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Effects of surface roughness on the reliability of magnetic particle inspection for the detection of subsurface indications in steel castings

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by

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DEDICATION

I dedicate this study entirely to my parents; they are the reason I am here today. They have always pushed me in academics and athletics which gave me the opportunities I have today. I am eternally grateful.

To my brother, sister, relatives, mentors, friends, and co-workers who have been there with advice and encouragement to help me get to the finish line.

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NOMENCLATURE

AC	Alternating Current
ACI	Alloy Casting Institute
ANOVA	Analysis of Variance
ANSI	American National Standards Institute
ASTM	American Society for Testing and Materials
DC	Direct Current
DOE	Design of Experiments
G	Green on the RGB scale
LPI	Liquid Penetrant Inspection
MPI	Magnetic Particle Inspection
MSS	The Manufacturer Standardization Society
NDE	Non-Destructive Evaluation
NDT	Non-Destructive Testing
POD	Probability of Detection
RGB	Red, Green, and Blue
UV	Ultraviolet

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ABSTRACT

The objective of this research is to quantify the effects of surface roughness on the reliability of magnetic particle inspection (MPI) when detecting sub-surface indications. Indications in this study refer to possible defects. The reliability of MPI can be influenced by factors such as process control, part and indication characteristics, and human factors [1], [2]. Surface roughness is known to influence the effectiveness of wet MPI as rougher surfaces tend to result in particles collecting in the valleys of the surface textures which likely result in false positives [3], [4]. The surface roughness of the steel castings poses a challenge as it could increase the collection of particles when performing wet MPI. The lack of research into the influence of surface roughness on wet MPI has led to the need for this research. Three sets of experimental designs were developed. Firstly, particle collection due to surface roughness was tested using samples containing three levels of surface textures where a metric for the accumulation of fluorescent particles was developed by obtaining a value to represent the average green intensity. Next, the noise area percentage caused by four levels of surface roughness with a common sub-surface indication was tested. Noise area percentage in this study was determined by the percentage of pixels surrounding the indication which have higher green intensity compared to the average green intensity of the indication. This experiment was conducted to evaluate the relationship between noise area percentage and surface roughness when testing for a fixed discontinuity. Noise area percentage is a metric to determine the level of difficulty in identifying an indication. The higher noise area percentage, the harder it is to identify an indication. Lastly, the effect of surface roughness compared to depth and diameter with regards to the influence it has on the response variable (noise area

percentage) was evaluated. This research will provide a quantifiable method for the effects caused by factors that were not available prior to this study. Additionally, a better understanding of the impacts surface roughness have on the effectiveness of wet MPI was achieved through this investigation.

CHAPTER 1. INTRODUCTION

This chapter is broken down into three main sections which are the Overview, Research Motivation and Questions, and Thesis Organization.

Overview

In the steel casting industry, NDT methods commonly used are visual, radiograph, magnetic particle, dye penetrant, and ultrasonic testing [5]. Magnetic particle inspection (MPI) is split up into two methods: wet and dry inspection. Wet MPI is the method investigated in this study. Indications in this study refer to possible defects. MPI can only be used on ferrous parts as the component must have the ability to be easily magnetized and remain magnetized [6]. If an indication is on or close to the surface of the part, the magnetic field will bend, and flux leakage will occur around the area of the indication. The magnetic particles will then start collecting on the top of the flux leakage area [7]. Thus, by detecting these collections of particles, one is able to detect indications. However, due to the smaller sized particles used in wet MPI, the particles tend to catch in the surface valleys of rougher surface textures [8]. Since, an indication is determined by a collection of particles, particle collection on surface textures would create false positives or deter the human inspector from finding the indication.

However, there is a lack of research into how much a given surface roughness would affect the dependability of MPI. Hence, three experimental designs were developed to test: 1) particle collection due to surface roughness, 2) the effect of surface roughness on noise area percentage when detecting a sub-surface indication, and 3) the effect of surface roughness, depth, and diameter on noise area percentage. Noise area percentage in this study was determined by the percentage of pixels surrounding the indication which had a higher green intensity value compared to the average green intensity of the indication. Noise area percentage is a metric to determine the level of difficulty in identifying an indication. The higher noise area percentage, the harder it is to identify an indication. The effect of surface roughness was also compared to the effect of the size and depth of a sub-surface indication on noise area percentage. The first experiment was created to test for particle collection on the surface on different surface texture. This is important because this study is based on the premise that rougher surfaces tend to catch more particles leading to false positives or interference when detecting indication. The second experiment was conducted to test the extent different surface roughness interferes with the detection of a fixed sub-surface indication. The addition of a sub-surface indication introduces magnetic flux leakage which may pull particles from the area surrounding the indication. This experiment is important as the purpose of MPI is to detect indications so this could provide valuable insight on how surface roughness affects the detection of a subsurface indication. Lastly, it is important to be able to compare the effect of surface roughness on the detection of a sub-surface indication to other factors to determine the level of its influence on the reliability of wet MPI. Depth and diameter were the two factors chosen to be included in the third experiment.

A program was created using C# in Visual Studio to analyze the density of fluorescent particles above a specified green (G) value based on the red, green, and blue (RGB) system which provides the noise area percentage. In addition, the program was used to calculate the average G value of an image which represents the average green intensity of the picture. The results from this investigation showed that surface roughness influences the collection of particles on the surface texture. When no indications were present, the results showed a rise in the intensity of the fluorescent coated particles in the picture as the surface roughness increased. The results from the study comparing the effects of surface roughness, diameter, and depth showed that the depth of the indication had the biggest effect on noise area percentage. Overall, surface roughness was found to play the smallest role in effecting on noise area percentage when compared to the depth and diameter of the indication. However, the sample size was relatively small, and further experiments need to be completed to be able to increase statistical significance. Additionally, more factors need to be considered to fully understand which factors have an influence on the effectiveness of wet MPI. The surface classification method used was subjective and may cause discrepancies in the determination of the actual surface roughness level.

Additionally, only one method was used to evaluate noise area percentage. This method may not have been the best representation of the interference experienced by a human inspector. Hence, using a few different method of evaluating noise area percentage might be useful to better simulate how the human inspector identifies an indication. Lastly, the results from this study provide metrics such as average green intensity and noise area percentage values, however, these metrics are still insufficient in the determination of acceptable or unacceptable criteria for the noise area percentage that makes wet MPI ineffective. Thus, it is necessary to conduct future research into: 1) using an objective measure for surface roughness, 2) bigger sample sizes, 3) a study with more factors and levels tested, 4) using a method for identifying interference that better represents a human operator's perspective, and 5) defining acceptable or unacceptable criteria for noise area percentage. This investigation established a method to measure and quantify the effects of surface roughness on the reliability of MPI when detecting subsurface indications in steel castings. The technique of measuring noise area percentage created in this research provides the groundwork for the quantification of other factors that have an influence on nondestructive testing methods using fluorescent coated particles.

Research Motivation and Questions

The motivation of this study is to contribute to the body of knowledge within the MPI area with regards to the influence of varying levels of surface roughness on the effectiveness of the method. This is a relevant issue as the steel casting industry is looking to further improve the NDT methods using quantifiable results. The creation of an objective method to quantify the effect of surface roughness on the reliability of wet MPI is the overarching goal of this research. The research questions driving this study are:

1. How does surface roughness affect the collection of particles when no indications present?
2. How does surface roughness affect the detection of a common sub-surface indication?
3. How do surface roughness, depth, and diameter of an indication, affect the detection of a sub-surface indication?

Thesis Organization

This thesis consists of five chapters. Chapter 1 contains an overview of the research which will provide background information along with the motivation of the research. Chapter 2 reviews surface roughness and surface roughness classification standards as it pertains to the steel casting industry. Additionally, the principles behind MPI is explained, and the connection between surface roughness and MPI is clarified. In Chapter 3, the methods utilized in the experiments are outlined in detail for the ease of reproducibility. The results and discussion section can be found in Chapter 4. Chapter 5 concludes the thesis by summarizing the discovery of the investigation, specifying its limitations, and providing direction for future research in this area.

CHAPTER 2. LITERATURE REVIEW

This literature review chapter is divided into two sections which cover past research in areas relating to surface roughness and MPI. The first section covers the background of surface roughness by outlining its definition, classification techniques, and industries measuring surface roughness. This section continues with studies pertaining to surface roughness classifications in the steel casting industry and the reason behind the method of classification used in this study. The second section begins with background information about the physics behind MPI and explains the two types of MPI tests that are available. Additionally, it elucidates the wet method of particle application in MPI which will cover the background of the method and will then highlight how surface roughness impacts the effectiveness of this method. This section then covers process control factors and indication characteristics that MPI is capable of detecting and its effect on flux leakage. The second section concludes with a review of MPI focusing on wet MPI and sub-surface defects.

Surface Roughness

Surface roughness is the difference in surface heights compared to the underlying geometry that creates a three-dimensional structure of a surface [9]. The importance of surface roughness is prevalent in various industries including medical [10], sports equipment [11], and aviation [12] industries to name a few. The two common quantitative scales of gauging surface roughness are nanoscale to atomic scale typically used by the physicists for finer details or the microscale which is frequently used by engineers. Both methods use either contact or non-contact types of instruments to measure roughness [9]. Processes such as casting, sandblasting or electrical discharge machining use comparator plates as industry standards when it comes to specifying surface roughness since there is no automated instrument currently available.

Surface Roughness Classifications in the Steel Casting Industry

The steel casting industry utilizes a variety of surface roughness classification methods such as The Manufacturer Standardization Society (MSS) SP-55 Visual Method, the Alloy Casting Institute (ACI) Surface Indicator Scale, the GAR C9 Comparator Plates, and the American Society for Testing and Materials (ASTM A802) A-Plates. All these methods are qualitative and use a physical or digital comparator to compare and match the surface to a set of comparators. A human operator is necessary to determine a feature by comparing a casting surface to comparator plates by touching the surfaces or through images to visually compare an image to the casting surface [13].

In this study, the standard chosen for surface roughness classifications is the ASTM A802 standard. Table 1 outlines several key factors in determining which of the four surface classification standards should be used in this study. The ASTM A802 A-plates standard was selected as the surface texture classification method for this research. This standard is the most commonly utilized in the steel casting industries in the United States of America [13]. The ASTM A802 standard is also recommended by the Steel Castings Handbook for surface classifications when compared to the ANSI MSS SP-55 Visual Method [14]. This is because the ASTM A802 applies both the physical and visual inspection method whereas with the ANSI MSS SP-55 Visual Method only compares visually. Additionally, the ASTM A802 comparator set is more complete when compared to the ANSI MSS SP-55 Visual Method [14]. Figure 1 shows the four A-plates used in this study.

Table 1. Studies Investigating the Common Standards for Surface Classifications in Steel Castings

Standard	Comparator type	Number of comparators	Number of features examined	Features examined	Advantages	Disadvantages
ASTM A802 [15]	Physical	62 (Full set + Precision set)	12	Surface Roughness (A), Surface Inclusions (B), Gas Porosity (C), Laps and Cold Shuts (D), Scabs (E), Chaplets (F), Surface Finish - Thermal Dressing (G), Surface Finish - Mechanical Dressing (H), Welds (J), Hot Tears, Mechanical Dressing -Chipping	1. Uses plastic plates replicated from real metal castings 2. Grouped according to plates 3. More complete set when compared to MSS-SP-55 [14]	1. Bulky 2. Only four levels for each feature 3. Most expensive standard out of the four
ANSI MSS SP-55 [16]	Visual	60	12	Hot Tears and Cracks (I), Shrinkage (II), Sand Inclusions (III), Gas Porosity (IV), Veining (V), Rat Tails (VI), Wrinkles, Laps, Folds, and Cold shuts (VII), Cutting Marks (VIII), Scabs (IX), Chaplets (X), Weld Repair Areas (XI), Surface Roughness (XII)	1. Defines acceptable and non-acceptable comparators 2. Inexpensive 3. Can be digitally stored	1. Relies on only the visual aspect 2. Less complete when compared to ASTM A802
ACI Surface Indicator Scale [13]	Physical	4	1	Surface roughness	1. Small comparator	1. Does not include other features that commonly exist in castings
GAR C9 [13]	Physical	9	1	Surface Roughness	1. Contains most levels for surface texture	1. Levels are difficult to distinguish between 2. Does not include other features that commonly exist in castings

Figure 1. ASTM A802 A-Plates.

Magnetic Particle Inspection

MPI is a fast and relatively simple NDT method used in various industries [6]. MPI is frequently used in the aviation industry with about 90% of ferrous parts being tested via this method in its lifespan [17]. One major limitation to this method is that it is limited to only ferromagnetic materials such as iron, cobalt, nickel and their alloys [18]. Another limitation to this method is its ability to only detect surface-breaking and sub-surface flaws which means if a flaw is not close enough to the surface, this method will probably not work [19]. The main advantages to this method include its ability to detect defects that are very fine and its inexpensiveness when compared to the other NDT methods.

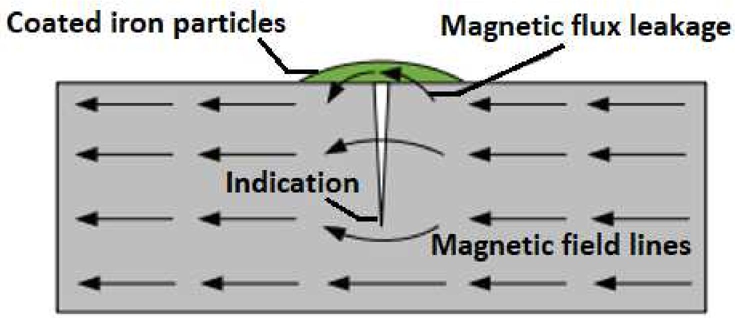


Figure 2. Animation of the Flux Leakage Phenomenon

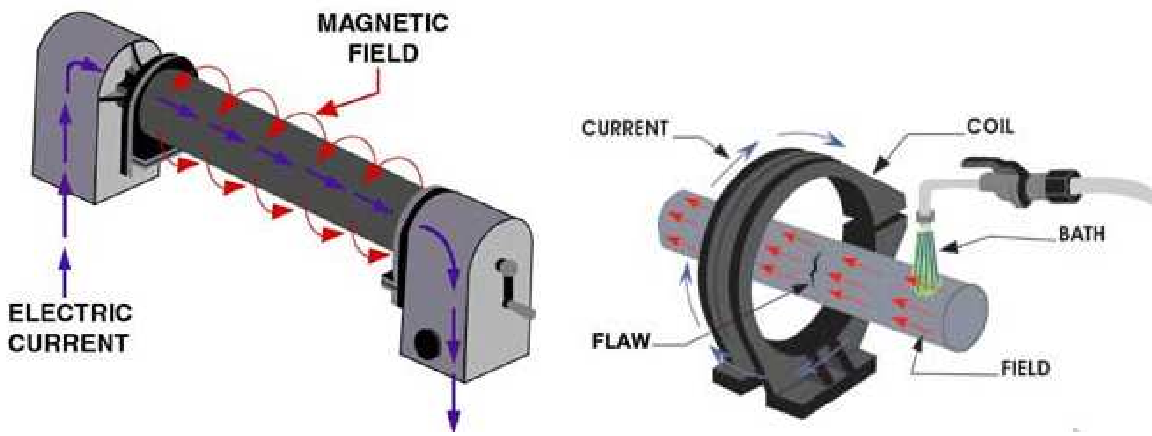
This method utilizes the occurrence of flux leakage at the area of the defect which attracts the collection of coated iron particles (see Figure 2). MPI can be run with either wet or dry particles depending on the part tested [20]. In dry particle inspection, an electromagnetic yoke is used to induce a magnetic field which enables the movement of the dry particles [21]. Dry particles come in many different colors and particle sizes. Common colors for visible magnetic particles are red, black, gray, and yellow which requires white light to be illuminated. Fluorescent magnetic particles are also commonly used but require ultraviolet (UV) light to be illuminated [22]. Particle sizes range from 50 μm to 150 μm and are typically used with a distribution of sizes because the larger particles are needed to locate larger discontinuity. Another reason for the distribution of sizes in the particles is to reduce the dusty nature of the powder, in which the smaller particles tend to catch in surface textures and surface contaminants [22]. In the wet method, visible or fluorescent magnetic particles are suspended in water or oil allowing for more particle mobility and ease of application for larger surfaces compared to the dry method [23]. Particles in the wet method are typically a mix of spherical and slender shapes with diameters around 10 μm in size which is 5 to 15 times smaller than dry particles [22]. Iron oxide particles are most commonly used due to their high permeability and low retentivity allowing them to be easily magnetized and retain their magnetism [24]. Table 2 summarizes the advantages and disadvantages of the wet and dry MPI methods.

Table 2. Advantages and Disadvantages of the Wet and Dry MPI [25]

Wet MPI		Dry MPI	
Advantages	Disadvantages	Advantages	Disadvantages
Good for shallow a fine surface crack	Less capable of detecting sub-surface defects	Good for locating surface and sub-surface indications	Not as sensitive as the wet method for very fine and shallow cracks
Variety of different geometry can be tested	Messy to work with	Easy to use on large objects with a portable system	Difficult to cover large surfaces
Good particle mobility on smooth surfaces	Potential fire hazard with the usage of oil and high levels of current	Easily used for field inspection	Difficult to cover irregular shaped parts
Easy to measure and control the bath concentration	Post-cleaning may be required	Not as messy as the wet method	Not as good for large-volume inspection
Can be used in automated systems	Small particles may get caught in rough surfaces [17], [22]	Less expensive when compared to the wet method	Difficult automate the system

Wet Magnetic Particle Inspection

In this study, wet MPI was investigated to quantify the influence of surface roughness on the dependability of wet MPI due to the smaller nature of the particles that have tendencies to catch in the surface textures [22]. Wet MPI is typically conducted on a bench unit that allows for various different parts to be tested with either direct or indirect magnetization [26]. Direct magnetization occurs when the current is induced directly into the part whereas indirect magnetization uses an external magnetic field to form a magnetic field within the part [27]. Figure 3 illustrates an example of direct and indirect magnetization with the set up on the bench. The direction of the current is in purple, while the direction of the magnetic field is in red. In this study, direct magnetization was used as this is the most common method used as it has better control of the field strength when compared to indirect magnetization [27].



A B

Figure 3. A) Direct Magnetization B) Indirect Magnetization [26]

Although the wet inspection method is known to have more advantages than the dry method, the wet inspection method is known to be less successful on rougher surfaces due to smaller particle size that leads to lack of mobility as it tends to settle in the valleys of the surface [8]. The ASTM E3024 standard states that "The surface of the part to be examined shall be essentially smooth, clean, dry, and free of oil, scale, machining marks, or other contaminants or conditions that might interfere with the efficiency of the examination" which implies that the smoothness of the surface may affect the efficiency of the test. However, the lack of literature to quantify this phenomenon has led to the need for this study. The steel casting industry utilizes both the wet and dry methods of MPI. Due to the nature of the surface texture of steel castings, the effectiveness of wet particle MPI with respect to surface roughness needs to be further investigated.

Factors that Influence the Effectiveness of Wet MPI

Several factors have impacts on the effectiveness of wet MPI. Main factors include process control, part and indication characteristics, and human factors [1], [2]. However, the lack of in-depth understanding of the method due to the combination of factors that have an impact on the effectiveness of MPI led to the need for this investigation [28]. This review focuses on two of the factors which are process control and indication characteristics. Process control factors which include: 1) particle concentration [29], 2) suspension contamination [30], 3) electrical system operation [31], 4) lighting [32], and 5) eye considerations [33]. Particle concentration is a critical process control factor. If the particle concentration is above the acceptable range, higher amounts of particles will collect on the surface which may create false positives. However, if the particle concentration is below the acceptable range, the areas of flux leakage may have fewer particles gathered hence reducing the indication's level of detectability. Suspension contamination could be caused by many factors. The flow of the particles could be disturbed by contamination in the solution which reduces the effectiveness of MPI [17]. The electrical system of a bench should also be checked to ensure the unit is functioning properly. The sensitivity of the test is affected by the electrical system [31]. MPI relies on visual inspection to detect indications. Thus, lighting is an important aspect of MPI tests. Appropriate intensity along with uniformity of the light sources is crucial in increasing the likelihood of detection [32]. Since visual inspection is a part of MPI testing, eye considerations of the human inspector are important. This includes considering the human's ability to see. Additionally, the adaptation time of the eyes must be taken into consideration to reduce mistakes caused by the vision.

Characteristics of surface-breaking and sub-surface indications have large effects on the detection ability of wet MPI. The characteristics of surface-breaking indications that affect its likelihood of detectability are: 1) depth, 2) width, 3) length to width ratio, and 4) depth to width ratio [34]. For sub-surface indications: 1) size, 2) shape, 3) orientation, and 4) depth of an indication in relation to the size of the part will determine whether an indication can be detected [34].

Figure 4 shows the effect that orientation has on the magnetic flux leakage where the coin-shaped indication at a 90-degree angle to the surface caused more of a disruption in the magnetic field lines, whereas, when laid horizontally, did not cause a disruption since the flow lines would streamline around the coin-shaped indication. If the coin-shaped indication went from 90 degrees to 60 or 70 degrees, there would be an obvious difference in the amount of flux leakage and ultimately the ability to detect that indication [34]. The depth is considered the most important characteristic of an indication and may significantly alter the reliability of MPI [17].

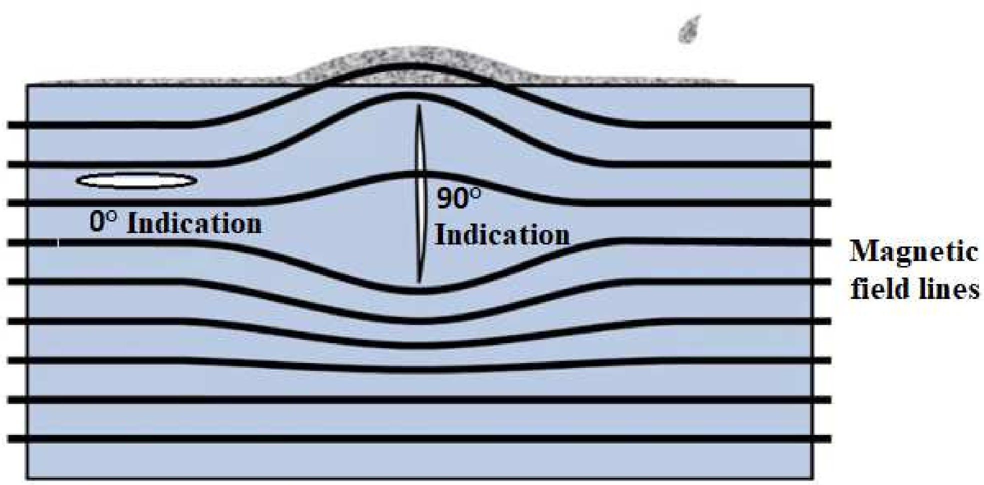


Figure 4. The Orientation of Indication and Its Effect on the Magnetic Flux Leakage [35]

Process control and indication characteristics are two critical factors that have an influence on the effectiveness of wet MPI. In this investigation, process control followed specifications outlined by ASTM E3024 and guidelines provided by the NDT Resource Center are used. Indication characteristics are also crucial factors that affect the abilities of wet MPI. To better understand wet MPI, the impact that indication characteristics and surface roughness have on the reliability of wet MPI should be further investigated. In this study, the effect of surface roughness, along with the depth and diameter of the sub-surface indications, on the effectiveness of MPI was investigated.

CHAPTER 3. METHODOLOGY

The methodology was set up to investigate the effects of varying surface textures on the effectiveness of MPI when detecting sub-surface indications. This chapter is broken down into two main sections which are the Materials and Methods section and the Data Analysis section. In the Materials and Methods section, sample preparation is outlined with the methods used to identify and classify surface textures as well as the procedures and parameters used in MPI testing. Additionally, the samples used in this study are shown in this section. The Data Analysis section explains the desktop application developed by the author for image analysis where a method of quantification for the effect of surface roughness, depth, and diameter is described. The statistical methods used to examine the data is also elucidated in this section.

Materials and Methods

Sample Preparation for A1, A2, and A3 Surface Test

The two types of samples used in this experiment are shown in Figure 5, which are actual castings made by typical manufacturing processes. There were 10 samples of each type. The casted numbers and letters on the samples were not unique to each part; therefore, unique identification was stamped onto each part. Surface classifications ranging from A1 to A3 were identified on the parts by two different people. Figure 6 shows an example of one of the parts stamped with “B7” which denotes the sample type and number enabling simple documentation of samples A and B.

Each sample was broken down into sections with labels shown in Figure 7. The labels represent the general location of the section. The first letter in the label represents the left (L), middle (M), or right (R) section of the part in relation to the area with the cast lettering. The second letter in the label represents the front (F), back (B), or side (S) of the part. The front section is the entire front area of the part with casted lettering. The back section is the area without casted lettering. Figure 7 shows the front section of the part (left image) and the back section of the part (right image). The sections of the part are left-side (LS), left-front (LF), middle-front (MF), right-front (RF), right-side (RS), left-back (LB), middle-back (MB), and right-back (RB). The surface classifications corresponding to the sections of each part were then recorded on a spreadsheet to ensure proper documentation.

Figure 5. Sample A (Left) and Sample B (Right)

Figure 6. An Example of an Identification Stamped on Sample

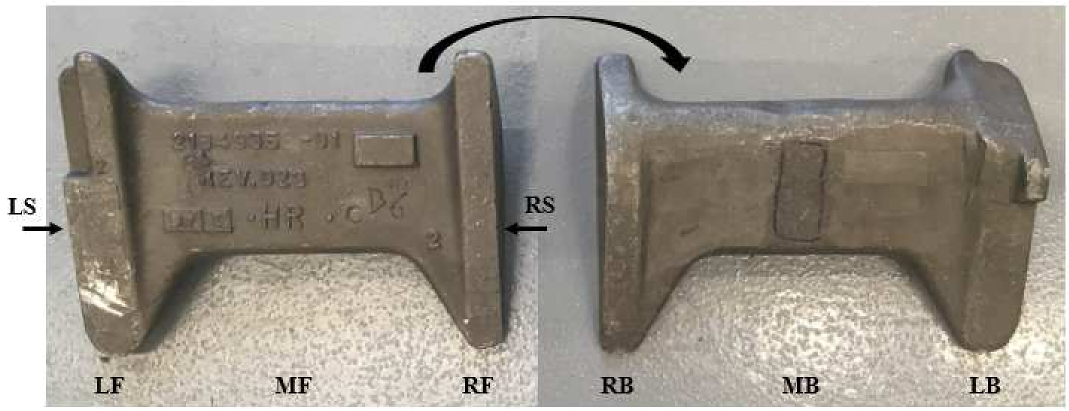


Figure 7. Labels of the Sections

The surface textures of the casted samples were classified using the ASTM A802 standard for textures. The A-plates, which contain four comparator plates for surface texture, were used to touch and compare against the sample’s casted surface. The areas of interest were marked in the shape of a rectangle with a permanent marker with the dimensions of 20 mm (0.8 in) by 50 mm (2.0 in), and the roughness classification is noted above the marked area as shown in Figure 8.

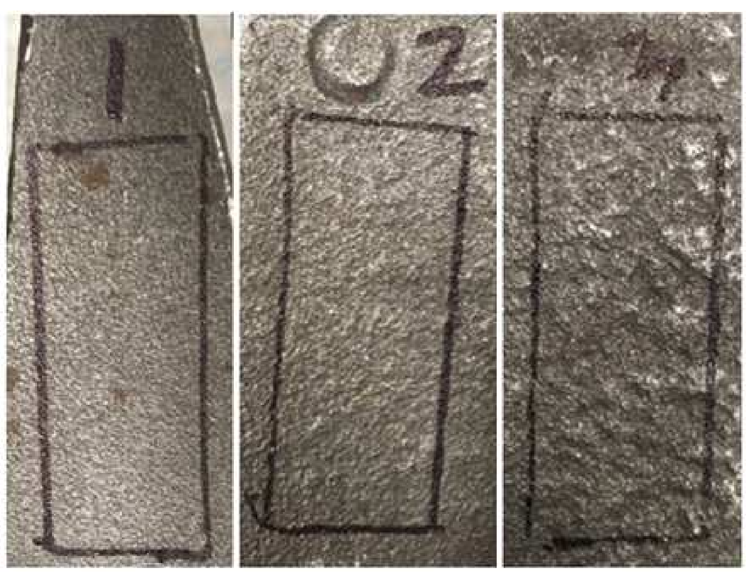


Figure 8. An Example of Marked Areas with Roughness Levels 1, 2, and 3

Sample Preparation for Samples with Indications

For the second set of experiments, manufactured indications in the shape of a hole were introduced to the parts. A cast plate 355.6 by 174.6 mm (14.00 by 6.875 in) with the dimensions of which was cut into eight pieces and used for the two sets of experiments is shown in Figure 9. Samples were stamped based on the location of the piece when viewed from the cope surface. For example, the top-left corner piece as viewed from the cope side was labeled “TL” which stands for top-left as shown in Figure 10. All the surface textures were then classified, and surface roughness levels ranging from A1 to A4 were found on the parts. Figure 10 shows the labels for each piece and the surface classifications found on the cope side of the pieces. The top-left (TL), top-right (TR), and bottom-left (BL) pieces were the only three pieces that contained all surface textures A1, A2, A3, and A4. These three plates were used to test the effect of surface roughness on noise area percentage when detecting a sub-surface hole which was drilled at a diameter of 1.78 mm (0.07 in) and a depth of 0.254 mm (0.01 in). The rest of the plates were used to test the effect of surface roughness, depth, and diameter on noise area percentage.

Figure 9. Sample Cut into Eight Pieces from Cope View

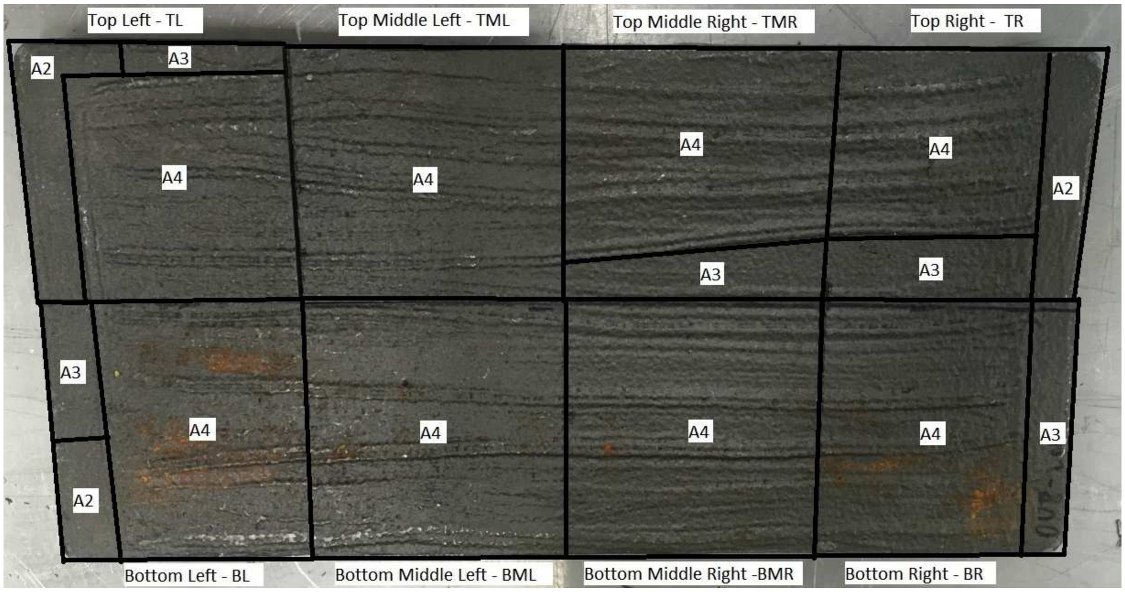


Figure 10. Labels and Surface Classifications on the Cope Side

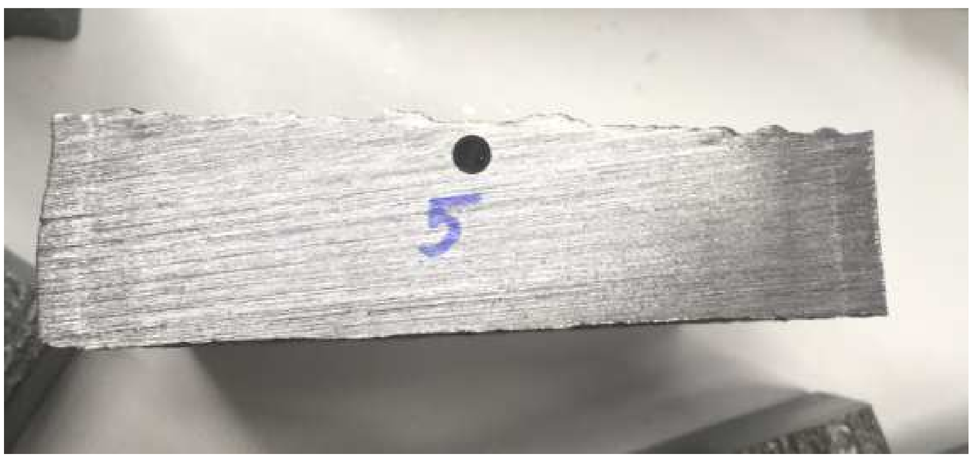


Figure 11. An Example of Sample with a Hole Drilled with a Diameter of 0.14 in and a Depth of 1.78 mm (0.07 in)

A 2^3 design of experiment with two replicates was used with a surface roughness of A1 and A4, a diameter of 1.78 mm (0.07 in) and 3.56 mm (0.14 in), and a depth of 0.254 mm (0.01 in) and 1.78 mm (0.07 in). Depth of an indication was measured from the surface to the top of the hole. The surface roughness levels determined by the minimum and maximum levels of surface roughness according to the ASTM A802 plates. The first level for diameter was determined based on the size of the holes in a ketos ring and the second level was double the value of the first level. The maximum depth sensitivity for detecting a sub-surface discontinuity in wet MPI is 2.54 mm (0.10 in) under perfect conditions [36] hence the depths were set with 0.254 mm (0.01 in) as the first level and 1.78 mm (0.07 in) as the second level. The factors and levels that were chosen for the 2^3 design of experiment are outlined in Table 3.

Table 3. Factors and Levels Selected for Screening Experiment

Factors	Levels	
1. Surface roughness	A1	A4
2. Depth	0.254 mm (0.01 in)	1.78 mm (0.07 in)
3. Diameter	1.78 mm (0.07 in)	3.56 mm (0.14 in)

The surface textures of the samples were classified using the ASTM A802 A-plates. The four plates provided by the surface classification standard were used to touch and compare against the sample's casted surface. An example of the classification of the surfaces is shown in Figure 10. The sides of the pieces that were not machined contained A1 surfaces.

Experiment Setup

To begin the tests, the bench (MD3-2060, Magnaflux, Illinois) was turned on, and the bath walls were scrubbed while the pump was left running for a minimum of 30 minutes to ensure even particle (CAS# 1309-37-1, Magnaflux, Illinois) flow [29]. The particle concentration, condition, and suspension contamination were monitored at the beginning of the testing day using a 100 ml centrifuge tube (14-A, Magnaflux, Illinois) which had a stem that progressed to 1.0 mm. The particle concentration was kept within a range of 0.3% to

0.4%, and the suspension contamination was monitored to ensure it was below 50% in accordance with the ASTM E3024 standard. Particles or oil were added if the particle concentration was outside the acceptable range.

Once the particle concentration is within range, the tests were started. A magnetic Anglemeter (700, Johnson, Wisconsin) was attached to the sample on the surface of the same plane as the test area, and then the part was mounted on the bench at a minimum of 45 degrees per ASTM specifications. While mounting the part, careful handling was needed to avoid touching the areas of interest. A stainless-steel brush (54022SP, Osborn, Indiana) was used to remove particle residue imparted on the part due to handling. Then, the Anglemeter was removed, and a Gaussmeter (5180, FW Bell, Oregon) was used with oil containing particles flowing on the part to detect the strength of the magnetic field close to the area of interest while it was magnetized during a shot of current.

Alternating current (AC) magnetization was used for the surface roughness test without indications while direct current (DC) magnetization was used for the surface roughness test with sub-surface indications. AC was chosen for the surface texture test without indications due to its ability to detect indications on the surface. DC magnetization was chosen because of its ability to penetrate deeper into the material, and thus it will be better at locating sub-surface indications [37]. The strength of a magnetic field was measured during a shot and was considered adequate if it was within 30 ± 1 gauss as suggested by the ASTM E3024 standard.

Next, magnetic particles suspended in liquid were allowed to flow over the surface as the part was magnetized three times in quick repetition. Afterward, pictures were taken under UV light to test the effect of the varying surfaces textures. For this, a camera with three surrounding UV lights (PX-45, Crack Check, China) was positioned at a distance of 508 mm (20 in) from the part perpendicular to the back section of the camera for the test with no indications, and at a distance of 305 mm (12 in) for the test with indications. Prior to using tape on the UV lights, a bright spot was visible which would reduce the likelihood of detecting an indication. Hence, the bright spot of the UV light was dispersed using tape to ensure even illumination of the area of interest. The taped UV lights are as shown in Figure 12.

Figure 12. Camera with Three Taped up UV Lights

After 10 surfaces of each surface classification were tested and the images were sorted. Since multiple images were taken, the best photograph was chosen for each treatment based on the quality of the image. These pictures were then cropped so that only the area within the 20 mm (0.8 in) by 50 mm (2.0 in) test area was left on the picture for the test with no indications. For the test containing indications, two parts of the photographs were cropped: firstly, the area containing the indication was cropped, and secondly, the area below the indication with the same surface classification as the area of indication was cropped. Once the photos were cropped, a program produced by the author was used to analyze the images. The program and its usage are further explained in the next section.

Data Analysis

C# Application for Image Analysis

The average G value was used to analyze the impact surface roughness has on the collection of particles when no indication was present. The higher average green intensity in the image the higher the average G value. The average green intensity of the image corresponds to the collection of particles. This value helps quantify the collection of fluorescent particles on the surface. A desktop application was created by the author using the C# language in Visual Studio to analyze the pictures taken after the MPI test was completed. Digital pictures consist of red, green, and blue (RGB) values for each pixel. In this thesis, the green value from the RGB scale will be referred to as the G value.

The user interface is shown in Figure 13, and the cropped images can be uploaded by clicking the "Upload photo" button. Next, the text box located under "Convert to black" button needs to have a value entered anywhere from 0 to 255. This value is the threshold G value. Once the value is entered, the "Convert to black" button must be clicked. Once the button is clicked, the program examines every single pixel in the uploaded image and checks if the G value is below the defined threshold. All the pixels below the entered threshold value are set to black. An example of this can be seen in the right image in Figure 13. The number of pixels in total and the number of pixels above the threshold are also counted. By dividing the total number of pixels above the threshold by the total number of pixels, one is able to calculate the density percentage of pixels with a G value above the threshold. The average G value is also obtained after the "Convert to black" button is pressed. The program sums all the G values of the pixels contained in the original photo and divides the sum by the total number of pixels in the original photo to provide the average G value. The average G value and the density percentage are displayed on the bottom of the form.

The density percentage was used to analyze the influence of varying surface roughness on the noise area percentage when indications were present. Two images were cropped for each test; the area containing the indication and the area below the indication with the same surface classification as the area of indication. An example of the two cropped areas is illustrated by the red rectangles in Figure 14. The indication section is determined by cropping the smallest rectangle surrounding the visible indication as shown by a red rectangle in Figure 15. If the indication area is not visible, the location of the indication would be identified by obtaining the pixel per inch measurement for the image and using this to identify the approximate location of the indication. The indication image would first be uploaded to the software, and its average G value would be entered into a spreadsheet. Next, the surface below the indication would be uploaded, and the threshold G value entered would be the indication's average G value above it. Hence, the density percentage would be the percentage of pixels above the average G value of the indication found in the surface below the indication. The density percentage can also be thought of as the percentage of noise in the area below the indication. In this thesis, the density percentage is referred to as the noise area percentage. The area chosen to be cropped can impact the results. For example, using the smallest rectangle around the indication compared to averaging five peak points will result in very different noise area percentages. Picking peak points would result in a lower noise area percentage compared to the smallest rectangle method are percentage since the threshold G value would be higher. Future work into which cropping method best represents a human inspector when identifiying indications will be useful in improving upon this study.

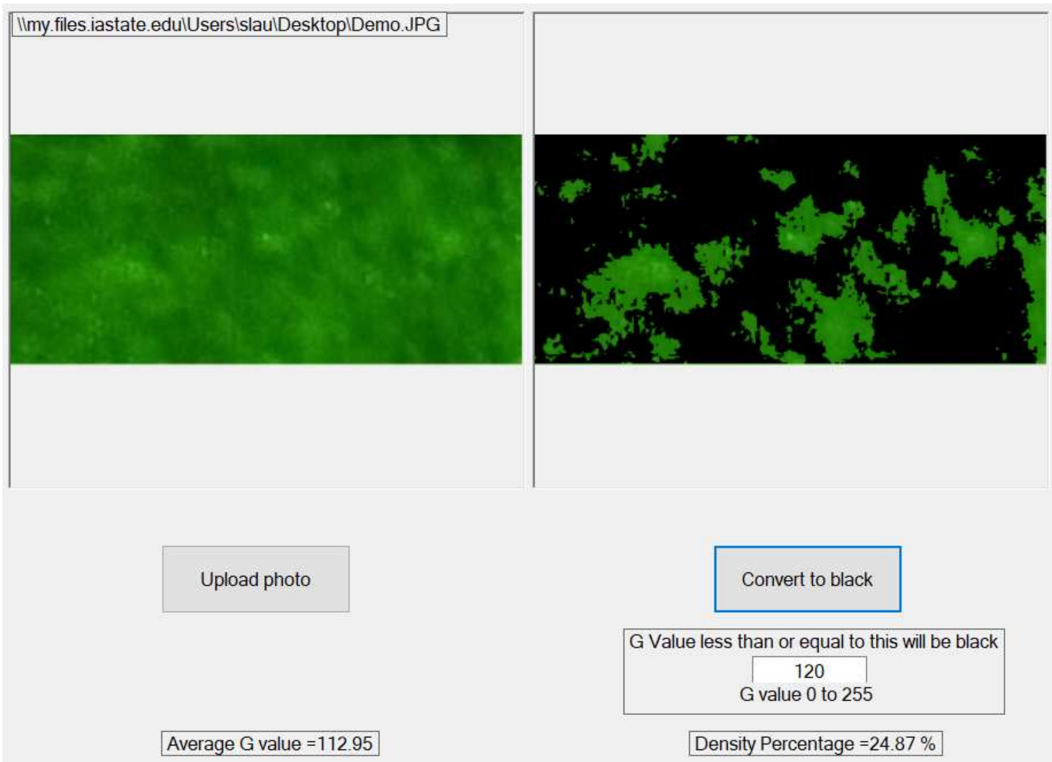


Figure 13. The Program Created to Analyze Cropped Images

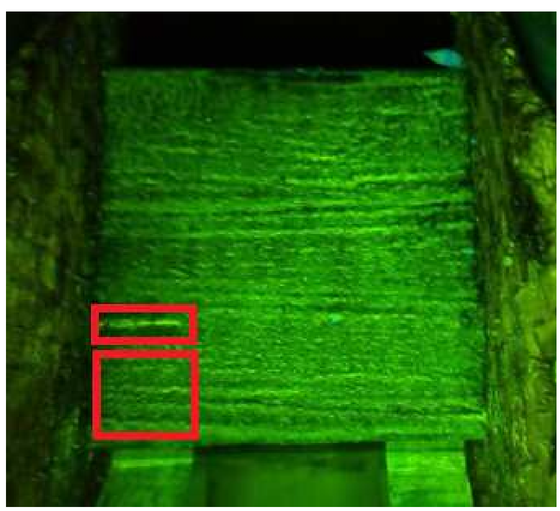


Figure 14. An Example of the Two Cropped Areas Used for Image Analysis for Samples with Sub-Surface Indications

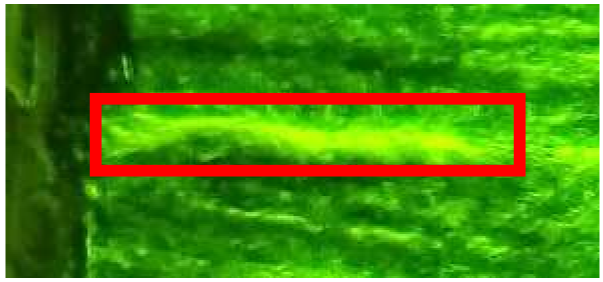


Figure 15. An Example of Indication Cropped Area

Statistical Analysis

All the data were compiled and analyzed using R (Boston, MA, USA). Statistical significance was determined by performing the F-test in the one-way analysis of variance (ANOVA) with a type I error rate of 0.05 for data with a single factor containing multiple levels. For the 2^3 experimental design, the ANOVA model with a logit transform on the response was used to evaluate the data. The logit transform was used on the response variable for the 2^3 design of experiments to better fit the normality assumption. Noise area percentage was used as the response variable with surface roughness, diameter, and depth as the three categorical explanatory variables. If the interaction was insignificant, the main effects model was used. Tukey's multiple comparison test was used to test for significant differences between the category means. The multiple comparisons test was done regardless of the outcome of the F-test to provide trends and conclusions for future research. The multiple comparisons test was accomplished via a package called "emmeans" which provided the estimated marginal means and contrasts of groups using Tukey's method. Diagnostic plots were used to check model assumptions of normality, constant variance, and independence. A logarithmic scale for the Y-axis was used in Figure 21 and Figure 23 due to increasing variance in the data identified in the scale location diagnostics plot [38].

CHAPTER 4. RESULTS AND DISCUSSION

The results and discussion chapter presents the findings and discusses the results of the experiments. This chapter is broken down into four main sections. The first part shows the results from preliminary testing and analyzes the reason behind the large variances in the data. Additionally, changes to the cleaning method as a result of the preliminary testing were explained. The next three parts answer the following research questions: 1) How does surface roughness affect the collection of particles with no indications present?, 2) What is the effect of surface roughness on the noise area percentage when detecting a common sub-surface indication?, and 3) How do surface roughness, depth, and diameter affect the noise area percentage? Through these experiments, the effects of surface roughness on the reliability of wet MPI were elucidated.

Experiments with Samples Containing No Indications

Preliminary Testing of Surface Roughness with No Indications

In preliminary tests for samples without discontinuities, the smaller sized sample, sample B, was used as they were lighter and hence easily handled. Results from initial testing showed no significant difference with large dispersion in the average G values across the different treatments as shown in Figure 16. Upon further investigation, it became apparent that the handling of the part plays a role in the outcome of results. Figure 17 shows an example of the effect of handling on the results. An area of a sample that had minimal fluorescent particles present under UV light was touched by the same rubber glove used in the preliminary tests. The red ovals marked in Figure 17 indicate the areas that had contact with the glove, and they have a brighter green color compared to those that were not touched. Even though a brush as shown in Figure 18 was used to clean the area of interest, the particles in the valleys of the surface could not be removed using this brush. This means that the results in Figure 16 could have been affected by the handling of the part and not by the surface roughness.

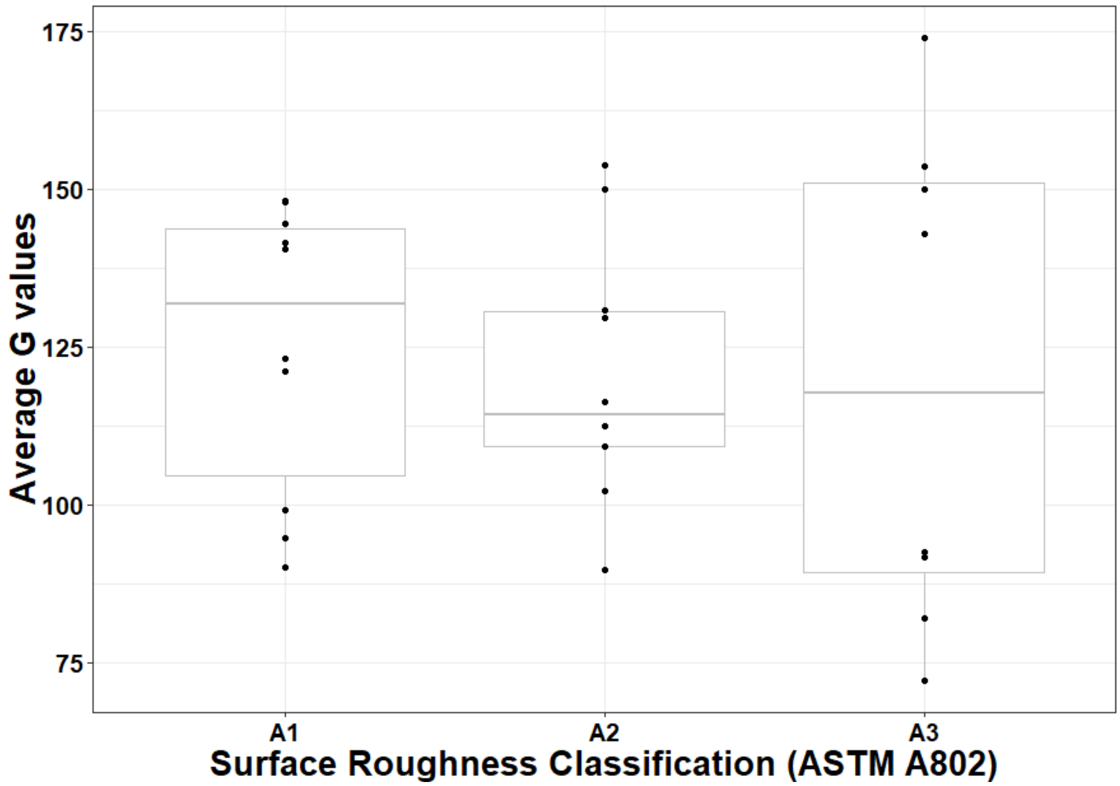


Figure 16. Boxplot for Preliminary Run with Sample B

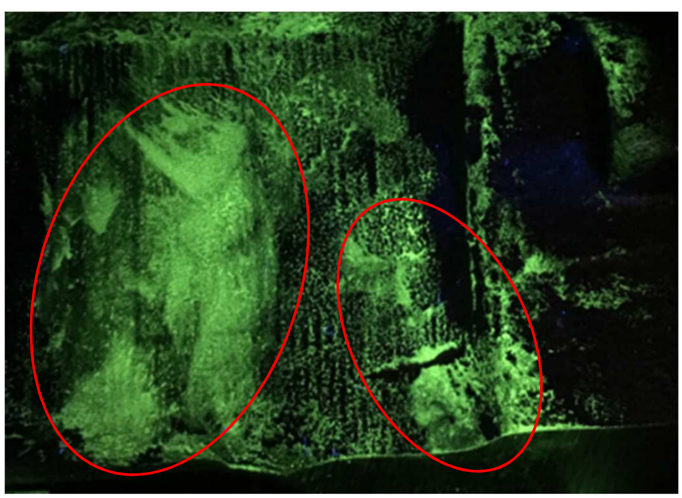


Figure 17. An Example of the Bright Green Areas of the Part After Glove Contact

Figure 18. Normal Brush

Parts used for this preliminary experiment were checked to ensure they had less than three gauss in residual magnetic flux from previous experiments. This helped ensure that the difficulty removing particle residue was not due to the magnetized particles [39]. The influence of glove contact was then further investigated by finding an area of the part that was relatively clean from contact and recording its average G value, subsequently touching it with the glove and recording its average G value again. This procedure was repeated using several different cleaning methods: first using the normal brush used in preliminary testing, followed by a toothbrush, a paintbrush, and a stainless-steel brush to capture the effectiveness of the different sizes and stiffness of bristles. The cleaning procedure entails the same steps in a regular MPI test by running the solution over the part while brushing with a selected cleaning tool. Pictures were taken before the area was touched, after it had glove contact, and after each method of cleaning, and the average G values were calculated as shown in Figure 19. The surface roughness for the area used had an A2 roughness level.

The average G value started at 8 and jumped to 151 after being touched by the glove. This shows that a significant amount of particle residue from the glove was imparted to the area, therefore increasing the G value. Results from Figure 19 suggest that using the toothbrush as a cleaning method successfully reduces the average G value imparted due to glove contact by approximately 11%. The normal brush and the paintbrush increased the average G value by approximately 2% and 18% percent, respectively. Since the normal brush had relatively large bristle size, it is not surprising that the average G values were close as the bristle size was too big to clean the particles in the valleys of the surface textures. The paintbrush had much smaller bristle size when compared to the normal brush; however, the bristles are soft hence the brush smeared more particles into the valleys rather than remove particle which consequently resulted in a higher average G value.

Lastly, a stainless-steel brush was used with a bristle diameter of 0.1524 mm (0.006 in). This brush was chosen because of its stiffer bristles when compared to the normal brush, toothbrush, and paintbrush which could help loosen and remove fine particles in the valley rather than spreading the particles on the surface as softer bristles tend to do. Figure 19 shows that using the stainless-steel brush reduced the average G value to 66 which corresponds to a 57% decrease when compared to the glove contact's average G value. It is important to note that the visibility of the green impression made by the glove had disappeared when the part was cleaned using the stainless-steel brush. Since the part was cleaned using a cleaning tool while the solution is being applied to the part, there is a layer of solution present on the part. Therefore, the average G value of an area that was relatively clean from contact was tested with the fluid applied to the part. The average G value of the area, after cleaned by the stainless-steel brush, was found to be close to the average G value of the fluid being allowed to flow over the part with no glove contact. This suggests that the stainless-steel brush was successful in removing particles imparted onto the surface via glove contact.

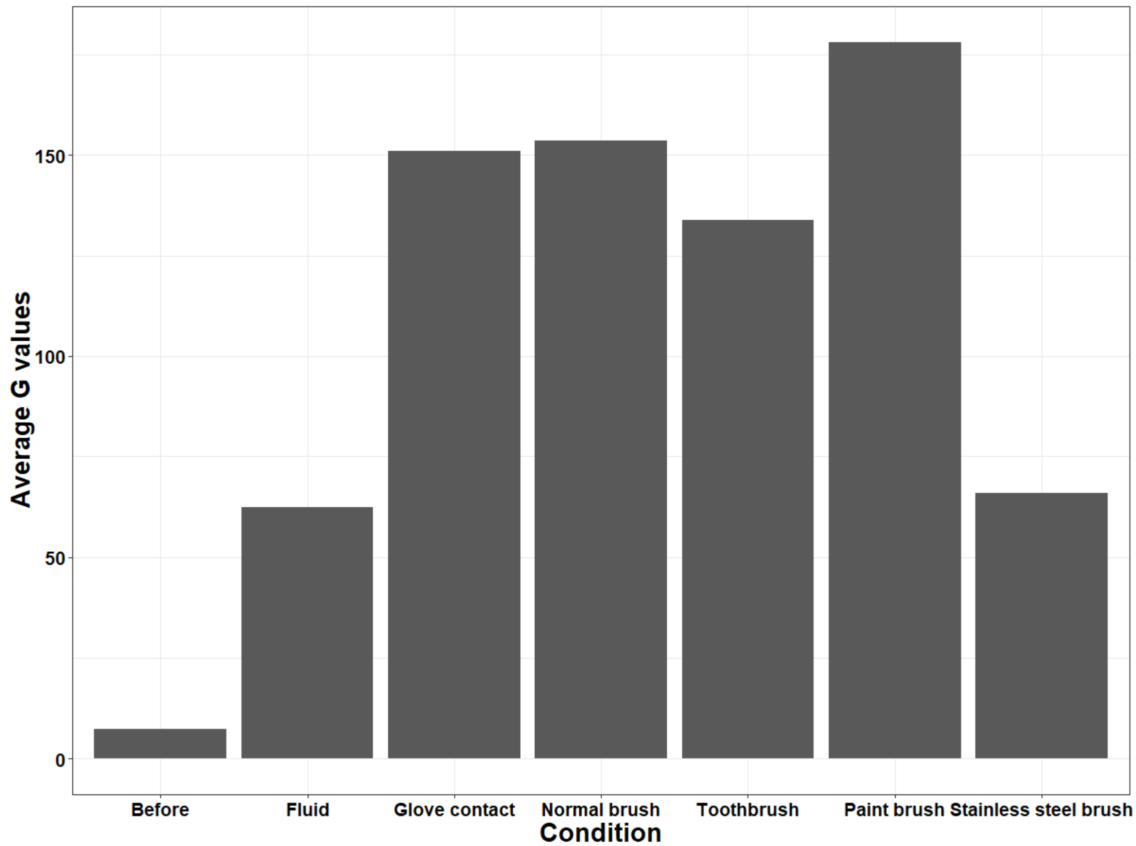


Figure 19. A Plot of the Average G Values for Various Conditions on Surface Roughness Level A2

To verify that the level of surface roughness contributed to the difficulty in removing particles from the surface due to the valleys in the surface, the same setup was done on a machined surface. Pictures were taken before the area was handled, after the glove had contacted the area, and after it was cleaned by the normal brush. The average G values for the three instances are shown in Figure 20. Results indicate that before the area was handled, it had an average G value of 6. Once the glove touched the area, the average G value shot up to 156. Using the normal brush as the cleaning method, the average G value decreased by approximately 57% compared to after handling. It is important to note that the normal brush on a machined surface managed to remove the finger-shaped marks that were visible due to handling. The average G value of the area after being cleaned by the normal brush was close to the average G value of the fluid being flown over the part with no glove contact. This suggests that for a machined surface, the normal brush was successful in removing particles imparted onto the surface via glove contact. The ASTM E3024 does not provide specific guidelines for which cleaning equipment should be used. Given that most of the literature is based on aerospace applications which are machined surfaces [40], it is not surprising that the issue of removing particle residue during post testing has not yet arisen.

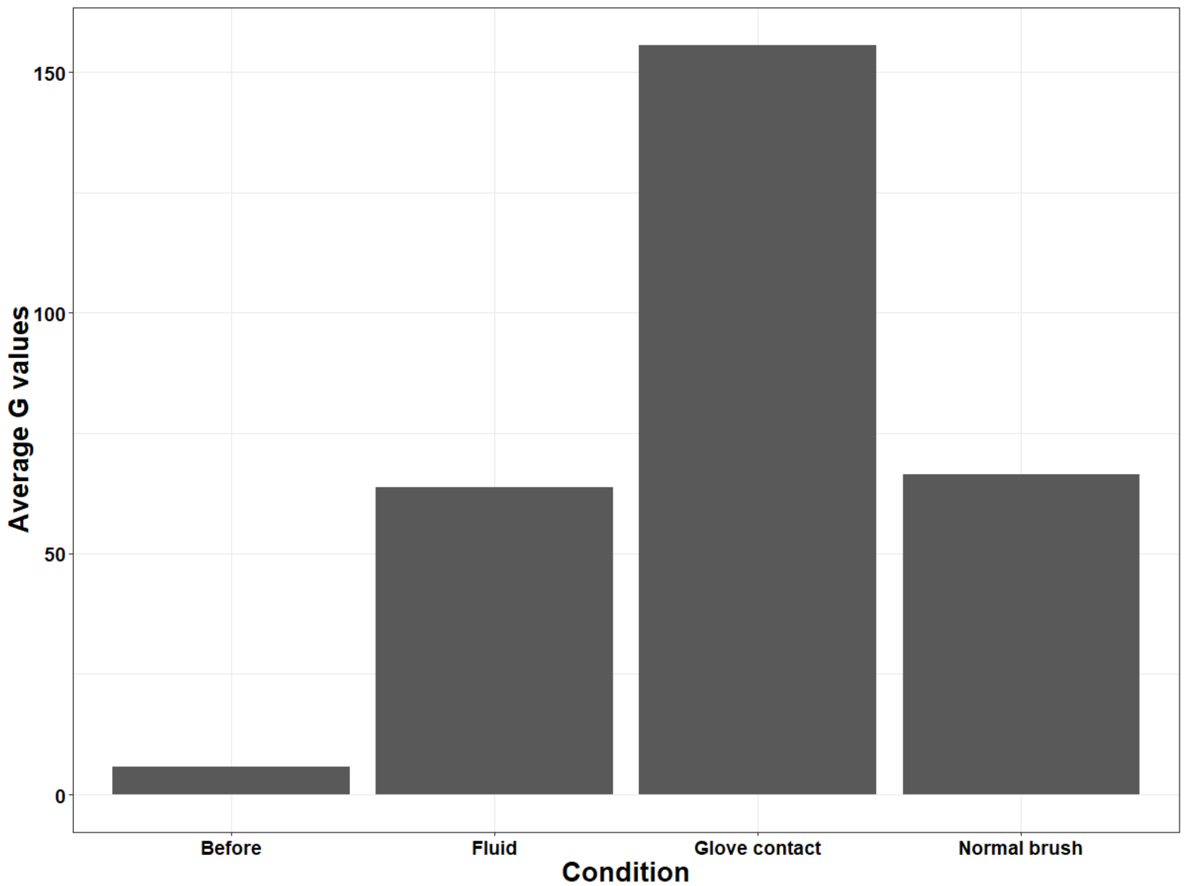


Figure 20. A Plot of the Average G Values for Various Conditions on the Machined Surface

The results show that for surface roughness level A2, a stainless-steel brush was needed to clean the surfaces of the parts from particle residue due to handling. Additionally, results show that for machined surfaces, a regular brush was sufficient in removing particles left due to glove contact. The preliminary test did not yield conclusive results due to the collection of particles from glove contact. Hence, in future experiments, stainless-steel brushes were chosen as the cleaning tool to remove particles imparted due to handling.

Effect of Surface Roughness on the Collection of Particles on the Surface with No Indications Present

Once the issue with handling was resolved, an experiment was designed to test for collection of particles due to surface roughness when no indication is present. This experiment was designed to test for the collection of particles in the valleys of the surface texture through evaluating the intensity of the green color in the image post MPI. Samples A and B were used in this experiment. MPI was done on surface classifications A1, A2, and A3, and areas used had no manufactured indications to ensure only particle collection due to surface texture was investigated. The logarithm of the average G value against surface roughness levels was plotted, and the results obtained are shown in Figure 21.

A one-way ANOVA between surface roughness levels was conducted to compare the effect of surface roughness on the average G values. The results show a significant influence of surface roughness levels on the average G values at a significance level of 0.05 for the three levels, $F(2,27) = 106.9$, $p = 1.48 \times 10^{-13}$. The estimated marginal means of the average G value for A1, A2, and A3 are 26 (95% CI [22, 31]), 88 (95% CI [74, 105]), and 148 (95% CI [124, 176]), respectively. Tukey multiple comparisons test was done between the surface roughness levels. The multiplicative effect on the mean from A1 to A2 and from A1 to A3 was significant at a significance level of 0.05. The multiplicative effect on the median of average G value from A1 to A2 is 3 (95% CI [2, 5]) while the multiplicative effect on the median of average G value from A1 to A3 is 6 (95% CI [4, 8]). Figure 22 provides a visual interpretation of the multiplicative effect on the median of average G value from A1 to A2 and A1 to A3.

This result supports past research concluding that the particles in the wet MPI method tend to settle in the valleys of the surface [17]. The higher the surface roughness the more particles collected in the surface texture of the area which then led to higher green intensity area as UV light was shone on the surface. However, the average G values computed from the results in Figure 21 cannot be directly used to indicate the noise area percentage that occurs during MPI testing when an indication is present. Flux leakage that occurs during MPI when a crack is present may pull the particles from the surrounding areas toward the crack, hence the noise (i.e., interference) in the area may not be the same as the average green intensity as evaluated by the average G value caused by the different levels of surface roughness. Further experiments with sub-surface indications were done to further understand the noise area percentage created by surface roughness in this situation.

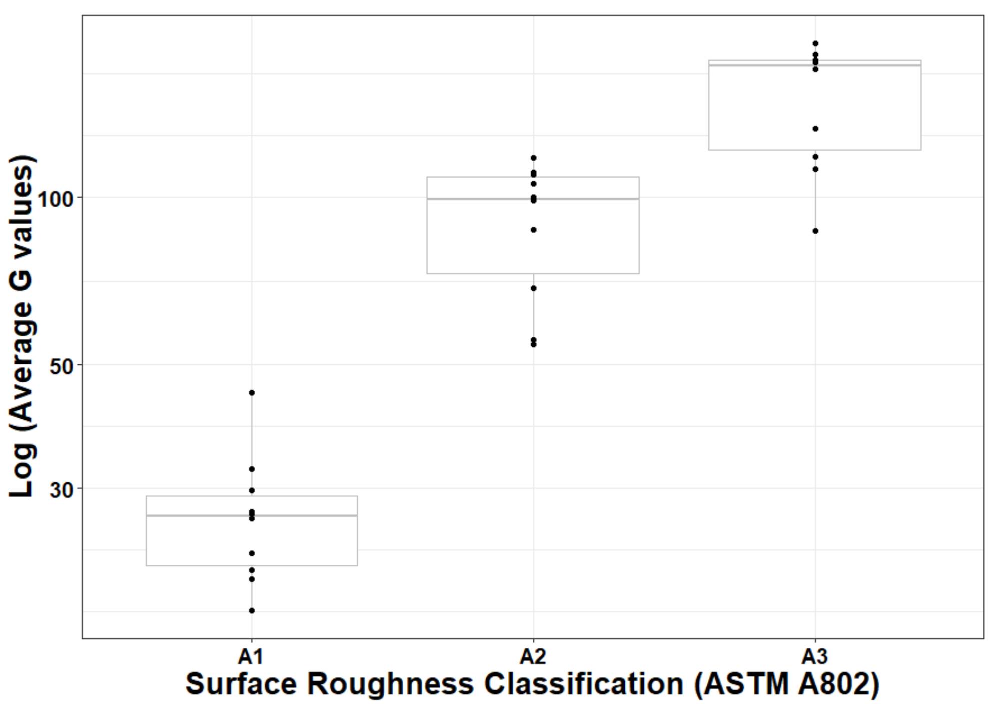


Figure 21. A Boxplot of the Average G Values of Three Surfaces

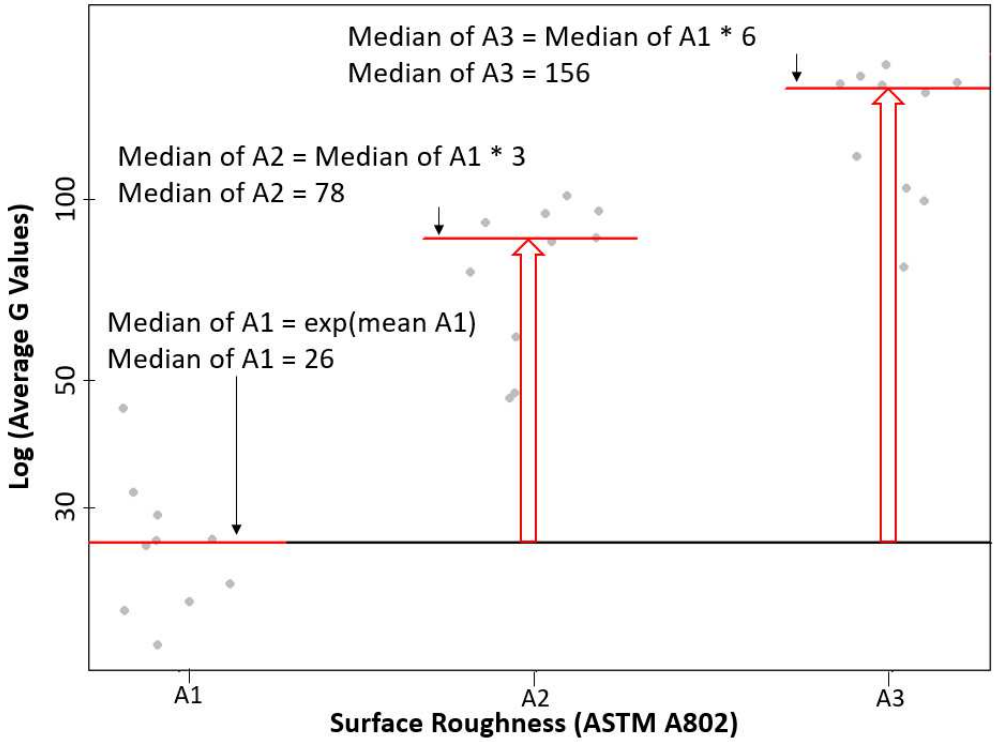


Figure 22. A Plot Illustrating Multiplicative Effect on Median

Experiments with Samples Containing Indications

Effect of Surface Roughness on Noise Area Percentage When Detecting a Common Sub-Surface Indication

The results from the experiment with no indication present indicate that particle collection on the surface texture increases as surface roughness increases. However, the purpose of this study is to determine the reliability of wet MPI when detecting indications. To determine the reliability of wet MPI when a common sub-surface indication is present, this study utilizes a metric called noise area percentage. Noise area percentage is measured by the calculating percentage of pixels in the surrounding area near the indication that has higher green intensity value compared to the average G value of the indication. The presence of an indication introduces magnetic flux leakage around the indication. If the flux leakage field strength is adequate, it will attract magnetic particles to the area of the flux leakage which will alter the noise area percentage [7]. Hence, the second experiment was designed to evaluate the effect of surface roughness on the noise area percentage when testing for a common indication. The indication that was manufactured was a hole with a depth of 0.254 mm (0.01 in) and a diameter of 1.78 mm (0.07 in) where surface roughness levels A1 to A4 were investigated. Due to the limited number of samples that were available, only three samples for each treatment were tested. The logarithm of noise area percentage against the surface roughness levels was plotted in a boxplot as illustrated in Figure 23.

A one-way ANOVA between surface roughness levels was conducted to compare the effect of surface roughness on the noise area percentage. The results show no significant influence of surface roughness levels on the noise area percentage at a significance level of 0.05 for the four levels, $F(3,8) = 3.261$, $p = 0.0805$. The estimated marginal means of the average G value for A1, A2, A3, and A4 are 16% (95% CI [7%, 36%]), 50% (95% CI [23%, 100%]), 29% (95% CI [13%, 64%]), and 65% (95% CI [30%, 100%]), respectively. Tukey multiple comparisons test was done between the surface roughness groups. The multiplicative effect on the median of noise area percentage from A1 to A2 is 3.07 (95% CI [0.66, 14.40]), the multiplicative on the median of noise area percentage from A1 to A3 is 1.81 (95% CI [0.39, 8.47], and the multiplicative on the median of noise area percentage from A1 to A4 is 4.03 (95% CI [0.86, 18.86]). The results of this exploratory experiment indicate that noise area percentage generally increases with surface roughness. The estimated marginal means of the noise area percentage of each surface roughness level can be found in Table 4.

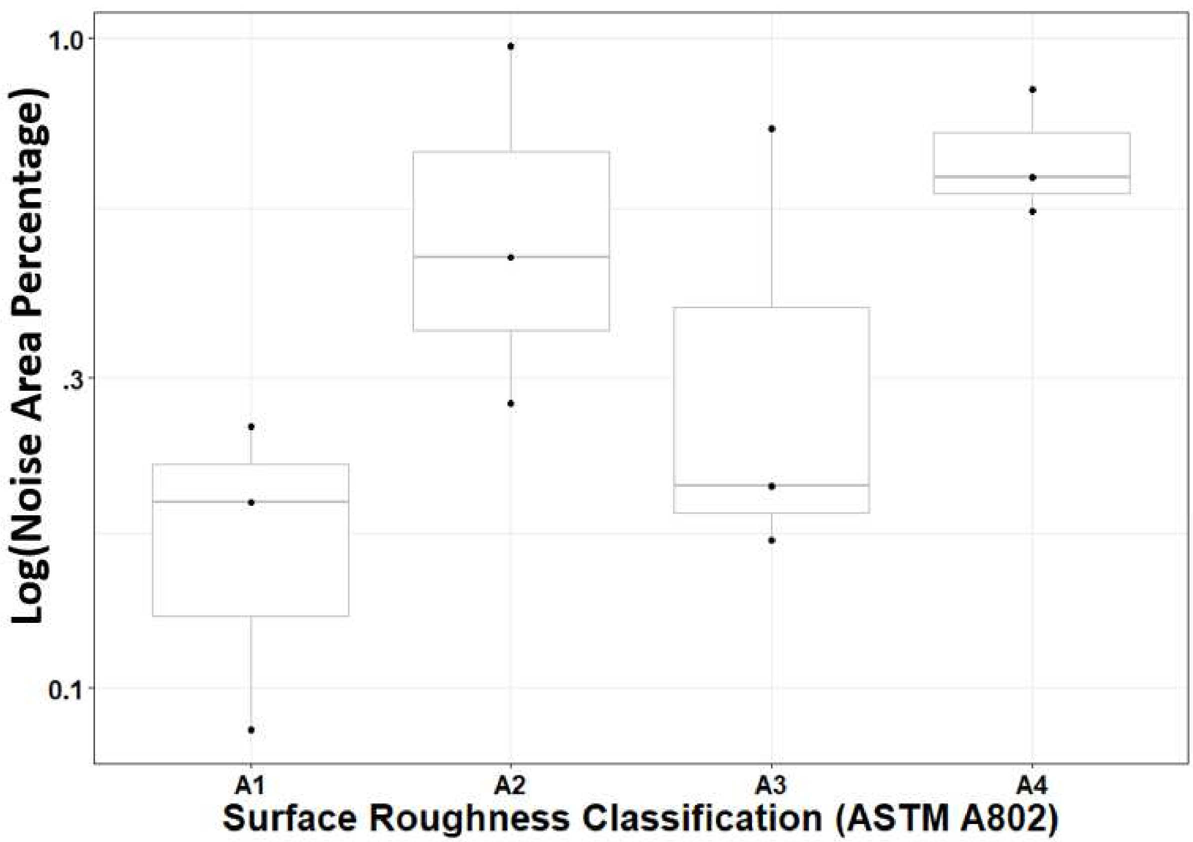


Figure 23. A Boxplot of the Noise Area Percentage for the Four Classifications of Surface Roughness for a Sub-Surface Indication with a Depth of 0.254 mm (0.01 in) and a Diameter of 1.78 mm (0.07 in)

Table 4. Estimated Marginal Means of Noise Area Percentage for Surface Roughness A1, A2, A3, and A4 for a Sub-Surface Indication with a Depth of 0.254 mm (0.01 in) and a Diameter of 1.78 mm (0.07 in)

Surface	Estimated Marginal Means of Noise %
A1	16% (7%, 36%)
A2	50% (23%, 100%)
A3	29% (13%, 64%)
A4	65% (30%, 100%)

This finding supports the hypothesis surface roughness affects the reliability of MPI [17], [22]. However, the median noise area percentage for surface roughness level A2 was higher than A3 which did not agree with the general trend. This discrepancy occurred because the difference between the A2 and A3 comparator plates for the ASTM A-plates standard were difficult to differentiate. This may have caused A2 surfaces to be classified as A3, and vice versa. Moving forward, an objective method for surface classification should be used to eliminate uncertainties between surface roughness levels. Overall, this shows a general increase in noise area percentage as surface roughness increases with the exception of A2. However, the results only indicate the effect of surface roughness on noise area percentage. Thus, the effect of surface roughness, depth, and diameter were investigated to enable comparisons between surface roughness and two main factors namely depth and size (i.e., diameter). The depth and diameter were chosen because past research states that the probability of detection of MPI depends on the depth and size of the discontinuity [41].

Effect of Surface Roughness, Depth, and Diameter on Noise Area Percentage When Detecting a Sub-Surface Indication

The movement of particles is affected by the flux leakage produced by the size, shape, orientation, and depth of the sub-surface indication which may play a role in the overall effect of surface roughness on the reliability of MPI. A hole was drilled parallel to the surface and was used as the sub-surface indication hence the shape and orientation were kept constant. The surface roughness, depth, and diameter were chosen as explanatory variables to understand better their relationship with the response variable (noise area percentage). Due to the limited number of samples and surface textures available, a 2^3 factorial design of experiments was conducted. The two levels of each factor tested were A1 and A4 for surface roughness, 1.78 mm (0.07 in) and 3.56 mm (0.14 in) for diameter, and 0.254 mm (0.01 in) and 1.78 mm (0.07 in) for depth to the top of the sub-surface indication.

ANOVA model was used with a logit transform on the response variable (noise area percentage) with the surface roughness, depth, and diameter as explanatory variables. Based on this model, Depth was found to impact noise area percentage the most ($p = 0.09$), followed by diameter ($p = 0.22$), and surface roughness had the least significant effect ($p = 0.72$). Table 5 shows the results from the ANOVA analysis.

Table 5. ANOVA Table

	Degrees of Freedom	Sum of Squares	Mean Square	F-value	P-value
Roughness	1	0.20	0.20	.14	0.72
Diameter	1	2.4	2.4	1.6	0.22
Depth	1	5.1	5.1	3.5	0.09
Residuals	12	17	1.5		

The estimated marginal means of the noise area percentage for surface roughness (A1 and A4) are 32% (95% CI [16%, 55%]) and 37% (95% CI [19%, 60%]), depth (0.01 in and 0.07 in) are 23% (95% CI [11%, 43%]) and 48% (95% CI [27%, 70%]), and diameter (0.07 in and 0.14 in) are 44% (95% CI [24%, 66%]) and 26% (95% CI [12%, 47%]). Tukey multiple comparisons test was done within categorical groups. The multiplicative effect on the median of noise area percentage from A1 to A4 is 1.13 (95% CI [1.04, 1.35]), the multiplicative on the median of noise area percentage from a depth of 0.01 in to a depth of 0.07 in is 1.88 (95% CI [1.05, 4.96]), and the multiplicative on the median of noise area percentage from a diameter of 0.07 in to a diameter of 0.14 in is 0.656 (95% CI [0.343, 0.847]). Noise area percentage (back-transformed from logit) against each factor, surface roughness, depth, and diameter, were plotted in a boxplot as illustrated in Figure 24, Figure 25, and Figure 26, respectively.

The results show that surface roughness did not show a difference on noise area percentage. This means that A1 and A4 surfaces have no differences in the ease of detecting an indication with the depths and diameters used in this experiment. As depth increases, there is a general increase in noise area percentage. This indicates the deeper the indication, the harder it is to detect it. Lastly, as diameter increases, there is a general decrease in noise area percentage. This indicates the smaller the indication, the harder it is to detect it.

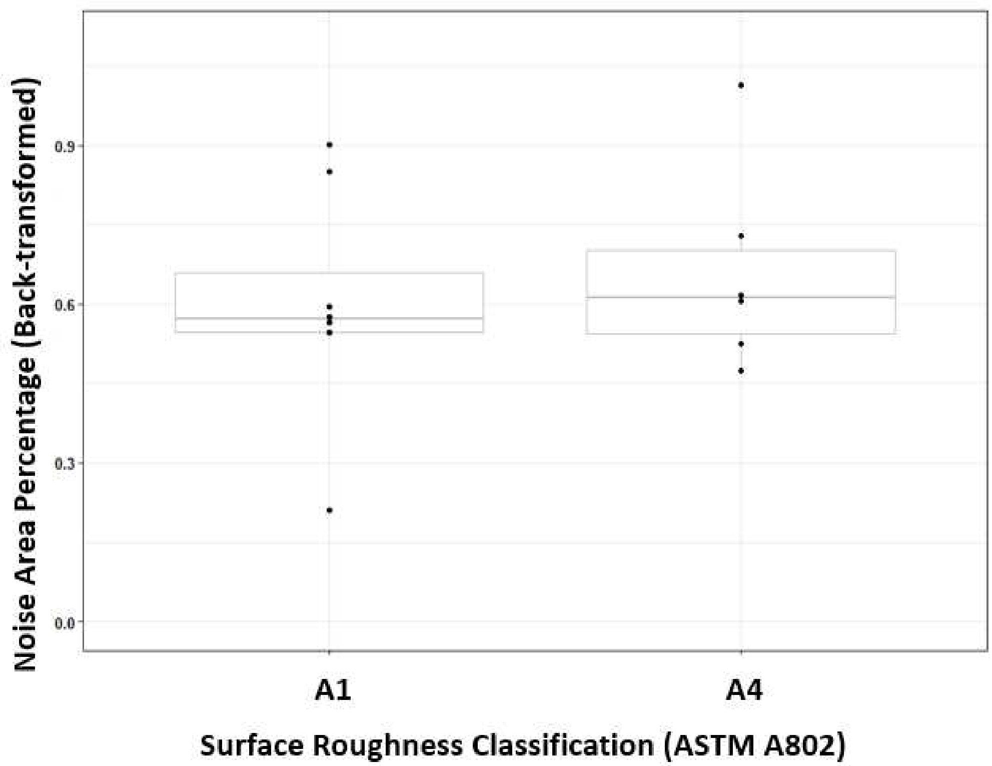


Figure 24. A Boxplot of Noise Area Percentage versus Surface Roughness across All Depth and Diameter

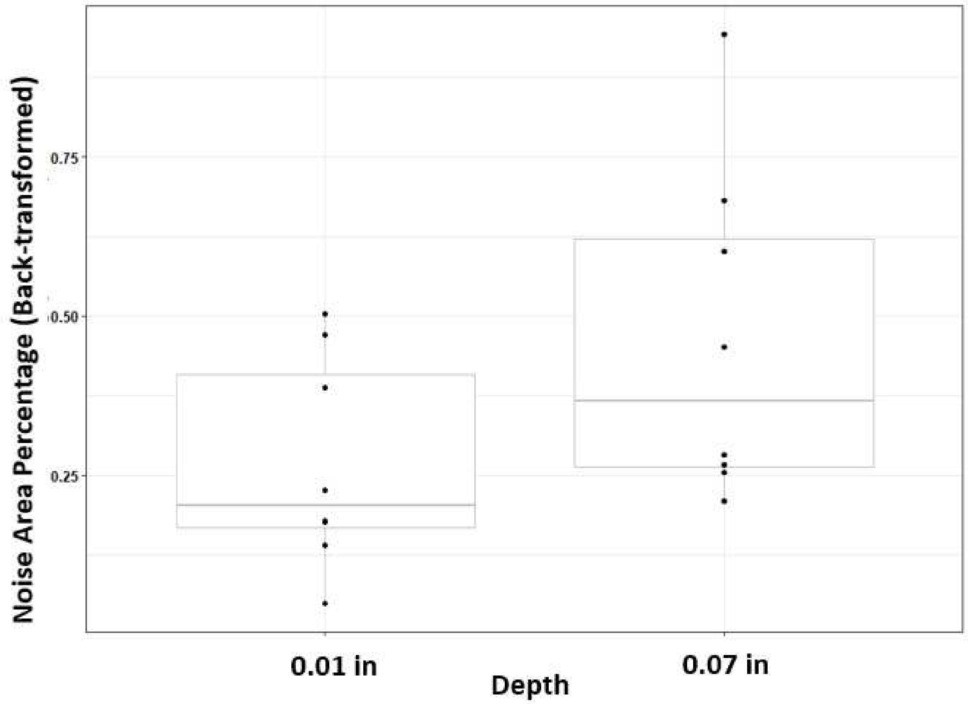


Figure 25. A Boxplot of Noise Area Percentage versus Depth across All Surface Roughness and Diameter

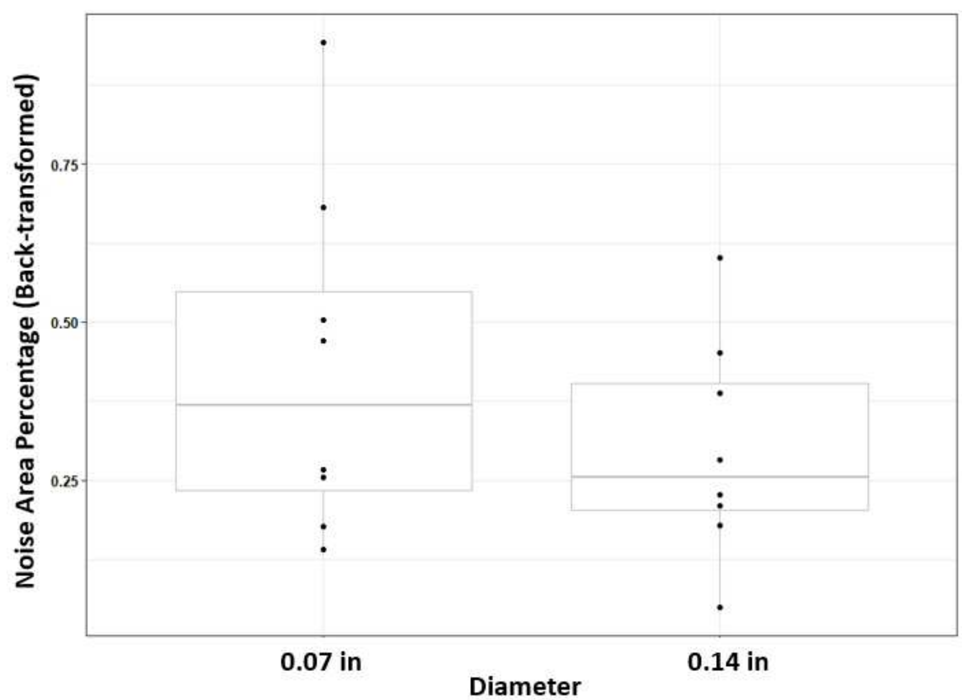


Figure 26. A Boxplot of Noise Area Percentage versus Diameter across All Surface Roughness and Depths

Plot A in Figure 27 shows the predicted point estimate and its prediction interval for all the surface roughness and diameter combinations when depth is at 0.254 mm (0.01 in). Plot B in Figure 27 shows the predicted point estimate and its prediction interval for all the surface roughness and diameter combinations when depth is at 1.78 mm (0.07 in). The wide prediction intervals are due to the small sample size (n=16). The plot suggests possible evidence of a difference in the depth and diameter. More experiments need to be done to increase confidence levels in the results. The larger diameter had generally lower predicted noise area percentage across all the combinations. Based on Figure 27, surface roughness does not show any trends in the predicted noise area percentage when comparing combinations of depths and diameters. The diameter showed a general decrease in predicted noise area percentage when going from 1.78 mm (0.07 in) to 3.56 mm (0.14 in) across all combinations of surface roughness and depths. The depth showed a general increase in predicted noise area percentage when going from 0.254 mm (0.01 in) to 1.78 mm (0.07 in) across all combinations of surface roughness and diameters. This means that the larger the size of the indication, the easier it is to detect the indication. Additionally, the closer an indication is to the surface of the part, the easier it is to detect the indication. Based on past research, the depth of a sub-surface indication is known to play a major role in determining the capability of wet MPI [4]. This result supports past findings indicating that the depth and size of an indication are the two main factors affecting the capability of wet MPI [37]. This finding illustrates the impact of surface roughness compared to depth and diameter. This exploratory experiment indicates that surface roughness has a minimal influence on the noise area percentage.

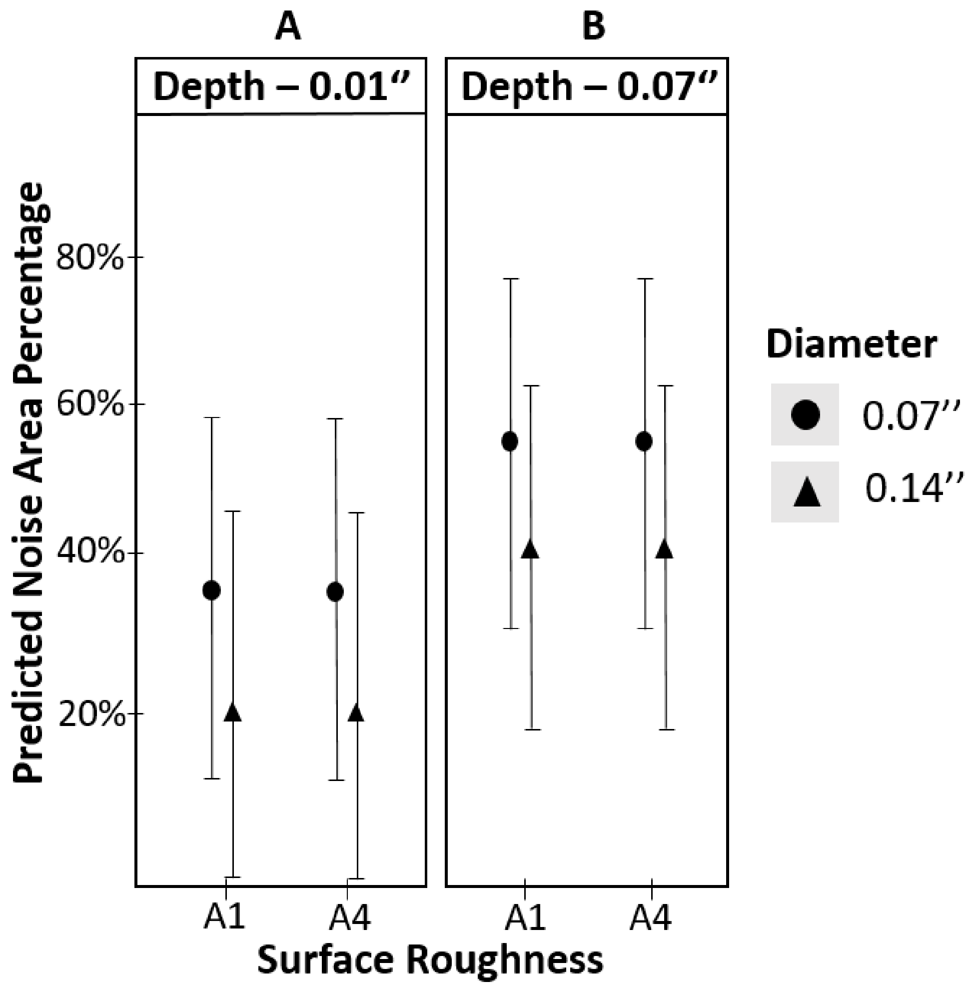


Figure 27. A) Predicted Values for Noise with All the Combinations of Roughness and Diameter at Depth of 0.254 mm (0.01 in); B) Predicted Values for Noise with All the Combinations of Roughness and Diameter at Depth of 1.78 mm (0.07 in)

Figure 28 shows the predicted noise area percentage plotted against all the treatment levels. It is interesting to note that in this plot for the same combinations of depth and diameter, A1 had generally less predicted point estimate of noise area percentage than A4 on average based on the model which can be seen by the bars sharing the same shade of gray in Figure 28. The plot suggests that the noise area percentage of indications that have the same depth and diameter may be affected by surface roughness. However, with a p-value of 0.72 is not statistically significant. Although the plot in Figure 28 seems to indicate a difference due to surface roughness, the variation of this difference remains in the variation of the error and combined with a small degree of freedom which resulted in a large p-value. This may indicate surface roughness is not significant relative to size and depth. Increasing the sample size would help improve confidence levels in results. Moving forward, it would be interesting to test surface-breaking indications where there is no depth and the width of the discontinuity needs to be tight-lipped for the indication to show up [34]. In this case, the depth will be a constant variable and the width will vary less hence surface roughness will have a different effect on noise area percentage.

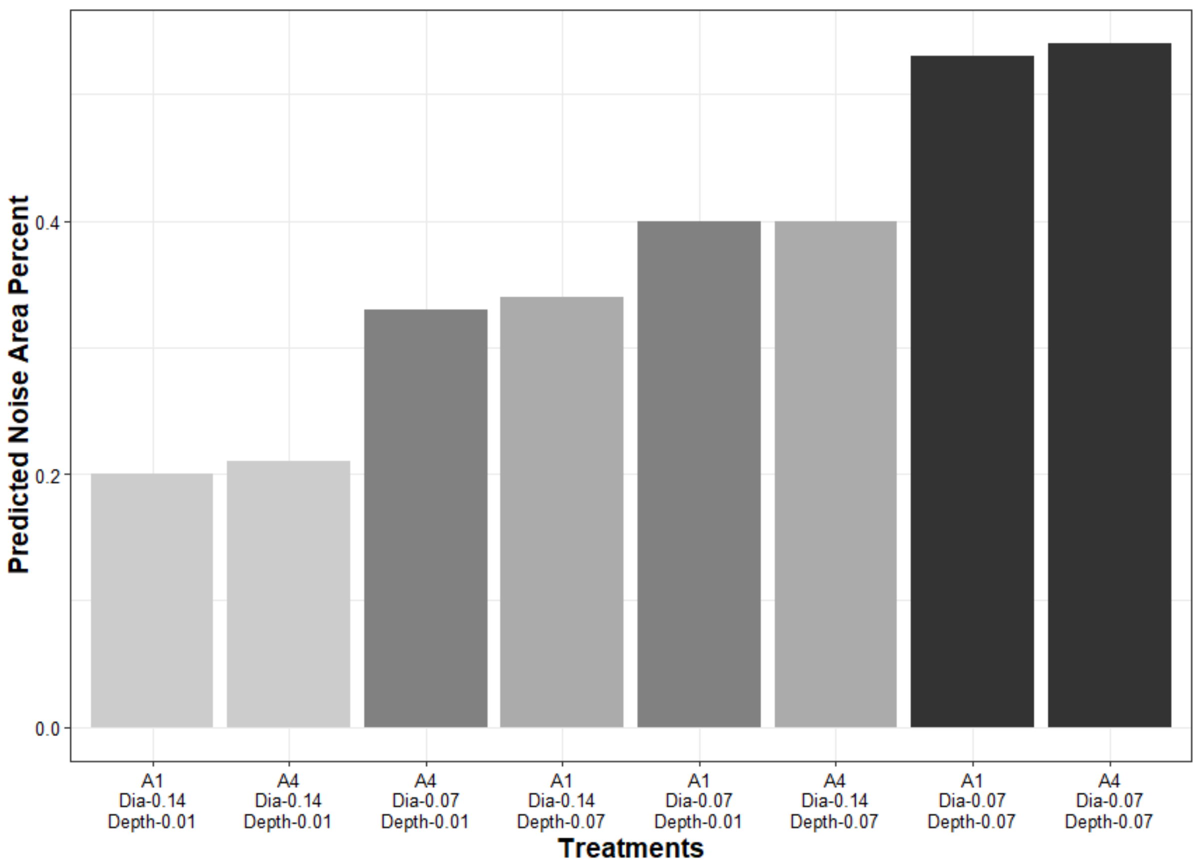


Figure 28. Predicted Noise Area Percentage versus All the Treatment Levels

CHAPTER 5. CONCLUSIONS AND FUTURE WORK

The Conclusions and Future Work chapter provides a summary of the findings, outlines the shortcomings of this research, displays future directions in this area, and shows the main contributions of this study. This chapter is broken down into three main sections which are the Conclusions, Limitations and Future Work, and Contributions. The Conclusion section highlights the important findings of this study that was conducted to explain the influence of surface roughness on the effectiveness of wet MPI. The Limitations and Future Work section shows various constraints in this investigation and recommends upcoming steps that could be taken to improve upon this research. Lastly, the Contributions section outlines the ways in which this research contributes to the area of wet MPI.

Conclusions

This study investigates the influence of surface roughness on the reliability of MPI for the detection of subsurface indications in steel castings. The findings shown in Figure 20 suggest that surface roughness has a significant effect (p-value = 1.48 x 10 ^ (-13)) on the collection of particles between surface texture levels A1, A2, and A3 when no indications were present. When a common indication is present, although no significant difference was shown between groups (p-value = 0.0805), a general increase is noise area percentage was displayed as shown in Figure 23. However, A2 surface roughness did not follow this trend which could have been caused by incorrect classification of surfaces as the A2 and A3 comparator plates are hard to tell apart. Next, two levels of depth, diameter and surface roughness, were investigated to compare their impact to the noise area percentage. This was done to compare the influence of each factor on the dependability of wet MPI. There was no significant differences found within the categorical variables of surface roughness (p-value =

0.72), depth (p-value = 0.09), and diameter (p-value = 0.22). In this investigation, the effect of depth and diameter of an indication were found to have more of an impact on the effectiveness of wet MPI when compared to surface roughness as illustrated in Figure 27.

Limitations and Future Work

There are several limitations in this study that should be addressed in future research. First, surface roughness was classified subjectively in this research due to a lack of automated surface roughness classification methods available for the casted surfaces. This created variability in the classification of surface textures in this study. Vision-based automated surface inspection systems for casted surfaces are still being developed to tackle this issue but face major challenges due to environmental and feature distinction factors [42]. Hence, the utilization of an objective method for surface roughness classification would yield better results for measuring the influence of surface roughness on the effectiveness of MPI tests. An objective method would provide continuous data for the measurement rather than categorical data for the surface texture. This would help create more distinction between surface textures. Second, the number of samples tested was relatively small which increased the variability in the results leading to less conclusive results. To address this issue, future researchers can increase the sample size. Furthermore, this study only looked at two levels of surface roughness, depth, and diameter. In the future, researchers should consider including more factors and levels that could affect the reliability of wet MPI. Increasing the levels of the factors studied would provide more clarity into the relationship between the factors and noise area percentage. Additionally, looking into different types of parts (e.g., composition and geometry) [43] and characteristics of sub-surface (e.g., shape and orientation) and surface breaking indications (e.g., length to width ratio and depth to width ratio) [34] would provide a deeper understanding of the effects of part and indication characteristics on wet MPI.

In this study, another limitation is the method of quantification. The method uses noise area percentage to gauge the reliability of wet MPI. However, taking the smallest rectangle around the visible areas as the average G value to represent the indication's average green intensity to compare to its surrounding area does not give a good representation to how a human operator identifies defects. Future studies into different methods of identifying the indication's average green intensity value could be done. For example, if the indication was linear, taking five linear points with the highest G values and averaging them. This could be a better way to simulate a human inspector doing MPI. Lastly, an acceptable and unacceptable criteria for noise area percentage was not established. Although a metric of noise area percentage was developed, which provided a measure for the reliability of wet MPI, the threshold for the level of noise area percentage that makes an indication undetectable was not determined. Multiple factors play into whether an indication can be detected, such as the characteristics of the part and discontinuity, human factors, and the system used (e.g., the equipment and process controls) [1], [2]. An experimental design to investigate which factors impact the ability to detect an indication should be completed to help narrow down the factors considered in determining the threshold for an acceptable and unacceptable criteria.

Contributions

Despite some limitations, this study developed a new technique for quantifying the influence of surface roughness, depth, and diameter on the reliability of wet MPI for the detection of sub-surface indications in steel castings. Previous research shows that surface roughness is expected to have an adverse influence on the reliability of wet MPI [17], [22]. However, a lack of objective data to support this belief has led to this investigation. This study has taken the next step by: developing a method for quantification of the effects of surface roughness on the dependability of wet MPI and providing data to help understand the influence of surface roughness on the reliability of MPI. Advantages to the technique created in this research are that the program: 1) is easy to use and understand, 2) can be utilized with all computer operating systems with an available C compiler, 3) can be applied to other NDT methods that utilize fluorescent coated particles, 4) provides a visual check of results with a post-processed image, and 5) provides objective evidence of the impact surface roughness has on the reliability of wet MPI.

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