and a probe handling device. The procedure for data acquisition and gating is detailed in this chapter.
CHAPTER 7.

RESULTS

7.1 OVERVIEW

The first part of this chapter presents the results obtained from ultrasonic immersion testing on selected armour ceramic components to determine local density variation. Attempts have been made by several researchers to estimate bulk density values of ceramic components[146-148]. Limited work has been carried out in showing the local density variation across an entire ceramic component, and none in reaction-sintered SiC armour ceramics. In this research, the porosity dependence of ultrasonic TOF of the reflected signals is investigated to establish a correlation between the velocity and density across the ceramic component that aids in characterizing the material. In particular, this chapter contains the procedure followed to establish a method to quantify density variation across ceramic components.

Several non-destructive testing methods (NDT) [147, 149] have been investigated for measuring density variations in sintered ceramics. These methods include ultrasonic, radiographic, and scanning acoustic microscopy (SAM). The literature review in Chapter.5 includes comparison of several NDT methods and has indicated that radiographic testing and SAM were proven not to be as effective as ultrasonic testing. Specifically, radiographic testing was proven not to be sensitive to density variations, whereas ultrasonic techniques were able to determine small density variations. The following section details the results obtained from investigations to determine local density variation.
PART ONE

7.2 POINT ANALYSIS OF ULTRASONIC VELOCITY

In immersion testing, a grid surface with 5 mm step has been drawn on the surface of ceramic tile as shown in Section 6.3, and every intersection of the grid is considered as a test point. These test points are clearly marked on the time-of-flight (TOF) C-scan image denoted using “*”. A ceramic sample with a grid surface is illustrated in Figure 6.2 (Chapter.6). The longitudinal ultrasonic velocity and TOF at each test point are recorded. The thickness of the sample at each test point is calculated using a coordinate measuring machine (CMM) to a tolerance of ±0.5 µm. It was observed that the difference in thickness across the tile was ±0.5mm.

There are 841 test points across the sample, and the average velocity value is calculated as 11,717 m/s. The accurate sound velocity measurements at eight different locations designated as A, B, C, D, E, F, G, and H are shown in Table 7.1. These locations were randomly chosen across the ceramic component and were characterized by having different TOF values. The bulk density (ρ) of the sample is measured as 2.94 g/cm³ using individual weight and volume of ceramic component within a tolerance of ±0.1 mm.

7.3 TIME-OF-FLIGHT C-SCAN IMAGING

The time-of-flight (TOF) C-scan image is plotted after collecting the TOF data points over the entire component area to look for distribution trends that could be used for comparison with an X-ray image. The TOF C-scan image along with the X-ray
image are shown in Figure. 7.1 with the measurement regions randomly chosen clearly marked on X-ray image (Figure. 7.1 (b)).

<table>
<thead>
<tr>
<th>Measurement Region</th>
<th>Thickness (mm)</th>
<th>Longitudinal Velocity (m/s)</th>
<th>Time-of-Flight (µs)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Red (A)</td>
<td>8.71</td>
<td>11870</td>
<td>1.46</td>
</tr>
<tr>
<td>Yellow (B)</td>
<td>8.15</td>
<td>11636</td>
<td>1.40</td>
</tr>
<tr>
<td>(C)</td>
<td>8.13</td>
<td>11529</td>
<td>1.41</td>
</tr>
<tr>
<td>(D)</td>
<td>8.12</td>
<td>11515</td>
<td>1.41</td>
</tr>
<tr>
<td>Blue (E)</td>
<td>8.08</td>
<td>11977</td>
<td>1.34</td>
</tr>
<tr>
<td>(F)</td>
<td>8.11</td>
<td>11905</td>
<td>1.36</td>
</tr>
<tr>
<td>(G)</td>
<td>8.02</td>
<td>11913</td>
<td>1.34</td>
</tr>
<tr>
<td>Dark Blue (H)</td>
<td>7.83</td>
<td>11846</td>
<td>1.32</td>
</tr>
</tbody>
</table>

**Table 7.1 Point Analysis Measurement**

7.3.1 **TOF C-Scan Data Analysis**

The sample appeared to be homogeneous visually, with no defects or inclusions as indicated in the X-ray image. However, when compared with TOF C-scan image, the sample appeared to show variations in some regions. The variations were caused by changes in volumetric micro-structural properties like grain scattering, free silicon metal and presence of a small amount of porosity which can affect physical material properties such as stiffness and thermal conductivity. The average TOF value over the sample was 1.38 µs. In addition, several data points in the C-scan image denoted as red and yellow in colour were noted to have thickness values >8.2 mm. These regions with high TOF values at the upper portion and corner edge of the component were believed to be less dense. For analysing the effect of micro-structural properties in this research, the measurement regions were chosen randomly and clearly marked on the X-ray image in Figure. 7.1b. These test points in Table I shows the thickness, velocity and TOF,
respectively. A large drop in ultrasonic TOF was noticed between the test points D and F with almost negligible change in thickness (0.01 mm). On the other hand, the test points C, D and E, G were found having the same TOF values irrespective of thickness. The results of measurements clearly show the presence of volumetric variations in microstructure of the ceramic components. Approximately 80% of the area of the sample indicated a denser region with TOF values less than or equal to the average value. This region is shown in blue colour in Figure. 7.1a. The results along with the difference in TOF values, which appeared to be quite significant in the C-scan image are related to overall change in density. To measure the changes in density or volumetric variation caused by grain scattering, a theoretical model with correlation of velocity and pore volume fraction has been used as detailed in Section 7.3.2.

![Figure.7.1](a) Time-of-flight C-scan image for ceramic tile.  
(b) X-ray image of ceramic tile
7.3.2 Correlation Between Velocity and Porosity

Various investigators[150-153] have investigated the porosity dependence of ultrasonic velocity and Young's Modulus and found that the dependence of these properties on porosity can be expressed as shown in equation (8)

\[ V_L = V_{Lo} (1 - P)^n \]  

(8)

Where \( V_L \) and \( V_{Lo} \) are ultrasonic velocities of porous and non-porous bodies respectively, \( P \) is porosity and \( n \) is an empirical constant which is dependent on the pore shape and size of the material.

The porosity is expressed in terms of the relative density as in equation (9)

\[ P = 1 - \frac{\rho}{\rho_o} \]  

(9)

Where \( \rho \) is the density with porosity and \( \rho_o \) is theoretical density. The theoretical density used is 3.21 gr/cm\(^3\).

As customary, porosity \( (P) \) is defined here as the volume fraction occupied by the pores, with the known bulk density \( (\rho) \) and theoretical density \( (\rho_o) \) values, the porosity value of the investigated sample was calculated as 0.058 %. With an increase in porosity, the drop in velocity can often be approximated by using the model proposed by Phani [150] described in equation (8). The basic assumption in the current approach is that pores are spherical in shape with \( n = 1.12 \). On combining Equations. (8) and (9), one gets

\[ \frac{\rho}{\rho_o} = \left( \frac{V_L}{V_{Lo}} \right) + n - 1 \]  

(10)

A linear regression of data yields a relation of the form \( V= (4104*\rho) – 1179 \), where \( V \) is the longitudinal velocity and \( \rho \) is the density at the test point. With the results obtained, a surface plot showing density variations correlated to
longitudinal velocity was plotted and is shown in Figure 7.2. A variation in density values between 3.08 and 3.16 g/cm³ (i.e., approximately 1–1.5% theoretical density) was noticed within the inspected ceramic component. The ceramic component showed consistent density values when compared with the TOF C-scan in Figure 7.1(a), having density values between 3.12 and 3.16 g/cm³ (80% of the region shown in red colour) and approximately 20% region with density values between 3.08 and 3.12 g/cm³, which is considered to have volume fraction porosity. The resulting density image allow one to see at a glance which regions of the ceramic component are well compacted and which are not. It is also clear from these observations that the sample contains small casting-like infiltrates and variation in grain size that occur during the high temperature process as the liquid silicon infiltrates the green compact.

![Surface plot of density variation](image)

**Figure 7.2.** Surface plot of density variation

### 7.3.3 Summary

To summarize, experiments carried out to determine density in reaction-sintered silicon carbide (RSSC) ceramics at a large number of test points demonstrate the usefulness of ultrasonic measurement to industrial manufacturers in achieving online
process control for armour ceramic components. Currently, these components are X-rayed or non-destructively inspected to ensure integrity of structure and, in turn, ballistic performance. At the current time, armour ceramic components are inspected off-line and this takes time and effort and is very expensive. An on-line system, based on ultrasonics, has been developed that would be far more cost-effective and moreover, as the density variation is clearly mapped and can be measured along with the values, it assists the manufacturers to check the location of high porosity areas and provide immediate quality control including implementation of accept/reject criteria.

PART TWO

7.4 ULTRASONIC SIGNAL CLASSIFICATION

7.4.1 Overview

Signals are a popular means of representing information and signal processing has significance in many applications. In signal classification problems, pre-processing of raw signals is an initial phase and extracting informative features from the pre-processed signals becomes an important basis for solving advanced signal processing problems.

The second part of this chapter presents the results obtained from ultrasonic contact testing on the selected armour ceramic components in order to evaluate the performance of this defect detection system. The signals obtained from both the defect and non-defect regions of the ceramic components were stored for further signal processing. A learning approach based on neural networks and different signal processing techniques was applied to classify the signals (Section 7.3). The percentage classification performance using different combinations of signal processing techniques is presented in Section 7.5. The results of the ultrasonic inspection system were validated against X-ray and micro-CT scan to confirm the
7.4.2 Signal Interpretation

I. ‘Defect-free’ signal

![Figure 7.3 Signal extracted from 'defect-free' region](image)

II. ‘Un-sintered silicon’ defect signal

![Figure 7.4 Signal extracted from 'Un-sintered' region](image)

reliability of the experimental results and in term the effectiveness of the developed ultrasonic inspection system.
III. 'Porosity' defect signal

Figure 7.5 Signal extracted from 'porosity' region

IV. 'Black spot' defect signal

Figure 7.6 Signal extracted from 'Black spot' region
7.5 **SELECTION OF NEURAL NETWORK PARAMETERS**

7.5.1 **Overview**

Various Artificial Neural Network configurations (ANNs) have different computation and storage requirements. In general, the number of inputs to the network is constrained by the problem, and the number of neurons in the output layer is constrained by the number of outputs required from the network. In this research, the output '1' represents the ‘no-defect’ regions and "2, 3, 4" represents various types of ‘defects’ respectively.

Incorrect selection of parameters such as number of epochs and number of hidden layer neurons would lead to poor network performance on a new data set. Hence, these parameters are to be selected with proper care as there will be a risk of 'over-fitting' to the training data. To determine the effect of each parameter, the characterisation rate of the neural network was evaluated by varying one parameter at a time, and the remaining parameters were kept constant, as presented in this section. In order to avoid the problem of over-fitting, several trial iterations were conducted to determine appropriate number of hidden neurons and epochs required.

7.5.2 **Transfer Function**

The behaviour of an ANN depends on the transfer function and multilayer networks often use the log-sigmoid or tan-sigmoid transfer functions and known as `logsig` and `tansig` in MATLAB. For the three layers of the feed-forward neural network used in this research, the combination of log-sigmoid and tan-sigmoid were selected as they performed best with raw input signals obtained from the ceramic samples.
7.5.3 Training Algorithm

In this research, both back propagation learning algorithms "Levenberg-Marquardt" and "Scaled Conjugate Gradient" methods were investigated as proposed in Sections 4.4.8 and 4.4.9. The scaled conjugate gradient (SCG) method was selected as the training algorithm in this research due to its advantage of less storage requirement. This algorithm is a good choice to perform feature selection specially using a complex wrapper method which is used in this research as well as for networks with a large number of weights [41]. The training parameters used for trainscg (MATLAB functions for SCG) are epochs, show, goal, time, min_grad, max_fai, sigma, lambda and lr. The number of epochs used is discussed in Section 7.5.4. The show was set to 25, to display the training status. The maximum time taken to train the network is set by the time function. However, the time factor is not considered to be too critical in defect classification applications. The performance goal is a critical factor in determining when the training stops. The training is stopped when the performance function goes below goal. In this research, a goal of $10^{-2}$ was selected to improve the network training performance. The SCG algorithm does not have any effect on the learning rate and momentum parameter values. The MATLAB function for memory reduction efficiency.memoryReduction is set to 1 which assists in reducing memory while training the network.

7.5.4 Number of Epochs

Random weights are used in the initial network configuration and weights are adjusted continuously during the training process. The function init is used in MATLAB to initialize the weights of the network. During training for each epoch,
input vectors are sent to the network, along with the target values. The target values and
the actual output values are then compared and the error value is calculated. The
calculated error is the difference between the target output and the actual network
output. The average of the sum of these errors is known as mean square error (mse) and
the network will tend to minimize this error. This error value is used in a transfer
function to calculate the new weights for the next training epoch. Training stops when a
given number of epochs elapse, or when the error value either reaches an acceptable
level or is minimised. The neural network does not produce generalised results, if the
number of epochs is not correctly selected.

The signals obtained from the ceramic components with and without through these
are actual defects were selected for the experiments to choose the number of epochs. It
was observed that when the number of epochs was increased while training the neural
network, the classification percentage of ultrasonic signals was increased. Nevertheless,
it was important that the network should not be over-trained. Hence, a training process
was followed in choosing the number of epochs by assessing the classification
percentage along with mean square error value (mse). After 1000 epochs, it was noticed
that the mse value started increasing and the classification percentage was decreasing.
Hence, 1000 epochs were selected to train the network.

### 7.5.5 Number of Hidden layer Neurons

Determination of the number of neurons for the hidden layer is often achieved
through experimentation[41]. According to the literature, a small number of hidden
layer neurons may prevent proper mapping of inputs to outputs, whilst too many
neurons may reduce the generalization capability by over-training the input dataset.
Another drawback of choosing a large number of hidden layer neurons is that it
increases the training time, which is un-acceptable for an online inspection process. Several combinations of input and hidden layer neurons were investigated and the mean square error value was evaluated. Figure 7.7 illustrates the mean square error of neural network configurations based on various combinations of hidden layer neurons. The lowest error value was obtained for neural network configurations containing 12 input neurons and 5 hidden neurons. It was noticed that the inclusion of an additional hidden layer did not improve the network performance. Hence, the network selected for ultrasonic signal classification contained 12, 5 and 1 neurons in the first, hidden and output layers respectively for classifying 4 classes of signals.

![Figure 7.7 Number of input and hidden layer neurons](image)

The selected parameters for the neural network topology are listed in Table 7.2 below. The learning rate, momentum term rate and error goal were fixed throughout the training and testing phase as they did not have any effect on the final outcome of the neural network with the Scaled Conjugate Gradient (SCG) training function.
Table 7.2 Feed-forward back propagation neural network parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of layers</td>
<td>3</td>
</tr>
<tr>
<td>Number of neurons in input layer</td>
<td>12</td>
</tr>
<tr>
<td>Number of neurons in hidden layer</td>
<td>5</td>
</tr>
<tr>
<td>Number of neurons in output layer</td>
<td>1</td>
</tr>
<tr>
<td>Epochs</td>
<td>2000</td>
</tr>
<tr>
<td>Goal</td>
<td>$10^{-2}$</td>
</tr>
<tr>
<td>Show</td>
<td>25</td>
</tr>
<tr>
<td>Activation Function</td>
<td>'tansig', 'logsig', 'tansig'</td>
</tr>
</tbody>
</table>

7.5.6 Normalization

In the current research, a min–max normalization is applied to the input feature dataset. When the normalization is applied, each feature lies within the new range of values but the principal distributions of the corresponding features within the new range of values will remain the same. The function `mapminmax` is used in MATLAB to perform the normalization process. This normalization has the advantage over other normalization techniques of exactly preserving all relationships in the data, and does not introduce any bias. It also allows more flexibility in designing the network and determining which features are more important[4].

7.5.7 Data Sets

The training of the network is done using a dataset of examples known as 'training data'. The training dataset consisted of 132 ultrasonic signals obtained from both defect (includes porosity, un-sintered silicon, black spots and cracks) and defect-free regions. Table 7.3 presents the dataset used for training the network.
<table>
<thead>
<tr>
<th>Region of Interest</th>
<th>Number of signals</th>
</tr>
</thead>
<tbody>
<tr>
<td>Porosity</td>
<td>32</td>
</tr>
<tr>
<td>Un-sintered</td>
<td>2</td>
</tr>
<tr>
<td>Black spots</td>
<td>45</td>
</tr>
<tr>
<td>Cracks</td>
<td>10</td>
</tr>
<tr>
<td>Defect-free</td>
<td>45</td>
</tr>
</tbody>
</table>

Table 7.3 Training dataset

To ensure that the network does not over-fit, a cross validation procedure was followed by presenting the network with a validation dataset consisting of 67 signals. The process of training and validating was repeated until the validation error was minimised and the weights of the network were saved at this time. Later, the testing dataset consisting of 400 signals was presented to the network to evaluate the network performance. The function 'divideind' available in the MATLAB signal processing toolbox was applied to the input matrix that divides the training, validation and testing datasets. A sample MATLAB m-file program with the 'divideind' function is presented in Appendix B.

### 7.6 Feature Extraction

#### 7.6.1 Discrete Wavelet Transform

In this research, the mother wavelet function used is ‘Coiflet5’ as the shape of the transient ultrasonic signal is similar to the shape of the ‘Coiflet5’ wavelet function. Also higher order wavelets are smoother and are better able to distinguish between the various frequencies[56]. Each signal is decomposed to 5 levels to yield detail signals $d_1$–$d_5$ and approximation signal $a_5$. The detail coefficients of $d_1$ belong to the highest frequency component of the signal and $d_2$ coefficients are half the frequency
component of $d_1$. In discrete terms, the 5 level decomposition of the signal $S(t)$ can be written as in Equation 11 below

$$ S(t) = a_5(t) + \sum_{n=1}^{5} d_n(t) $$  \hspace{1cm} (11)

All the data collection was done using a transducer with a central frequency ($f_{cf}$) of 10MHz. The time series A-scan signals were sampled at 100 MHz ($f_q$). The decomposition level (L) of the wavelet transform is determined by the sampling frequency ($f_q$) and frequency component to be identified in the signal, is expressed as shown in equation 3 [154]

$$ \frac{f_q}{2^{(L+1)}} \leq f_{cf} \leq \frac{f_q}{2^L} $$  \hspace{1cm} (12)

Hence $d_1, d_2$ have frequency components of 25-50 MHz, 12.5-25 MHz respectively as seen from the Figure 7.8 below.
The frequencies that are most prominent in the original signal will appear as high amplitudes in that region of the DWT signal that includes those particular frequencies [3]. Signal components with specific frequencies also appear in surrounding sub bands, however with lower amplitudes as the low-pass and high-pass filters are not perfect brick-wall filters. Furthermore, a higher order wavelet will produce less undesired frequency content in the surrounding sub-bands [56]. After decomposing all the signals, each signal is filtered from noise using a "de-noising technique" and then reconstructed back as shown in Figure 7.9. The de-noising technique is detailed in Section 7.6.2.
The frequency of interest for this work, 10 MHz, lies in decomposition level $d_3$ as most of the signal energy is present in this frequency band. In addition, detail coefficients from levels $d_2$ and $d_4$ were also selected and used for feature extraction as information from small defects occasionally appear in these levels.

The DWT function `'mdwtdec'` available in the MATLAB signal processing toolbox was applied on the matrix of input signals. This function performs a multi-signal wavelet decomposition at level 5 using the `'coif5'` wavelet. A sample MATLAB m-file program with the `'mdwtdec'` function is presented in Appendix B.

### 7.6.2 De-noising Technique

The MATLAB function `'mswden'` is used to perform de-noising of the multi-signal wavelet decomposition matrix. This function basically applies a threshold ('rigrsure') on the signal matrix that filters the scaled white noise in the signal. MATLAB m-file code was written to carry out this procedure as presented in Appendix B.

![Figure 7.9](image.png)  
**Figure 7.9** A raw signal and de-noised signal
7.6.3 Features Used For Analysis

In this research, statistical features from the time-domain such as kurtosis, mean, median, energy of samples and peak value are considered for classification of defects in armour ceramics. Other features investigated include the features extracted using DWT proposed by Kesharaju and Nagarajah [155], which have been shown to be more indicative of defect information along with characteristic frequencies of each signal. An initial set of twelve features are selected based on the literature [59, 106, 137]. These features are listed in Table 7.4 below.

<table>
<thead>
<tr>
<th>Time Domain</th>
<th>Wavelet Domain</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. First back-wall echo amplitude (BWE_1)</td>
<td>8. Sum of energy samples of d₃ coefficients (W3Energy)</td>
</tr>
<tr>
<td>2. Second back-wall echo amplitude (BWE_2)</td>
<td>9. Absolute Mean of d₃ coefficients (W3Mean)</td>
</tr>
<tr>
<td>3. Front wall echo amplitude (FWE)</td>
<td>10. Absolute Mean of d₂ coefficients (W2Mean)</td>
</tr>
<tr>
<td>4. Median (median)</td>
<td>11. Sum of energy samples of d₄ coefficients (W4Energy)</td>
</tr>
<tr>
<td>5. Sum of energy samples (energy)</td>
<td>12. Absolute Mean of d₄ coefficients (W4Mean)</td>
</tr>
<tr>
<td>6. Kurtosis (variance)</td>
<td></td>
</tr>
<tr>
<td>7. Mean (mean)</td>
<td></td>
</tr>
</tbody>
</table>

**TABLE 7.4 Initial Set of Features used for Analysis**

7.6.4 Classification Accuracy Using Initial Set of Features

The features extracted (shown in Section 7.6.3) from each ultrasonic signal were used as input to the neural network by means of a MATLAB software program presented in Appendix C. Once the network training was completed the test data was
fed into the network and the mean square error was estimated. This value was found to be 0.63. The neural network combined with initial features (Table 7.4) used has produced a classification accuracy of 91%.

7.7 Feature Selection

7.7.1 Overview

In order to increase the classification accuracy as well as to minimize the training time two different approaches known as 'Dimensionality reduction' (PCA) (Section 7.7.2) and feature subset selection (GA) (Section 7.7.4) were investigated in this research. The methodology used for two techniques and the results obtained along with the classification percentage is presented in the following sub sections.

7.7.2 Principal Component Analysis (PCA)

The purpose of the Principal Component Analysis (PCA) approach being used in this research is to reduce the number of the input features listed in Table 7.4. This is based on the consideration that a large number of inputs, while increasing the computational load, do not inevitably contribute to improving the effectiveness of defect classification. As detailed in Section 4.3.2, the principal components are orthogonal to each other and capture maximum amount of variation in the data. The percentage of variance described by the first five principal components is shown in Figure 7.10. Table 7.5 lists the proportion of total variance exhibited by each component, along with cumulative percentage of variation exhibited by the first 5 components. MATLAB m-file code was written to carry out the PCA procedure as presented in Appendix B.
Figure 7.10 Variance explained by each principal component

<table>
<thead>
<tr>
<th>Components</th>
<th>Variance (Eigenvalue)</th>
<th>Variance explained (%)</th>
<th>Cumulative %</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>9.54</td>
<td>79.51</td>
<td>79.51</td>
</tr>
<tr>
<td>2</td>
<td>1.02</td>
<td>8.57</td>
<td>88.08</td>
</tr>
<tr>
<td>3</td>
<td>0.43</td>
<td>3.61</td>
<td>91.69</td>
</tr>
<tr>
<td>4</td>
<td>0.30</td>
<td>2.53</td>
<td>94.22</td>
</tr>
<tr>
<td>5</td>
<td>0.23</td>
<td>1.95</td>
<td>96.17</td>
</tr>
</tbody>
</table>

TABLE 7.5 Variance explained by each Principal Component

From the eigenvalues and cumulative percentage of variation listed in Table 7.5, it can be concluded that the first two principal components together describe 88% of total variance and third and subsequent components have similar eigenvalues which means that they represent a similar but small proportion of total variance. The loadings of 12 features (Table 7.4) are plotted against first two principal components that benefit in reducing the dimension of feature set. The loadings for the first two components are shown in Table 7.6 and are plotted in Figure 7.11.
The loadings of the first component are all positive and fairly large when compared to the second component as shown in Table 7.6. As the loadings can be interpreted as correlations between the feature scores and the component, it can be inferred that first component represents something that is common to the performance of all the features. The second component is a contrast between features representing positive and negative variances and has the ability to separate those features that significantly contribute to defect classification. Figure 7.11 illustrates the same point graphically with the loadings. The PCA identified features are listed in Table 7.7.
<table>
<thead>
<tr>
<th>Feature</th>
<th>$x'_1$ (PC1)</th>
<th>$x'_2$ (PC2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.31</td>
<td>0.08</td>
</tr>
<tr>
<td>Variance</td>
<td>0.31</td>
<td>-0.06</td>
</tr>
<tr>
<td>Median</td>
<td>0.27</td>
<td>0.14</td>
</tr>
<tr>
<td>Energy</td>
<td>0.31</td>
<td>-0.06</td>
</tr>
<tr>
<td>FWE</td>
<td>0.28</td>
<td>0.08</td>
</tr>
<tr>
<td>BWE_1</td>
<td>0.30</td>
<td>-0.07</td>
</tr>
<tr>
<td>BWE_2</td>
<td>0.28</td>
<td>-0.14</td>
</tr>
<tr>
<td>W2Mean</td>
<td>0.25</td>
<td>-0.39</td>
</tr>
<tr>
<td>W3Energy</td>
<td>0.28</td>
<td>-0.38</td>
</tr>
<tr>
<td>W3Mean</td>
<td>0.31</td>
<td>-0.16</td>
</tr>
<tr>
<td>W4Energy</td>
<td>0.23</td>
<td>0.58</td>
</tr>
<tr>
<td>W4Mean</td>
<td>0.26</td>
<td>0.50</td>
</tr>
</tbody>
</table>

**TABLE 7.6** Loadings for the first two principal components

<table>
<thead>
<tr>
<th>Features Identified</th>
</tr>
</thead>
<tbody>
<tr>
<td>BWE_1</td>
</tr>
<tr>
<td>mean</td>
</tr>
<tr>
<td>W2Mean</td>
</tr>
<tr>
<td>W3Mean</td>
</tr>
<tr>
<td>W4Mean</td>
</tr>
</tbody>
</table>

**TABLE 7.7** PCA Identified Features
7.7.3 Classification Using PCA Selected Features and Principal Components

The PCA identified features listed in Table 7.7 and the first five Principal Components were used as inputs to the neural network and the mean square error value was estimated between the actual output values and the desired output values. Figure.7.12 illustrates the error value evaluated along with the classification percentage of PCA selected features and first five Principal Components. The classification percentage was evaluated based on the ultrasonic results validated against X-ray results.

![Classification using PCA selected features and Principal Components](image)

**Figure.7.12** Classification using PCA selected features and Principal Components

7.7.4 Genetic Algorithm

The main objective of this aspect of the research is to minimize the dimensionality of input feature set, while maximizing the defect classification accuracy. In order to accomplish this, an algorithm is developed, where GA maintains a population of chromosomes. Each input feature is multiplied by its representative chromosome, producing a set of transformed feature matrices. These transformed feature matrices are then sent to a classifier for fitness evaluation. The MATLAB function 'divideind' basically divides each of the patterns into training, validation and testing sets. The error rate obtained from...
the classifier is then returned to GA as a measure of quality of the chromosome used to obtain the corresponding set of transformed feature matrices. The structure of GA based feature selection is shown in Figure.7.13. MATLAB m-file code was written to carry out the above procedure as presented in Appendix B.

### 7.7.4.1 Variable Encoding

To conveniently implement the genetic operators of GA, individual chromosomes of a population are represented as a binary string and parameters are coded into binary string. For the feature selection, each bit of the chromosome is associated with an input parameter (f1 – f12) and interpreted in a way that if the $k^{th}$ bit of the chromosome equals 1, then the corresponding $k^{th}$ parameter is counted in as a feature for classification; the other way around if the bit is 0. Each obtained feature subset is assessed according to its fitness value. Based on the measure of classification performance, fitness values are assigned.

![Figure 7.13 The structure of GA based feature selection](image)
7.7.4.2 Problem Optimization

In this research, the independent variables to be optimized are the set of original features. A population size of 100 individuals and 100 generations is produced. Tournament selection procedure is one of the popular methods for parent selection in GA. In this approach, players with given tournament size are randomly selected and the best individual based on fitness value is chosen out of the set to be a parent. The crossover operation is performed in each generation to generate a better solution from available solutions. This is performed by interchanging genetic material of chromosomes in order to create individuals that can benefit from their parents fitness. In this research, a single point crossover with a crossover fraction rate of 0.5 has been chosen. Mutation is the genetic operator responsible for maintaining diversity in the population by randomly “flipping” bits of the chromosome, based on some probability. The probability of mutation chosen is 0.1. In addition to the above mentioned genetic operators, ‘elitism’ has been used that guarantees the best string individual to survive until the last generation. The fitness of the selected population is calculated from the trained neural network. The process is repeated until the termination criterion is met.

The fitness of the transformed feature matrix is decided according to the following equation (13)

\[
\text{Fitness} = \sum_{i=1}^{n} \left( \frac{Y_i - t_i}{Y_i} \right)^2
\]

(13)
Where \( n \) = total number of training patterns,

\[ Y_i = \text{output of ANN classifier and} \]

\[ t_i = \text{target given while training the network} \]

### 7.7.5 Classification Using GA Selected Features

The GA algorithm employed evolved the population of individuals for 100 generations. At 100 generations, GA has identified the optimum number of features with minimum error rate (best fitness value). The fitness value is found to be 0.602. Figure 7.14 shows the best fitness value obtained for 100 generations.

![Figure 7.14](image-url)

**Figure 7.14** Variation of fitness function value with generations
In order to compare the defect classification performance of various approaches investigated in this research, a comparative study is performed with neural network coupled GA-based feature selection, dimensional reduction using Principal Component Analysis and original feature set. The extracted features from these approaches explored are provided as input to the NN classifier to classify the features into four defect groups, namely, Un-sintered, Defect-free, Black spots and Density variation (Porosity). The performance of the classifier for each of these methods is shown in Figure 7.15 below. Among the four methods, the features that contributed most to the first five Principal Components listed as PCA_features in Figure 7.15 produced the lowest error rate. It was surprising to observe the differences in producing optimal feature subsets consisted of 5 features by GA and PCA. Table 7.8 shows the feature subsets selected by both PCA and GA methods.

<table>
<thead>
<tr>
<th>Feature Selection Methods</th>
<th>Number of Features</th>
<th>Feature Subset chosen from original feature set</th>
</tr>
</thead>
<tbody>
<tr>
<td>PCA</td>
<td>5</td>
<td>(1,6,8,10,12)</td>
</tr>
<tr>
<td>GA</td>
<td>5</td>
<td>(1,3,4,6,7)</td>
</tr>
</tbody>
</table>

Table 7.8 Comparison results of feature selection performed by PCA and GA
The efficiency of the ANN classifier is also tested for the original feature set containing 12 features along with the Principal Components. The results of classification error rate are shown in Figure 7.15. Principal Components are found to have an error rate close to the GA based feature subset but the original features are found to have the highest error.

7.9 VALIDATION OF ULTRASONIC INSPECTION METHOD

The ultrasonic signal data sets used for defect classification in Section 7.5.7 includes the signal extracted from both defect and defect-free regions. Validation was necessary to ensure that those signals obtained from various defective regions correspond to physical defects present in the ceramic components. Similarly, it was necessary to ensure that those signals identified as non-defect signals actually corresponded to regions in which defects were not present. As stated previously ceramic tiles were selected to perform ultrasonic inspection. ultrasonic inspection results were validated against the X-ray results. On the other hand, only a single...
ceramic component (Tile no-55) was used to validate against micro-CT scan results, as the majority of defects were present in this sample.

7.9.1 X-ray

The defects classified using the methodology presented in Section 7.7.4 were compared against the X-ray results. These results are illustrated in Figure 7.16 and Figure 7.17 below.

Figure 7.16 Ultrasonic C-scan mapping of a ceramic tile (Tile no-55)

- Defect free region
- Porosity (Density variation)
- Un-sintered silicon
- Variation in Thickness and small porosity
- Border of ceramic tile
Figure 7.17  X-ray of a ceramic tile (Tile no-55)


When comparing the ultrasonic test results against the X-rays, defects such as un-sintered silicon and porosity and defect free regions at a number of locations were detected successfully by the ultrasonic inspection method. On the other hand, the Black spots shown on the X-ray were identified as high dense regions with thickness variation using ultrasonic testing. Hence, there is a requirement for cross validation using another technique that confirms the results of ultrasonic testing.
As described in Chapter 1, one of the main objectives of this research is to determine density variation in armour ceramic components along with other defects (large amount of porosity, un-sintered silicon, cracks and black spots). Although X-ray images were used previously to determine where the real defects were located within
the ceramic components, they were not suitable to detect the local density variation as well as the thickness variation across the components. In order to further validate existence of density variation (porosity) and defects the ceramic components was cut into small sections of 5mm in diameter for performing a Micro-CT analysis on each of the small sections and the results are presented in Section 7.9.2.

7.9.2 Micro CT scan

A total of 23 samples were cut from Tile No:55 for performing Micro-CT scanning on them. These 23 samples included cut sections from both defect and defect-free regions. These samples were numbered with the same numbers that were given to the location of grid point on ultrasonic C-scan image shown in Figure 7.16. This process assists in identifying the location of the defect and the defect type. Table 7.9 shows the samples with respective numbers assigned to them and the corresponding defects classified using X-ray.

<table>
<thead>
<tr>
<th>Defect type</th>
<th>Number of Samples (Location of grid point on Tile -55)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Un-Sintered Silicon</td>
<td>22</td>
</tr>
<tr>
<td>Porosity</td>
<td>6,9,32,54, 82, 96, 116,124</td>
</tr>
<tr>
<td>Black spots</td>
<td>414,439,467,471,513,542,551,583,589</td>
</tr>
<tr>
<td>Defect-free</td>
<td>169,173,201,251,341</td>
</tr>
</tbody>
</table>

Table 7.9 Sample numbers with corresponding defects classified using X-ray
7.9.2.1 Un-sintered Silicon

When validated against the micro-CT scan image the ultrasonic results classified the defect 'Un-sintered silicon' with 100% accuracy rate. Figure 7.20(a) illustrates a large 3mm defective (green and yellow) region and the blue region represents high density region with grain size variation.

![Micro-CT scan image with defect](image)

**Figure 7.20** Sample No- 22 with defect 'Un-sintered silicon' (a) micro-CT scan image (b) Ultrasonic testing
7.9.2.2 Porosity

Figure 7.21 (a) and (b) illustrates micro-CT scan image of a cut section from location No-124 and No-116 showing 0.5 - 1 mm porosity. As discussed earlier in Section 7.9.2.1 the red spots and yellow region shown in micro-CT scan represents a low density region and blue spots represent high density region. The region shown as red confirms the presence of porosity. The results obtained from the micro-CT scan were used to validate the ultrasonic results shown in Figure 7.21 (c). The ultrasonic results clearly shows the detected porosity with 100% accuracy when validated against results obtained from the micro-CT scan.

(a)

(b)
The red spots and yellow region shown in micro-CT scan images in Figure 7.22 (d) and (e) represents a porosity defect as pointed earlier in Section 7.9.2.2. The ultrasonic testing image shown in Figure 7.22 (e) precisely classified the porosity defect.
7.9.2.3 Black Spots

Figure 7.23 (a) and (b) represents micro-CT scan images that were initially interpreted by the expert operator as 'Black spots' from X-ray results. However, the ultrasonic testing classified the cut sections as a 'defect-free'. The micro-CT scan confirmed the results obtained using the ultrasonic technique and disagreed with X-ray interpretation of 'Black spots'. These results are shown in Figure 7.23 (c) along with the location. Besides, the validated results of micro-CT scan, also demonstrated the defect-free region (blue colour) indicating high density region. The green spots in the images represents the grain size variation.
Figure 7.23  (a) micro-CT scan image of sample No- 414
(b) micro-CT scan image of sample No- 467
(c) Ultrasonic testing image
As in Section 7.9.2.3, the validated results of micro-CT scan of sample demonstrated the defect-free region (blue colour) indicating high density region in Figure 7.24 (d) and (e). On the other hand, ultrasonic results for sample No-513 indicated as defect-free and sample No-589 as variation in thickness with small porosity contradicting the X-ray results indicating the presence of defects. Further to confirm the thickness variation across the component which was one of the objective of this research a measurements of thickness were conducted using ultrasonic testing. Table 7.10 shows the thickness measurements at few test points chosen from defective and non-defective regions across Tile No-55.

(d)

(e)
Figure 7.24 (d) Micro-CT scan image of sample No- 513
(e) Micro-CT scan image of sample No- 589
(f) Ultrasonic testing image

<table>
<thead>
<tr>
<th>Location of grid point on Tile-55</th>
<th>Defect Region</th>
<th>Thickness</th>
</tr>
</thead>
<tbody>
<tr>
<td>24</td>
<td>Un-Sintered</td>
<td>7.49 mm</td>
</tr>
<tr>
<td>20</td>
<td>Un-Sintered</td>
<td>7.49 mm</td>
</tr>
<tr>
<td>95</td>
<td>Porosity</td>
<td>7.79 mm</td>
</tr>
<tr>
<td>88</td>
<td>Porosity</td>
<td>7.55 mm</td>
</tr>
<tr>
<td>110</td>
<td>Porosity</td>
<td>7.55 mm</td>
</tr>
<tr>
<td>108</td>
<td>Porosity</td>
<td>7.67 mm</td>
</tr>
<tr>
<td>449</td>
<td>Black Spots</td>
<td>6.55 mm</td>
</tr>
<tr>
<td>466</td>
<td>Black Spots</td>
<td>6.37 mm</td>
</tr>
<tr>
<td>488</td>
<td>Black Spots</td>
<td>6.25 mm</td>
</tr>
<tr>
<td>512</td>
<td>Black Spots</td>
<td>6.31 mm</td>
</tr>
<tr>
<td>562</td>
<td>Black Spots</td>
<td>6.61 mm</td>
</tr>
<tr>
<td>159</td>
<td>Defect-free</td>
<td>7.14 mm</td>
</tr>
<tr>
<td>209</td>
<td>Defect-free</td>
<td>7.08 mm</td>
</tr>
<tr>
<td>387</td>
<td>Defect-free</td>
<td>7.02 mm</td>
</tr>
</tbody>
</table>

Table 7.10 Thickness Variation Across Ceramic Tile
The component thickness required by customers is specified at $7.00 \pm 0.15$ mm and it was noticed that 'Black spot' regions had a lower thickness values than that required by the specification. This lower thickness is probably the reason for the display of 'Black spots' in the X-ray image.

**7.9.2.4 Defect Free**

X-ray results shown in Figure.7.17 indicate that the sample points No-201, 341 and 251 are 'defect-free' regions. On the other hand, ultrasonic results and micro-CT scan images of sample point No-251 shown in Figure.7.25 (c) identifies it as defect 'porosity'. The samples No-201 and 341 were classified as defect-free regions by both the ultrasonic image and micro-CT scan.
7.10 SUMMARY

This chapter presented the results obtained from the traditional TOF C-scan imaging used to confirm and analyze a small amount of porosity present across the inspected ceramic component, leading to relative local density variations. A variation in density of approximately 1–1.5% theoretical density was noticed within the ceramic
component as described in Section 7.2. The resulting density image allow one to see at a glance which regions of the component are well compacted and which are not. This could be useful for controlling the production process.

In addition, the second part of the chapter presented results obtained from the feed-forward back propagation neural network classifier after subjecting the input ultrasonic signals to different pre-processing techniques and feature selection methods as described in this chapter. It is not possible to select the most suitable combinations of neural network parameters in advance to address a given problem. It depends on many factors, and generally a trial-and-error method has to be used to determine the optimum neural network configuration. The final parameters as selected for the feed-forward back propagation neural network for this research were presented in Table 7.2. Artificial Neural Networks were used to classify signals obtained from various defect and defect-free regions of selected ceramic components.

The results obtained by applying DWT as a pre-processing technique for feature extraction and de-noising were shown in Section 7.6. It was noticed that the neural network combined with initial features alone (Table 7.4) has produced a classification accuracy of 91%. In order to achieve a better classification performance, PCA and GA were investigated in this research and the results obtained were shown in Section 7.7. The experimental study has shown that PCA followed by GA performed best as the feature selection methods for reducing computation time and improving classification accuracy of defects in ceramic components. Moreover, in this research a new technique using GA for feature selection has been proposed that generates the initial population in such a manner that the classifiers use different feature subsets. The combination of fitness function with the neural network assisted in finding significant features with less effort and due to this reason GA coupled neural network performed better than the
neural network with 12 original features. Principal Component Analysis (PCA) reduces the dimension of the feature set by projecting the data linearly and by representing the majority of data variance with a few Principal Components, thereby improving the classification accuracy. Furthermore, a significant contribution of this research has been in demonstrating that the features that contribute most to first the five Principal Components produced the best results.

The results obtained from ultrasonic testing were compared and validated against both X-ray and micro-CT results as shown in Section 7.9. The classification accuracy of 96% (as stated in Section 7.7.3) was obtained by comparing the ultrasonic results against visual inspection and X-ray results which were proved less sensitive in detecting defects and measuring porosity in SiC ceramic armour tiles in this research. Nevertheless, an overall classification accuracy of 100% was achieved using ultrasonic inspection coupled with artificial intelligence based signal processing methods and validated against micro-CT scan results. It was proved that X-radiography does not lend itself to differentiating between defects in many regions of the ceramic components tested. This was clearly demonstrated in Section.7.9.2.5, where a porosity defect region was shown as a defect-free region in the X-ray image. In addition, the validated results demonstrate that ultrasonic testing would be beneficial in assisting manufacturers to check the location of high porosity areas (density variation), other defects and has the potential for providing real time online quality control including implementation of accept/reject criteria.
CHAPTER 8.

DISCUSSION

8.1 OVERVIEW

In this research, an attempt has been made to identify various types of defects present in reaction sintered silicon carbide (RSSC) armour ceramic components. The discussion presented in this chapter focuses on the main research findings such as experimental methodology (Section 8.2) and results obtained (Sections 8.3 and 8.4). Furthermore the results obtained from using different signal processing approaches with neural networks for defect classification are discussed. In addition, this chapter includes an evaluation of the effectiveness of the developed ultrasonic inspection system in relation to approaches described by other researchers.
8.2 EXPERIMENTAL PROCEDURE

In order to fulfil the objectives of this research as presented in Chapter 1, an experimental methodology was developed and was described in Chapter 6. This experimental methodology focused on obtaining the best possible ultrasonic signals from representative reaction sintered silicon carbide (RSSC) armour ceramic components. This was achieved through the selection and implementation of a suitable inspection regime and inspection parameters to carry out the investigations.

The selection of suitable inspection parameters that characterize the behaviour and properties of an acoustic wave was assisted by the literature on relevant past research as presented in Chapters 3 and 5. The literature includes reports on using high frequency ultrasound (50MHz) for discontinuity detection in silicon nitride [156, 157].

Brennan [18] used high frequency (50 and 75 MHz) ultrasound to detect micro-meter scale features in SiC ceramic samples in his doctoral research work. Brennan's [18] work in the implementation of the ultrasonic pulse echo method clearly emphasised the importance of selecting suitable inspection parameters and also recommended procedures to obtain them. However, Brennan [18] did not address the signal dampening issues caused due to selection of higher transducer frequency and near-field resolution. This research work addresses the issue of selecting higher frequency in inspecting highly dense SiC ceramic tiles as described in Chapter 6.

The application of focused probes in testing various materials is often described in the literature [31] and various researchers [35, 41, 42, 158] have also confirmed the
benefit of using focused probes compared to unfocused probes in immersion testing.

However, it is observed that researchers have not explored the use of focused probe in inspecting armour ceramics. In this research, the determination of local density variation is difficult to achieve with unfocused ultrasonic probes due to very low sensitivity in high density SiC ceramic tiles. The application of focused probes assists in achieving better results compared to unfocused probes. These results enable the elimination of the use of unfocused probes at an early stage in this research and assists in automating the inspection process as detailed in Section 6.4.2.

The detection of various defects within the curved surface ceramic components is another important issue in the development of the contact inspection procedure. The immersion testing rig is not be suitable as the focusing point is different at various locations on the curved surface and this generates difficulty in obtaining accurate ultrasonic signals. Hence, the selected ceramic components with curved surfaces are manually inspected using ultrasonic contact testing. In addition, a delay-line contact ultrasonic transducer is used that provides excellent near surface resolution compared to the normal contact transducers. In order to obtain the repeatability in ultrasonic signals, a grid surface is drawn across the surface of the ceramic tiles and each grid intersection is used as a testing point in the contact inspection method. The methodology used in this research to obtain accurate repeatability using the contact testing as observed in Chapter 6 (Section 6.11) is unique and has not been published elsewhere in the literature. This methodology also assists in identifying the location of the defect easily, when mapping ultrasonic C-scan images as shown in Chapter 7 (Section 7.9.1) .
The unavailability of standard calibration blocks from the same material as the reaction-sintered SiC ceramic components being inspected requires the development of a new calibration technique as described in Chapter 3. Several experiments were carried out to determine the actual velocity of ultrasound energy in the selected material and suitable frequency. Thereafter, the signals were obtained from ultrasonic contact testing of the ceramic components to determine the presence of defects.

In addition, the implementation of a calibration methodology for the experimental devices reduces the amount of uncertainty and increases the inspection accuracy associated with the experimental results significantly as shown in Chapter 6.

**8.3 Local Density Variation**

Attempts have been made by several researchers [147, 148, 159] to estimate bulk density values of ceramic components. This has been addressed in Chapter 5 under Section 5.3.4. However, there is no published research describing the local density variation across an entire ceramic component.

The measurement method proposed by Revel [99] described in Chapter 5 (Section 5.3.4) shows a correlation between velocity and apparent density; however, the method does not appear as practicable for online process control for industrial manufacturers due to the calibration procedure being based on hydrostatic weighing in a mercury bath. Moreover the method is not sensitive to small density variations within the sample.

Panakkal and Gosh [160] investigated the density dependence of ultrasonic velocity in sintered uranium dioxide pellets over a narrow density range varying from
9.76 to 10.52 g/cm³. They concluded that there was a linear relationship between density and velocity. However, the linearly interpolated relationship given by Panakkal et al [160] was proven to be incorrect by Phani [150] in his research.

Portune and Haber [96] and several others [100] [141, 161, 162] as described in the literature review (Chapter 5), have presented their research into defect determination and volume fraction porosity in SiC components using ultrasound C-scan images of bottom and top surface reflected signal amplitudes. A Fast Fourier Transform (FFT) approach was taken on bottom surface reflections, which were used to graph the attenuation of the ultrasound as a function of frequency. It was emphasized that a strong dependence of bottom surface amplitude values on the top surface quality (i.e., the influence of surface roughness and flaws) has reduced the confidence in conclusions drawn solely from the bottom surface amplitude data.

Klima [159] has investigated the characterization of structural ceramics and it was shown that bulk density variations could be estimated by velocity measurements for a SiC specimens both in as-sintered and in hot-pressed conditions of different temperatures. According to Kilma [159], variations in microstructure features such as grain size and shape have a minor effect on velocity. On the contrary, with the results obtained in the research published in this thesis, it was demonstrated that microstructure and volumetric variations have quantifiable effects on time-of-flight (TOF) as well as velocity. In addition, the research described in this thesis presents local density variations across an entire ceramic component not subject to changes in sintering temperature.
As proposed in Chapter 7 (Section 7.3), the traditional TOF C-scan imaging was used to analyse and confirm a small amount of porosity and volumetric variations in microstructure present across ceramic components, leading to relative local density variations. A variation in density of approximately 1–1.5% from the theoretical density was observed within the ceramic components investigated. The resulting density image (Figure 7.2) allows one to observe at a glance which regions of the component are well compacted and which are not. This could be useful for controlling a armour ceramic component production process. Further, it has been demonstrated that X-ray radiography testing in this research is not sensitive to density variation as well as identifying the small amount of porosity present across the tested ceramic components. In addition, it requires more setup time and is less quantitative than the TOF C-scan. Moreover, it has been stated by other authors [96, 98, 141] that the amplitude C-scan data can provide information on presence of defects and porosity. However, in this research, it has been observed that amplitude variation is minimal and cannot be used to indicate variation in density/volume fraction porosity. Therefore, TOF C-scan imaging is well suited and sensitive to changes in material’s microstructure, especially for high-density reaction-sintered silicon ceramics as the contribution from grain scattering and effect of free silicon observed across test points are extremely small.

**8.4 SIGNAL PROCESSING TECHNIQUES**

As emphasized in Chapter 5 (Section 5.4.2) there is a requirement for signal pre-processing to be applied on the input signals to achieve acceptable classification levels. In this section, the process of selecting signal pre-processing technique and parameters has been described with reference to the work carried out by other researchers on similar NDT applications. It is apparent that the choice of the signal processing
techniques is application dependent. The next step was the analysis of the performance of the different signal pre-processing techniques. The results of this exercise were presented in Chapter 7. Other researchers’ contributions to this field are presented in the following sections, with reference to the research described in this thesis.

Palanisamy [41] has demonstrated that the use of signal features as input to a neural network based classifier contributes to the achievement of a higher classification percentage than using the raw signal waveform. The author have emphasized that using FFT on its own for signal pre-processing did not produce a high classification percentage. Lee [109] has addressed important issues relating to signal feature extraction approaches and provided evidence of the superiority of the Discrete Wavelet Transform (DWT) to the Fast Fourier Transform (FFT) as a feature extraction method[109].

Polikar et al [103] developed a ultrasonic signal based classification system obtained during weld inspection of piping in boiling water reactors. The Discrete Wavelet Transform (DWT) was employed and the features extracted were used as inputs to neural networks that were used to classify defects. However, there were a few disparities in the study that was reflected in the confidence level of network prediction [103].

Sambath et al [106] in their research presented a signal processing technique based on a Wavelet Transform (WT), which enhanced the sensibility of flaw detection in characterization defects during weld bead inspection. This is similar to the approach followed in this research where a Discrete Wavelet Transform (DWT) was used for feature extraction. In addition, DWT was also used as a 'de-noising technique' in this
research that scaled white noise in the signal. The selection of an appropriate WT type to pre-process the ultrasonic signals was described in Chapter 7 (Section 7.6). The selection of a suitable mother wavelet is a critical step in the application of the Wavelet Transform in any signal processing application [3]. Merry et al [56] in their study proposed that higher order wavelets are smoother and are better able to distinguish between the various frequencies. Through experimentation 'Coiflet5' wavelet type (Coif5) was identified as the most suitable wavelet in achieving the highest classification percentage in this research. The selection of a suitable mother wavelet for pre-processing generated a classification performance of more than 90% for the ultrasonic signals from both defect and defect-free regions as described Chapter 7 (Section 7.6.4).

8.5 DEFECT CLASSIFICATION

8.5.1 Overview

Defect classification refers to the identification of defective regions in armour ceramic components. To identify the most significant features from the data collected and as stated earlier in Chapter 7 (Section 7.7), feature selection was used in this research in order to increase the classification accuracy as well as to minimize the training time of the neural network classifier. Two different techniques Principal Component Analysis (PCA) and Genetic algorithm (GA) were considered for feature selection and the results obtained along with the classification percentage is presented in Chapter 7.
8.5.2 Neural Network Configuration

In terms of the neural network (NN) configuration, in order to determine the smallest applicable number of neurons in the hidden layer, several neuron topologies were investigated. This is a well known general procedure which has been followed by a number of researchers[163-167]. As presented in Section 5.4.4, Margrave et al [133] reviewed three types of neural network configurations developed for the purpose of accurate interpretation of flaws in steel plates. Amongst three types of neural network configurations investigated, Multi-layer perception architecture using a back propagation training algorithm performed better than the Learning Vector Quantisation (LVQ) and Kohonen networks.

Selvakumar et al [135] used a four-layered neural network architecture with back propagation learning algorithm to study the deformation characteristics of sintered aluminium preforms. The results in a comparative study between regression analysis and the NN revealed that the NN could predict the material characteristics of sintered aluminium preform better than regression polynomials.

According to the literature, the most frequently used neural network architectures are Feed-forward neural network (FF), Multi-layer Perceptrons (MLP), Adaptive Resonance theory (ART) and Learning Vector Quantization (LVQ) networks [133, 134]. In this research, a feed-forward neural network with a back propagation algorithm was used as this combination produced the highest classification accuracy in simulation application proposed by several authors in the literature[41, 106, 135]. Palanisamy [41] in his research, applied a systematically optimised method to select neural network parameters for signal processing and it is relevant to this research in terms of selecting
suitable neural network parameters. To determine the effect of each parameter, the characterisation rate of the neural network was evaluated by varying one parameter at a time, and the remaining parameters were kept constant. In order to avoid the problem of over-fitting, several trial iterations were conducted to determine the appropriate number of hidden neurons and epochs needed. The selection of neural network parameters is detailed in Section 7.5.

8.5.3 Feature Selection

As the dimensionality of the data increases, many types of data analysis and classification problems become significantly harder to address. Sometimes the data also becomes increasingly sparse in the space it occupies. This can lead to big problems for both supervised and unsupervised learning. In the literature, this phenomenon is referred to as the curse of dimensionality [168].

The application of PCA for dimensionality reduction has been carried out by Janecek et al [121], Howley et al [120] and Malhi et al [59] and this has been presented previously in this thesis (Section 5.4.3.2). There were difference in their approaches in applying PCA in reducing feature sets. Janecek [121] used sets of linear combinations of the original features computed with three variants of PCA to compare with feature subsets determined with a wrapper method. The authors emphasized that Support Vector Machine (SVM) performed well when all original features were used yet, lowest accuracy was achieved for all three PCA subsets used [121].

Howley et al [120] have investigated the effect of PCA on machine learning accuracy with high dimensional spectral data based on different pre-processing steps.
The authors have used the NIPALS method previously been proposed by Geladi and Kowalski [169], to iteratively compute only the first $n$ principle components (PCs) of a data sample until a required number of PCs have been generated. The authors emphasized that the addition of the PCA step resulted in either the same classifier error or a numerically smaller error.

Malhi et al [59] investigated a PCA based approach to select the most representative features for the classification of defective components and defect severity in three types of rolling bearings, where no prior knowledge on the defect conditions was available. In this study, eigenvalues and eigenvectors were calculated for four selected features. Later, feature ranking was performed by choosing the eigenvector corresponding to the largest magnitude eigenvalue that represents the maximum variance in the dataset. The author highlighted that the addition of other features not selected by PCA to the input feature set has led to an increase in the misclassification rate of the neural network classifier.

A different approach to that described by other researchers was used in this research to identify PCA selected features that has produced the highest classification percentage (Section 7.7.3). This approach is detailed in Section 7.7.2, where five features were identified as most significant by PCA analysis. From the eigenvalues and cumulative percentage of variation listed in Table 7.5, it can be concluded that the first two principal components together describes 88% of total variance. Therefore, the loadings of 12 features (Table 7.4) are plotted against first two principal components that benefit in reducing the dimension of feature set. The loadings for the first two components are shown in Table 7.6 and are plotted in Figure 7.11. The feature
identification process was followed by selecting the loadings of the first Principal Component and comparing them against the loadings of the second Principal Component. As the loadings can be interpreted as correlations between the feature scores and the Principal Component, it can be inferred that first Principal Component represents something that is common to the performance of all the features. The second Principal Component is a contrast between features those representing positive and negative variances and has the ability to separate those features that significantly contribute to defect classification.

In addition, PCA was also investigated as a 'Dimensionality reduction technique' in this research. The percentage of variance described by the first five Principal Components was used and each of these Principal Components were used as inputs to the classifier. The results under Section 7.7.3 shows the classification percentage obtained by first five Principal Components and PCA identified features. It was interesting to note that the classification percentage obtained using the first five Principal Components was lower than that obtained with to PCA identified features, even though the principal components in general contain information from all original features. No study has been carried out to date to investigate the relationship between the variability captured in the Principal Components and the accuracy of the classifier as investigated in this research. Besides, the smallest subset of original features was identified that yielded a highest classification percentage of 96%.

A wrapper-based GA method followed by PCA was investigated as a feature selection method in this research to improve the defect classification percentage. Muni et al [112] proposed a methodology that determines the size of the feature subset by
assigning higher probabilities to smaller sizes. The classifiers that are more accurate using smaller number of features are given higher possibility to pass through the genetic program operations. Thus, a good classifier with high classifier accuracy was chosen for the selection of a small feature subset.

Sasikala et al [128] investigated genetic algorithm based feature selection of optimal texture features extracted to classify brain tumors. The authors achieved a classification performance of 98% using a genetic algorithm based approach with only four of the available 29 features. The authors also emphasized that PCA and classical sequential methods require a larger feature set to attain similar classification accuracy of 98%. Kabir et al [129] presented a similar approach for feature selection called as hybrid genetic algorithm feature selection (HGAFS). Their search technique works on the basis of the distinct and informative input features computed by their correlation information.

The experimentation methodology described in this thesis to perform feature selection by GA, adopted a similar approach to that of Sasikala et al [128], where each chromosome of the population represents a feature subset and a neural network classifier is used to evaluate each chromosome (feature subset) based on the classification accuracy (Section 7.7.4.1). The application of GA based feature selection has improved the classification percentage to 94% compared to 91% obtained using the original feature set. The results obtained along with the classification percentage is presented in Chapter 7 (Section 7.7.4). It is surprising to observe the differences in producing optimal feature subsets (Section 7.8) consisted of 5 features by GA and PCA. Another interesting aspect observed in
both PCA and GA feature subsets selection was the PCA extracted both combination of time-domain and wavelet domain features (Section 7.6.3), while GA selected only features from the time-domain.

Finally, it could be concluded from the results presented in Chapter 7 (Sections 7.3, 7.6 and 7.7) that:

- This research can lead to the development of an online inspection system for armour ceramics based on high frequency ultrasound that would be more cost-effective than current methods. Moreover, as the density variation is clearly mapped and can be measured along with the defects, it assists manufacturers in checking the location of high porosity areas and providing immediate quality control including implementation of accept/reject criteria.
- DWT not only provides excellent feature extraction, but also provides significant data reduction and filters the noise from the signals thereby reducing the computational burden considerably. The results indicate that feature extraction for input to neural network is very important for good performance.
- PCA identified features followed by GA selected features were found to have the highest defect classification percentage.

8.6 Validation Methods

Although, X-ray has been used earlier to identify defective and non-defective regions of ceramic components, it was proven not to be sensitive to density and thickness variation. Therefore, other non-destructive techniques, namely, Infrared Thermography (IR) and Scanning Electron Microscopy (SEM) suggested from literature were explored to perform validation of the results obtained from this research.
The IR technique is based on the concept that after applying a uniform heat pulse to the sample surface, a localized disruption of the heat flow will occur when defects or flaws are present in the material [77]. Contrary to proposed literature [72], [77] Infrared Thermography and Scanning Electron Microscopy techniques were found not suitable in analysing the defects as well as density variation as required in this research. In addition, SEM was found to be time-consuming and highly dependent on factors like surface roughness. Moreover, SEM was unable to highlight differences between porosity and grain size variation.

In this research, the tested ceramic components were cut into small samples and micro-CT scan was used to validate the results obtained by ultrasonic testing and are presented in Section 7.9 (Chapter.7). It is apparent noticed that no previous study has been performed using micro-CT scan to evaluate defects or porosity in reaction-sintered silicon carbide ceramic components. Moreover, micro-CT scan provided results with high resolution of 0.7 µm that confirmed the presence of defects, density variation and thickness variation.

8.7 SUMMARY

This research program was focused on determining various defects along with local density variation in reaction-sintered silicon carbide ceramic components using high frequency ultrasound. Two different coupling testing methods (immersion and contact) were investigated in this research and a suitable experimental methodology was developed that aided in the selection of an appropriate frequency to detect defects and density variation. A calibration process was developed that ensured repeatability of the ultrasonic signals and hence the results.
This research attempted to classify defect signals and determine density variation across reaction-sintered silicon carbide (RSSC) ceramic components. The research led to the successful neural network classification of defects including un-sintered silicon, porosity, black spots and cracks. The analysis of the performance of the signal pre-processing method (DWT) on ultrasonic raw signals when used on its own emphasised the need for a feature selection approach. However, it is evident from the research conducted that what is termed the most suitable pre-processing approach varies with the characteristics of the signal obtained. A success rate of 96% was achieved with feature selection performed using PCA technique. It was observed that GA based feature selection improved the classification percentage to 94%, nevertheless this method requires more computation time and effort as it belongs to a wrapper type algorithm.

The inspection methodology described in this thesis can be used in the development of an automated ultrasonic based inspection technique for armour ceramic components. However, current research was only undertaken in a narrow domain i.e., detecting defects of size 0.5 mm or higher in reaction sintered silicon carbide ceramic components.
CHAPTER 9.

CONCLUSIONS AND FUTURE WORK

9.1 CONTRIBUTIONS OF THE RESEARCH

Currently, the ceramic components used in body armour are inspected offline using X-ray techniques that involve considerable time and expensive equipment. Moreover, identification of defect types depends exclusively on the experience and knowledge of the operator. Hence, this research program was undertaken in accordance with the following problem statement:

To investigate the use of an ultrasonic inspection technique and artificial intelligence based signal processing methods to detect, locate and classify various defects in reaction-sintered silicon carbide (RSSC) ceramic components. Furthermore to develop an inspection system that is more reliable and cost effective than currently used X-ray technology.

The following were the major outcomes from each chapter presented in this thesis:

i. The literature search (Chapter 5) focused on several Non-destructive testing and evaluation (NDT&E) techniques to inspect ceramic components and identified a need to determine the limitations of current non-destructive techniques in the inspection of ceramics. Additionally, the literature focused on obtaining a deeper understanding in the area ultrasonic inspection of metals, composites and ceramics along with different
signal processing techniques that can be used for defect classification. Several attempts were made by researchers to estimate the bulk density of an entire sample, but no study have been carried out to investigate local density variation across ceramic components. Moreover, the literature indicated that the application of an artificial intelligence approach had not been explored for classification of ultrasonic signals obtained from armour ceramic components.

ii. The background information on ultrasonic inspection (Chapter 3) and neural networks has assisted in the development of a suitable experimental procedure for the inspection of armour ceramic components.

iii. The development of a reliable calibration methodology (Chapter 6) greatly reduced the uncertainty and notably increased the accuracy and consistency of the experimental results. It also provided a foundation for developing a generalised procedure to ensure the repeatability of results in experiments involving ultrasonic immersion and contact testing.

iv. A methodology (Chapter 6) was developed to identify a suitable frequency for inspecting high density reaction-sintered silicon carbide ceramic components. The results provided guidelines for the selection of a suitable ultrasonic transducer frequency range (7.5 MHz to 10 MHz) that enables identification of changes in density and thickness as well as the detection of critical defects.

v. Classification of the raw ultrasonic signals was difficult using only the neural network approach. Hence, the use of Discrete Wavelet Transform (DWT) in pre-processing of signals prior to input to the neural network for signal classification was investigated (Chapter 7). As detailed in Chapter 5 (Section 5.4.2) 'Signal enhancement' and ‘Extraction of local features’ was performed on raw ultrasonic signals. DWT not only provides excellent feature extraction, but also provides significant data reduction and
filters the noise from the signals thereby reducing the computational burden considerably. Use of a neural network approach for defect detection in combination with DWT technique assisted in achieving improved results.

vi. As discussed in the literature review (Chapter 5), feature selection is essential as all available features may not be useful. Some of the features may be redundant, while others may cause confusion during the learning phase. PCA and GA were investigated in this research and the smallest subset of original features was identified by PCA that yielded a highest classification percentage of 96% (Chapter 7). The results also showed that the classification percentage obtained by first five Principal Components was lower compared to PCA identified features, even though the principal components in general contain information from all original features. Besides, the application of GA based feature selection has improved the classification percentage from 91% of 94 %, however was found lower when compared to PCA identified feature subset which produced a classification percentage of 96%. The validation results obtained through micro CT scan and X-ray presented in Chapter 7 confirms the reliability of the developed ultrasonic inspection method.

vii. The discussion of the results (Chapter 8) compared the outcomes of this research with the contributions of other researchers. The inspection technique developed in this research lead to the determination of density variation as well as identification of various defects in ceramic components from ultrasonic signals. This has not been accomplished before. In this research, the investigation of DWT as a signal pre-processing approach has been carried out. This work has also demonstrated the advantages of using a PCA and GA as feature selection methods in improving the classification accuracy of neural networks in the context of defect detection in armour ceramics.
There were a number of important contributions made throughout the research program in relation to the ultrasonic inspection of armour ceramic components. These contributions relate to the literature review, ultrasonic inspection of ceramics, ultrasonic data processing, and use of artificial intelligence for signal classification in ultrasonic inspection applications. Finally, significant contributions of this research can be summarised as follows:

- An investigation was carried out to select an appropriate inspection technique and transducer frequency suitable for armour ceramic components.
- An ultrasonic inspection methodology was developed for detecting various defects namely, Un-sintered silicon, Porosity, Black spots and Cracks in armour ceramic components.
- The efficacy of classification of ultrasonic signals using artificial neural networks was demonstrated and it was shown that it was possible to detect, locate and classify defect and defect free regions in armour ceramic components. In addition, correlation between ultrasonic velocity and porosity was used to determine density variation across ceramic components.
- Another significant outcome was to minimize the time to a few minutes required to classify the defects compared to the inspection and evaluation time needed for the currently used X-ray technique.

9.2 Proposed Future Work

Identification of various defects that occur in reaction sintered silicon carbide ceramic components was carried out in this research. A experimentation methodology based on contact testing method was used, where each test location was manually
scanned to acquire the ultrasonic signals. In future, the experimental approach similar to the one developed in this research (Part one of Chapter 6) to carry out immersion testing using robotic arm can be implemented, realizing that these ceramic tiles are curved in shape and have different focus at different locations across the tiles. This inspection methodology will assist the quality control operators to scan the armour ceramic components automatically rather physically moving the ultrasonic probe to each test location of the ceramic component.

Another factor, with respect to the current system, is the application of MATLAB for signal processing. As this is not the ideal solution for quality control in an industry based environment, there is a requirement for integrating the signal processing unit within the ultrasonic inspection system to provide a solution for on-line real time inspection. Hence, a future investigation could combine both signal processing techniques and artificial neural network software algorithms in a single software package. This software package could also incorporate data interpretation techniques with the ability to detect defects in different materials and component shapes for ultrasonic inspection.

The highest signal classification rate has been achieved by combining DWT as a feature extraction technique and PCA as a feature selection method in this research. Research can be conducted to develop a mother wavelet with a shape similar to that of each defective ultrasonic signal identified in this research, instead of selecting a pre-defined mother wavelet type such as Coiflet wavelet. If a new mother wavelet can be developed to match individual defect signals, it will improve the performance of the neural network classification system.
In the current research, a calibration methodology was implemented by drawing a grid surface with a step of 5mm across the ceramic components being inspected and thus various defects along with their location were identified at a resolution of 5mm. Further research could involve improving this resolution to much smaller.

9.3 Final Summary

The main motivation for this research on ultrasonic inspection of armour ceramics was to detect various defects and determine local density variation across ceramic components used in body armour. In order to address the project's objective an inspection methodology was developed. A critical part in the research was to identify a suitable ultrasonic transducer frequency particularly in the context of high density reaction-sintered silicon carbide ceramic components, due to high signal dampening and low sensitivity issues. Hence, the developed experimental procedure provided guidelines in selecting a suitable frequency both in immersion and contact testing, while taking into account the material properties along with types of critical defects that required detection.

Further, the appropriate parameters required for the feed-forward back propagation neural network were identified to process the input dataset. The results showed that classification of ultrasonic signals using Discrete Wavelet Transform (DWT) as a pre-processing technique and PCA identified features have provided superior signal classification compared to other signal processing techniques investigated in this research. The use of DWT aided in identifying defects by providing both frequency as well as time domain information. An overall classification accuracy of 96% was achieved using ultrasonic inspection coupled with the described artificial intelligence based signal processing methods.
The results obtained using ultrasonic inspection were validation against X-ray and micro-CT scan images. It was demonstrated that X-radiography does not lend itself to differentiating between defects in many regions of the ceramic components. This was clearly validated in Section 7.9.2.5, where a porosity defect region was shown as a defect-free region in the X-ray image. In addition, the validated results demonstrate that ultrasonic testing would be beneficial in assisting manufacturers to check the location of high porosity areas (density variation), other defects and has the potential for providing real time online quality control including implementation of accept/reject criteria.

The research documented in this thesis provides an insight into the performance of the ultrasonic non-destructive method in detecting various defects in reaction-sintered silicon carbide ceramic components along with determining density and thickness variation. The research has led to a number of contributions to the field of ultrasonic inspection and demonstrated the effectiveness of the signal processing techniques used in this research in classifying ultrasonic signals using artificial neural networks.
REFERENCES


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LIST OF PUBLICATIONS & PRESENTATIONS

JOURNAL ARTICLE AND CONFERENCE PROCEEDINGS


RESEARCH PRESENTATIONS

APPENDIX A

PROBE AND PART DISTANCE CALCULATION

An immersion tank of $20 \times 30 \times 15$ cm was filled with water in which the ceramic sample is placed at a fixed location using supporting blocks. The immersion transducer is positioned at a water path (WP) distance of 78.3 mm from the top surface of the sample, as to focus on the material at depth of 7.0 mm inside the sample which had a thickness of 8.7 mm. Ultrasonic focus effect of sound path in the sample is illustrated in Fig.3.11 below. A LED fiber-optic pointer has been used (at an angle of 51.0 degrees) to trace the path of transducer along the surface of the ceramic sample at each of the test points.

Figure A1. Ultrasonic focus effect of sound path in the sample
APPENDIX B
MATLAB NEURAL NETWORK PROGRAM

This appendix shows a sample program for the DWT as a feature extraction method detailed in Chapter 7,(Sections 6.5.2) The following program is written using MATLAB in an m-file format. The purpose of the program is to read input features from the folder stored in the system (extracted from a database of ultrasonic signals). Then the DWT was applied on the input signals to extract the features fed to artificial neural networks. Also, the following program used PCA and GA methods for feature selection as proposed in Section . The neural network parameters were defined and training, simulating and testing were carried out on the input dataset.

% Clear All the Contents in the Memory
clear all;

% To Perform Gating of Signals
for i=1:632
    gated_data55(:,i)=data_55_first(230:530,i)
end

% Reading the Input Dataset
load (gated_data55.mat);

% Perform a Wavelet Decomposition using Discrete Wavelet Transform at level 5 of Column Signals
% using the coif5 wavelet
dec_1 =mdwtdec('c',gated_data55,5,'coif5');

% De-noising the Signals using Universal Threshold
[XD,decDEN,THRESH]= mswden('den',dec_1 ,'rigrsure','mln');
% Perform a Wavelet Reconstruction of Signals

Xbis = mdwtrec(decDEN); % reconstructs the original signals
A5 = mdwtrec(decDEN,'a',5);
D5 = mdwtrec(decDEN,'d',5);
D4 = mdwtrec(decDEN,'d',4);
D3 = mdwtrec(decDEN,'d',3);
D2 = mdwtrec(decDEN,'d',2);
D1 = mdwtrec(decDEN,'d',1);

%% Feature Extraction

% Set up Gates on First and Second back wall echoes

for i = 1:632
    gatedData(:,i) = Xbis(1:300,i).*((abs(Xbis(1:300,i)) >= 15);
end

for i = 1:632
    Feat_D1(1,i)= mean(abs(Xbis(:,i)))); % Absolute mean of the signal
    Feat_D1(2,i)= var(Xbis(:,i)); % Variance of the signal
    Feat_D1(3,i) = median(abs(Xbis(:,i))); % Absolute median of the signal
    Feat_D1(4,i) = sum(abs(Xbis(:,i)).^2); % Sum of absolute Energy of the signal
    Feat_D1(5,i) = max(gatedData(:,i)); % amplitude of First Back-wall echo
    Feat_D1(6,i)= max(gatedData(100:150,i)); % Max Amplitude of First Back-wall echo
    Feat_D1(7,i)=max(gatedData(180:220,i)); % Max Amplitude of Second Back-wall echo
    Feat_D1(8,i)= mean(abs(D2(:,i))); % W2_mean
    Feat_D1(9,i)= mean(abs(D3(:,i))); % W3_mean
    Feat_D1(10,i) =sum(abs(D3(:,i)).^2); % W3_Energy
    Feat_D1(11,i)= mean(abs(D4(:,i))); % W4_mean
    Feat_D1(12,i)=sum(abs(D4(:,i)).^2); % W4_Energy
end

% PCA Analysis for Training Data

AMean=mean(Feat_D1);
stdr = std(Feat_D1);
sr = (Feat_D1-repmat(AMean,632,1))./repmat(stdr,632,1);

% Finding the Principal Components.

% [coefs,scores,variances] = princomp(sr);

[COEFF SCORE LATENT] = princomp(sr);
VS= var(SCORE);
xx= cumsum(((var(SCORE))/sum(var(SCORE))))*100;

percent_explained = 100*LATENT/sum(LATENT);
figure(222);
pareto(percent_explained)
xlabel('Principal Component')
ylabel('Variance Explained (%)')

VReduced = COEFF(:,1:5);
PCReduced = sr * VReduced;
Z = ((PCReduced * VReduced').* repmat(stdr,633,1) + repmat(AMean,633,1));

% % % Feature Subset Selection using GA

% Initialising Parameters for Calling GA
load 'defect_dataset.mat';       % load 'initial_population';

Nvars = 12;
nParents=20;     % totalPopulationSize
tournamentSize =4;

type create_popu.m

type fitscalingshiftlinear_popu.m

type selectiontournament.m

type crossoversinglepoint_popu.m

type mutate_popu.m

type fitness_popu.m

FitnessFcn = @(x)fitness_popu(x);

type gaplotbestf.m

my_plot = @(options,state,flag) gaplotbestf(options,state,flag);

options = gaoptimset('CreationFcn',@create_popu,...
    'EliteCount',3,...
    'TimeLimit', inf, ...
    'MigrationDirection','forward',...
    'FitnessScalingFcn',@fitscalingshiftlinear_popu,...
    'SelectionFcn',{@selectiontournament,tournamentSize}
    ..., ...
    'CrossoverFcn',@crossoversinglepoint_popu,...
    'CrossoverFraction',0.5,...
    'MutationFcn',@mutate_popu,...
    'FitnessLimit',0.4,...
    'Generations',200,...
'PopulationSize', 100, ...
'TolFun', 1e-6, ...
'StallGenLimit', 100, 'Vectorized', 'on', ...
'PlotFcns', 'my_plot', ...
'Display', 'iter');

rand('seed', 1)
randn('seed', 1)
numberOfVariables = 12;
[x, fval, exitflag, output, population, scores] = ga(FitnessFcn, numberOfVariables, options);

%%%% Creating a Initial Population

function pop = create_popu(Nvars, FitnessFcn, options)  %Create_popu creates a population of permutations.

% The input arguments to the function are
% Nvars : number of variables
% FitnessFcn : Fitness function
% Options : Options sturcture used by the GA

totalPopulationSize = sum(options.PopulationSize);
pop = cell(totalPopulationSize, 1);
load 'Y1.mat';
for j = 1:totalPopulationSize
    tmp(j, :) = rand(1, Nvars) > 0.3;
end
for k = 1:totalPopulationSize
    for i = 1:12
        pop{k, 1}(i, :) = (tmp(k, i) * (Y1(i, :)));
    end
end

function expectation = fitscalingshiftlinear_popu(scores, nParents, MaximumSurvivalRate)
if nargin < 3 || isempty(MaximumSurvivalRate)
    MaximumSurvivalRate = 2;
end
scores = -scores(:);
maxScore = max(scores);
meanScore = mean(scores);
minScore = min(scores);
if (~isfinite(meanScore))
    error(message('globaloptim:FITSCALINGSHIFTLINEAR:finiteScore'));
if(maxScore == minScore)
    expectation = ones(length(scores),1) ./ length(scores);
    return;
end
desiredMean = nParents/length(scores); % mean
scale = desiredMean * (MaximumSurvivalRate - 1) / (maxScore - meanScore);
offset = desiredMean - (scale * meanScore); % offset so that the mean is desiredMean
if(offset + scale * minScore < 0)
    scale = desiredMean / (meanScore - minScore);
    offset = desiredMean - (scale * meanScore);
end
expectation = offset + scale * scores;

%% Function for Parent Selection

function parents = selectiontournament(expectation,nParents,options,tournamentSize)
if nargin < 4 || isempty(tournamentSize)
    tournamentSize = 4;
end
%   Choose the players
playerlist = ceil(size(expectation,1) * rand(nParents,tournamentSize)); %   Play
tournament
parents = tournament(playerlist,expectation);

function champions = tournament(playerlist,expectation) % tournament between
players based on their expectation
playerSize = size(playerlist,1);
champions = zeros(1,playerSize);
% For each set of players
for i = 1:playerSize
    players = playerlist(i,:);
    % For each tournament
    winner = players(1); % Assume that the first player is the winner
    for j = 2:length(players) % Winner plays against each other consecutively
        score1 = expectation(winner,:);
        score2 = expectation(players(j,:));
        if score2(1) > score1(1)
            winner = players(j);
        elseif score2(1) == score1(1)
            try
                if score2(2) > score1(2)
                    winner = players(j);
                end
                catch
            end
        end
    end
end
end
end
champions(i) = winner;
end

%% Function for Crossover Operation of Parents Selected

function xoverKids =
crossoverSinglePoint(parents,options,Nvars,FitnessFcn,unused,thisPopulation)

% Number of children to produce
nKids = length(parents)/2;
% Extract information about linear constraints, if any
linCon = options.LinearConstr;
constr = ~isequal(linCon.type,'unconstrained');
% Allocate space for the kids
xoverKids=cell(nKids,1);
% xoverKids = zeros(nKids,Nvars);

% To move through the parents twice as fast as the kids are
% being produced, a separate index for the parents is needed
index = 1;
for i=1:nKids
    parent1 = thisPopulation(parents(index),:);    % get parents
    index = index + 1;
    parent2 = thisPopulation(parents(index),:);
    index = index + 1;
    xOverPoint = ceil(rand * (length(parent1) - 1));
    xoverKids(i,:) = [ parent1(1:xOverPoint),parent2(( xOverPoint + 1 ) : end ) ];
    if constr
        feasible = isTrialFeasible(xoverKids(i,:),linCon.Aineq,linCon.bineq,linCon.Aeq,
        ...
        linCon.beq,linCon.lb,linCon.ub,sqrt(options.TolCon));
        if ~feasible % Kid is not feasible
            % Children are arithmetic mean of two parents (feasible w.r.t
            % linear constraints)
            alpha = rand;
            xoverKids{i} = alpha*parent1 + (1-alpha)*parent2;
        end
    end
end

%% Function for Mutation Operation of Parents Selected

function mutationChildren = mutate_popol( parents,options,Nvars,...
FitnessFcn,state,thisScore,thisPopulation,mutationRate)

mutationChildren = cell(length(parents),1);  % Swapping two elements of the
population
for i=1:length(parents)/2
parent=thisPopulation{parents(i)};
p=ceil(length(parent)*rand(1,2));
child=parent;
child(p(1))=parent(p(2));
child(p(2))=parent(p(1));
mutationchildren{i}=child;
end

%% Creating a Fitness Function
function scores = fitness_popu(x)
load 'Z1.mat';
load 'Y1.mat';
scores = zeros(size(x,1),1);
for j=1:size(x,1)
    inputs = x{j};
    f= classify_data_ANN_3(inputs,Z1);
    scores(j)=f;
end

%% Building the Neural Network Classifier
% The next step is to create a neural network that will learn to identify the defects.
function mse_calc = classify_data_ANN_3(inputs,Z1)
[pn,ps] = mapminmax(inputs);
[tn,ts] = mapminmax(Z1);

    X = pn;     % Neural network Inputs
    t = tn;     % Neural network targets
    rand('seed', 491218382)
    net= newff(minmax(X),[12,5,1], {'tansig','logsig','tansig'}, 'trainscg');
    net.performFcn = 'mse';
    net.performParam.regularization = 0.01;
    net.trainParam.goal = 0.01;
    net.trainParam.show = 25;
    net.trainParam.epochs= 1000;
    net.trainParam.min_grad = 1e-10;
    net.trainParam.lr = 0.5;
    net.trainParam.mc = 0.09;
    net.trainParam.max_fail = 1000;
    net.trainParam.mu_max   = 1e10;
    net.divideFcn = 'divideind';
    net.divideParam.trainInd = 1:132;
    net.divideParam.valInd   = 133:200;
    net.divideParam.testInd  = 201:632;
    net.efficiency.memoryReduction=1;
    % net = train(net,X,tn);
    y = net(X);
    mse_calc = sum((y-tn).^2)/length(y); end