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**Department of
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Modelling of Alloying Elements and Ageing Effects on Mechanical Properties of 6063 Aluminium Alloys

A Thesis Submitted in Partial Fulfilment of the Requirements for the
M.Sc.Degree in Engineering Management

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☐ Without making any changes to the thesis.

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Abstract

This study seeks to optimise the mechanical properties of the aluminium alloy 6063, taking into account the levels of alloying elements and artificial ageing heat treatment conditions. The aluminium alloys, particularly those belonging to the 6000 series, are known for their good mechanical properties, which include ductility, weldability, resistance to corrosion, and strength-to-weight ratio, the combination of preferred properties makes them suitable for wide diverse industrial applications. The study explores how the mechanical properties of 6063 aluminium alloys, measured as hardness (H), elongation percentage (%El), yield and ultimate tensile strengths (YTS) and (UTS), are dependent on the change in weight percentages of the following alloying elements Silicon (Si), Iron (Fe), Manganese (Mn), and Magnesium (Mg), as well as the difference in ageing temperature and time affects these mechanical properties.

This study utilised a hybrid experimental methodology with computational modelling tools using the application of Design of Experiment (DoE) and Response Surface Methodology (RSM) to investigate correlations between these alloying and ageing variables, together with the mechanical properties of the aluminium alloy. Numerical models were constructed to evaluate the mechanical properties as a function of the levels of these variables. The alloying and ageing conditions were optimised to meet the mechanical properties requirements using a combination of optimisation techniques, the desirability method and genetic algorithm (GA). The optimum conditions to maximise the mechanical properties of the 6063 alloy for Si, Fe, Mn, and Mg were found to be (0.559, 0.100, 0.012, 0.453) respectively. The optimum ageing temperature and time were found to be 175°C and 5.812 Hrs. The study findings illustrate how the different mechanical properties, such as hardness, ductility, UTS, and YTS, are affected by the variations and interactions of the alloying elements levels and the ageing conditions.

The study's conclusion and recommendations for future research work suggest an opportunity for more comprehensive studies on the influence of the change in alloy composition. It also suggests a wider investigation of the heat treatment processes the alloy undergoes before and after artificial ageing. Broader investigations have been suggested to provide a more compressive understanding of the factors that can be optimised to meet the requirements for different mechanical properties.

Dedication

I would like to dedicate this thesis and my work to my beloved parents, who have always provided me with support and encouragement throughout my life. Their belief in me, their sacrifices, and their prayers have been, are, and will always be the main reasons for my success and achievements.

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First, all praise is due to Allah for all his blessings on me. Without the blessings from Allah, I would not be able to achieve any of the work.

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List of Abbreviations

%El: Elongation Percentage

Al: Aluminium

ANN: Artificial Neural Networks

ANOVA: Analysis of variance

ASTM: American Society for Testing and Materials

BBD: Box-Behnken Design

BHN: Brinell Hardness Number

CCD: Central Composite Design

CHp: Cow Horn particles

Cr: Chromium

Cu: Copper

DoE: Design of Experiment

DSDs: Definitive Screening Designs

FDS: Fraction of Design Space

Fe: Iron

GA: Genetic Algorithm

H: Hardness

ME: Modulus of Elasticity

Mg: Magnesium

ML: Machine Learning

Mn: Manganese

MOGA: Multi-Objective Genetic Algorithms

RSM: Response Surface Methodology

Sc: Scandium

Si: Silicon

SI: Système International d'Unités

Sr: Strontium

SVR: Support Vector Regressor

Ti: Titanium

UTS: Ultimate Tensile Strength

VIF: Variance Inflation Factor

wt%: Weight Percentages

YTS: Yield Tensile Strength

Chapter One

Introduction

1.1 Background

1.2 Research Purpose

1.3 Problem Statement

1.4 Research Questions

1.5 Research Objectives

1.6 Research Plan

1.7 Thesis Outline

Chapter One

Introduction

1.1 Background

Due to the notable combination of mechanical characteristics, studies on aluminium alloys, like 6000 series alloys, have been of interest to several researchers. These alloys exhibit a combination of several desired properties that include ductility, an advantageous strength-to-weight ratio, favourable weldability, and corrosion resistance. Several alloys within the 6000 series, like aluminium alloys 6063 family, are preferred choices for different and multiple industries, including automotive, aerospace, and construction, due to their adaptable properties.

The characteristics of aluminium alloys are impacted by several factors, some of them related to the production processes and some to the different treatments the alloy goes through. For example, alloying elements like Mg or Si contribute to the ductility and strength. The ageing process conditions, which involve heating the alloy to a set temperature and maintaining it for a certain duration of time, also influence the microstructure of the alloy, which in itself leads to changes in the different properties of the material. The ageing heat treatment

In order to customise the aluminium alloy's characteristics to satisfy specific application needs, the different alloy properties should be optimised. Various modelling and optimisation approaches, including RSM and DoE, were used to do so. These statistical tools are used to investigate how the input variables and their interactions control the response variables. Optimisation techniques such as the desirability method and GA

have also been applied to determine the ideal combinations of variables to achieve the required mechanical characteristics.

The aim of the research is to provide a clear understanding of how alloying elements and artificial ageing affect the different mechanical characteristics of the aluminium alloy. In order to help produce high-performance aluminium alloys for various industrial applications, the research utilises modelling and optimisation approaches to determine the optimum variables combination that results in the desired mechanical properties.

1.2 Research Purpose

The study intends to understand the influence that the different alloying elements and ageing conditions have on the mechanical characteristics of aluminium alloy 6063. Obtaining this understanding will enable the enhancement of these characteristics to satisfy the different industries' requirements.

1.3 Problem Statement

This research addresses the problem of optimising the mechanical performance of aluminium alloy 6063. The wide use of these alloys in different applications in several industries with wide applications that require a combination of mechanical qualities such as tensile strength, ductility, and hardness. That keeps aluminium producers facing different customer requirements for the targeted combination of mechanical properties based on their industries' needs. The need arises to understand how to model and optimise the influence of different variables to meet the required combination of mechanical properties.

1.4 Research Questions

1. How do changes in levels of Si, Fe, Mn, and Mg impact the mechanical properties of 6063 aluminium alloy?
2. What are the effects of artificial ageing temperature and time on the mechanical performance of the alloy?
3. Do the interactions between the different alloying factors and artificial ageing factors influence the mechanical properties?
4. Can predictive models be developed to predict the mechanical properties of 6063 alloy considering the alloying elements levels and ageing conditions as independent variables?

1.5 Research Objectives

The objectives of the study are listed below:

1. To explore how the change in weight percentages of Si, Mg, Mn, and Fe impacts the strength, hardness, and ductility of aluminium alloy 6063.
2. To investigate how the ageing temperatures and time influence the mechanical properties of aluminium alloy 6063.
3. To produce numerical models that can estimate the mechanical properties taking the alloying elements levels and ageing conditions as input variables.
4. To optimise the developed models to target specific requirements of mechanical properties.

1.6 Research Plan

The research approach used to address the research problem and achieve the research objectives are as follows:

1. Conduct a literature review on the modelling methods of aluminium alloy properties, along with the impacts of alloying levels and ageing variables on different properties.
2. Develop experimental plan design using DoE and RSM.
3. Acquire samples of 6063 aluminium alloy and prepare them according to the defined experimental design.
4. Perform solution treatment and ageing processes on the prepared samples according to the experimental design.
5. Measure and calculate the mechanical properties of alloy samples, for example, strength, hardness, and ductility.
6. Develop numerical models based on the experimentally measured properties, then evaluate and validate the models.
7. Apply optimisation techniques to identify the best combination of alloying elements and ageing parameters under different requirements for the aluminium alloy mechanical properties.
8. Conclusion of findings to reach a better understanding of the mechanical behaviour of aluminium alloys.

1.7 Thesis Outline

The thesis study includes five chapters, and each chapter contains different sections and sub-sections.

Chapter one provides a summarised background regarding the research and presents the study objectives and plan.

Chapter two reviews the research related to studying how alloying elements, and heat treatment conditions, affect the characteristics of aluminium alloys. It starts by presenting the key characteristics of the 6000 series aluminium alloys through the literature. Then, the chapter reviews various modelling and optimisation techniques that were utilised in the

literature for the modelling and optimisation of aluminium alloy mechanical properties, including DoE, RSM, GA and desirability functions. This chapter concludes by viewing studies that investigated the impact of ageing and alloying levels on the mechanical qualities of aluminium alloys.

Chapter three lays out the details of the methodology that was used to study, model and optimise the effects of alloying elements and ageing variables on the mechanical properties of 6063 aluminium alloy. It presents details on the research design, including the variables and mechanical characteristics that were measured. This chapter also shows the experimental setup and the materials that were used. The chapter also presents the heat treatment processes and the mechanical testing for both tensile and hardness evaluations that the samples experienced. Then, the chapter presents the assumptions made in this study. Finally, the chapter discusses the numerical modelling and optimisation techniques that the study used to model and optimise the relationship of the alloying and ageing variables with the different properties of the alloy.

Chapter four represents the experimental findings and the discussions on the effects of the alloying elements levels and ageing variables on the mechanical characteristics of aluminium alloy 6063. It starts by presenting the experimental data. Then, it presents the validation of the assumptions made before. Subsections are divided based on different mechanical properties, each subsection discusses how the variables and the interactions between the variables affect specific mechanical properties. The chapter concludes with the conformation of the developed models and optimising the mechanical properties using the desirability method and GA.

Chapter five is the final chapter; it summarises the main findings of the research. It summarises the findings on how the alloying elements and artificial ageing conditions on the characteristics of aluminium alloy 6063. It also highlights the success of the modelling and optimisation strategies implemented during the study. Finally, it offers recommended suggestions for future studies.

Chapter Two

Literature Review

2.1 Introduction

2.2 Aluminium Alloy 6000 Series

2.3 Properties and Ageing Modelling

2.4 Alloying, Ageing and Mechanical Properties

2.5 Literature Review Conclusion

Chapter Two

Literature Review

2.1 Introduction

This chapter displays the literature that discussed the relationships between the alloying elements levels, the conditions of heat treatment, and the resulting characteristics of aluminium alloy 6063.

Section 2.2 presents the main characteristics of the 6000 series aluminium alloys, it shows that they are known to have a combination of properties like ductility, strength, corrosion resistance, and weldability. It gives an introduction to the fact that the different mechanical properties are influenced by different alloying elements and heat treatment processes.

The following sections discuss the modelling and optimisation techniques that the literature shows were used to model and enhance the mechanical properties of these alloys. Section 2.3.1 shows how the DoE and RSM could be used in modelling and optimising the properties of the aluminium alloys. Section 2.3.2 presents other advanced tools and methods, which have been used in the optimisation of aluminium alloy mechanical properties, including GA and desirability functions.

Section 2.4 presents recent findings obtained from studies on the effects of ageing and alloying elements on the properties of alloys. Finally, section 2.5 presents the conclusion to the literature review.

2.2 Aluminium Alloy 6000 Series

Due to the interesting mechanical properties that include ductility, strength, corrosion resistance, and weldability, the 6000 series aluminium family have become highly recognised and become an attraction to varied

industries (Georgantzia et al., 2021; Zhang et al., 2016). These different characteristics mentioned, and other properties may be influenced by the introduction of different alloying elements, they could be also impacted by the parameters of the heat treatment process, for example the ageing temperature and time (Krishnanunni et al., 2019; J. Ren et al., 2023).

Alloying is done through adding different elements such as Si, Mn, and copper (Cu) into the alloy, these different added elements form precipitates during heat treatment processes. These precipitates formed due to alloying elements could result in a considerable impact on several characteristics of the alloys. The precipitates get affected by the changes in the microstructure that happen during the ageing heat treatment process, which leads to effects on the properties of the material (J. Ren et al., 2023; Sekhar et al., 2019). Because of the effects of alloying and ageing, it becomes necessary to model and optimise the influence of the heat treatment cycle along with the impact of elements levels in order to achieve the desired balance between the required strength and required ductility or to reach various goals for the material properties (Krishnanunni et al., 2019; Vishwakarma et al., 2017).

2.3 Properties and Ageing Modelling

The modelling and optimisation of the characteristics of aluminium alloys and composite materials have been addressed and explored by researchers using different techniques and approaches. DoE and RSM are a few of the prominent approaches that were used to optimise heat treatment parameters for achieving desired mechanical properties. These statistical methods would enable the investigation of the impact of several variables and their interferences on the response variables, such as tensile strength and hardness, in a systematic way. Advanced optimisation

techniques using GA and desirability functions have also been employed to reach the optimal conditions for the ageing process. (Arslankaya, 2020; Razzaq et al., 2020).

2.3.1 DoE and RSM in Literature

Several researchers utilised the approach of DoE to model and study the properties of the aluminium alloys utilising statistical techniques.

Vembu et al. (2015) studied how the optimisation of heat treatment conditions led to the improvement of the mechanical characteristics of aluminium composite material. The study was based on the performance of a composite material of Al alloy 8011 and silicon carbide. The study used DoE which allowed the effective study of the parameter space, while the researchers developed predictive models applying RSM. The experimental design of the study was according to Central Composite Design (CCD), it contained twenty experiments for the systematic investigation of the influence of three key variables: solution treatment temperature, ageing temperature, and ageing time. The response variables modelled in the study were the tensile properties, specifically YTS, UTS, and microhardness. The ANOVA was used to evaluate the numerical models that were produced for the individual properties. Then, the optimality search was applied to these models to identify the best heat treatment conditions that lead to the maximum hardness and strength of the material. This study demonstrated the effectiveness of RSM in optimising complex processes and presented useful information on the heat treatment of aluminium metal matrix composites.

In their research, Mohammed Iqbal et al. (2016) focused on how to optimise the twist extrusion production variables of 6061 aluminium alloy. To achieve that the research utilised the RSM to produce models that cover

the relationship of the extrusion parameters, with the mechanical properties. The variables of the extrusion process were the temperature, forming load, and the number of passes. While the measured characteristics of the material were the tensile strength and hardness. The models established using RSM offered the researchers the optimal combination of process parameters that optimise the desired mechanical properties where the desirability function was used in optimisation by converting multiple responses into a single composite desirability value, which ranges from zero (completely undesirable) to one (fully desirable). The application of RSM in this study exhibited its success in modelling and optimising the different properties of aluminium alloys through process optimisation.

In Vishwakarma et al. (2017) study the focus was on using RSM to model and optimise the thermal performance of 6082 aluminium alloy through ageing conditions improvement. In this study, RSM was applied to carry out a systematic study of effects caused by solution time, ageing temperature, and ageing time on the aluminium alloy thermal characteristics. The material properties that were measured in the study were the thermal expansion coefficient and the thermal conductivity. The study utilised CCD composed of five levels of the input variables to develop models capable of calculating the thermal properties of the material using ageing parameters. The optimisation based on the developed models was implemented using the desirability function approach, which is used with RSM models to find out the optimal conditions that satisfy multiple criteria. The paper found that ageing temperature and time had a considerable impact on the thermal performance of the alloy that was studied. This study underscores the effectiveness of RSM and CCD in optimising complex processes and highlights the critical role of ageing parameters in determining the thermal properties of aluminium alloys.

Nwobi-Okoye and Ochieze (2018) researched age-hardening of an aluminium alloy A356 composite reinforced with cow horn particles (CHp). The study utilised the RSM and Artificial Neural Network (ANN) to model the hardness of the composite material. Three major variables involved in ageing temperature, ageing time, and weight percentage CHp were considered in this investigation. The two-level factorial design used in the study allowed the researchers to create a comprehensive model describing the interactions of these variables. It showed that increasing the ageing temperature and weight percentage of cow horn particles significantly enhanced the composite hardness. The model developed using RSM was a sound basis for understanding the relationships, which were complex and interacted between process parameters and mechanical properties. This work represents an effective employment of RSM in the modelling and optimisation of mechanical properties of aluminium composites.

Arif et al. (2018) study objective was to model the wear behaviour of zirconia-reinforced aluminium material. This was achieved through employing both statistical and artificial intelligence techniques for analysis. In the statistical approach, the researchers used a full factorial design to study the impact of three input variables on the composite material wear properties. The paper applied ANOVA to numerically measure how different process parameters impact wear loss. In the ANN approach to model the wear behaviour, a feed-forward back propagation neural network model was composed. The model showed very high efficiency in predicted values compared to experimental results, which proved that it is efficient in predicting wear behaviour. This paper aimed at effectively combining a statistical method and ANN modelling to analyse

and predict the tribological properties of zirconia-reinforced aluminium hybrid composites.

The primary goal of Shaikh et al. (2019) was to explore the performance of aluminium composite material through microstructure, mechanical, and wear analysis. To perform a thorough investigation on the influence of different variables on the composite material characteristics the study employed DoE. The percentage of reinforcement material and the wear parameters were the variables that the study focused on. The wear loss and hardness of the composite were the measured characteristics of the composite. This was statistically supported through the use of ANOVA in identifying the significance of the different parameters that affect wear loss, with the Taguchi method applied for the optimisation of these properties. While ANN model was developed to forecast the tribological behaviour of these materials, which demonstrated the efficacy of ANN in modelling such complex relationships between input variables and composite properties.

Goyal et al. (2019) study investigated modelling and optimisation of the tensile performance of 5086 aluminium alloy. It focused on the characteristics of the welded aluminium joints. The primary focus of the paper was formulating mathematical relationships that could predict UTS and elongation of the welded joints. In the paper, RSM was employed to model the impact of six input process variables on the UTS and elongation. To build the experimental plan a five-level CCD was chosen, which consisted of fifty-two experimental runs. The models developed were further validated using ANOVA and proved adequate. To optimise the process variables RSM was used with the objective of maximising the UTS and the elongation of the aluminium joints. The study symbolises a

successful application of RSM in the modelling and optimisation of the different characteristics of aluminium alloys.

Maboud et al. (2019) studied the optimisation of processed 1050 aluminium alloy using RSM. The research developed CCD to explore the impacts of main process parameters. Utilising RSM, the study developed regression models to forecast several characteristics of the aluminium alloy, they were %El, microhardness, YTS and UTS. The paper used ANOVA to ensure the model's accuracy and the reliability of the predicted values. This research shows the ability that RSM and CCD have to model and optimise the mechanical performance of aluminium alloys.

Ali et al. (2019) conducted research on the mechanical performance of 2026 aluminium alloy made through the squeeze casting process. The study's primary focus was on examining the impact of process variables on the surface quality and mechanical performance of the alloy. The process conditions that were taken into consideration were three variables. The researchers used RSM with CCD in the study for modelling of relationships between the process parameters and the mechanical characteristics of the alloy which were surface roughness, UTS, and hardness. The statistical significance of the process factors in the models and the model performance were analysed using ANOVA. To optimise the mechanical properties simultaneously the desirability was used as it allows optimisation for multiple and different responses. The results obtained in the study prove the effectiveness of this method in identifying the best settings of the control variables to improve the mechanical performance and surface finish of 2026 aluminium alloy produced through squeezed casting.

The research by Razzaq et al. (2020) took advantage of RSM to model and optimise several process variables that impact the response characteristics of aluminium alloys and their composites. In the paper, the CCD was employed to conduct an experimental plan to assess the impact of critical process parameters on the tribological performance of an aluminium composite. The paper considered wear rate and friction coefficient as the measured performance characteristics. The RSM was used to establish the relationships between inputs and outputs, the relationship models were validated with ANOVA, and RSM response surfaces with the desirability method were used to identify the optimal combination of variables for desired properties. The study showed that RSM is a valuable tool for modelling and optimising the tribological characteristics of aluminium composites.

Pouyafar and Meshkabadi (2024) researched the optimisation of the anodising process for 6063 aluminium alloy, with the aim of improving the mechanical performance of the alloy. The researchers in the paper used the RSM along with an experimental plan based on CCD to investigate important anodising process variables such as electrolyte concentration, anodising duration, and current intensity and their influence on the properties. The experimental plan consisted of three variables with five different levels and thirty experiments. The paper considered the thickness and hardness of the anodised layer of the material as the measured characteristics, The study's objective was achieved by developing quadratic models using RSM to predict the anodised layer characteristics. The model validation was achieved through using ANOVA, which assessed the significance of the variables and their interactions. Desirability method optimisation was employed to determine the recipe of anodising conditions to maximise the anodised layer thickness and hardness.

2.3.2 Artificial Intelligence in Literature

The mechanical performance of aluminium alloys has been extensively studied due to their significant applications in various industries. Optimising these properties as a function of ageing conditions and alloying elements is fundamental for enhancing performance. Several modelling techniques including different artificial intelligence-based techniques have been employed to predict and optimise these properties.

A notable study by Dey et al. (2016) used computational intelligence methodologies, specifically ANN and Multi-Objective Genetic Algorithms (MOGA), to model and optimise the tensile characteristics of aluminium alloys in different temperature regimes of ageing. The research needed a big dataset on the tensile performance of aluminium alloy across the 2000, 6000, and 7000 series to carry out the training of ANN models effectively. The paper employed the ANN models as objective functions in MOGA, which was then used to search for the optimal solutions that would balance high strength with adequate ductility. The integration of ANN and MOGA in this research provides a comprehensive framework for optimising mechanical performance and it also highlights the importance of large datasets in developing robust predictive models and highlights the potential of computational intelligence methods in alloy design.

Ganguly et al. (2016) study presented an approach to alloy design using ANN and a MOGA. The research focuses on the aluminium–magnesium–chromium–scandium alloy system (Al-Mg-Cr-Sc). The study utilised a dual-stage training approach for the ANN. Initially, a model was trained utilising a primary dataset containing eight hundred samples. The dataset consisted of variables like alloying elements composition (Mg, Sc, Cr), ageing temperature, and ageing time, with hardness as the resultant

property. The model was further refined in the second stage with the addition of a small experimental dataset consisting of sixty-sine samples. In this work the large data sets from the initial training phase were highly relevant for neural network generalisation capabilities, allowing property predictions within a wide window of composition and processing conditions

In their study Nwobi-Okoye et al. (2018) modelled the hardness of the aluminium composite with RSM and ANN techniques. The paper used a feed-forward multilayer perceptron network, The paper noted that the neural network showed higher accuracy than the conventional RSM. The network's inputs included the ageing temperature, composite material weight percentage, and ageing holding time, while the model output was the measured microhardness of the composite. The paper showed in the findings that the ANN model had a high correlation coefficient, significantly outperforming the RSM model. This high level of accuracy underscores the efficacy of ANN in predicting the mechanical performance of composites, making it a valuable instrument for optimising process parameters in material engineering.

Belayadi and Bourahla (2019) study focused on a producing model for assessing the mechanical properties of 7000 series aluminium alloy and classifying them into brittle or ductile. The research study used artificial intelligence through ANN to arrive at more decisive decision-making processes. The ANN model developed used the concentrations of seven elements as input parameters, along with six mechanical properties that were considered which were hardness, density, elongation, compressibility modulus, shear modulus, and the ratio of the compressibility over shear modulus. The model's output variable was categorising the alloys into two distinct classes: "hard and ductile" or "hard and brittle."

Sekhar et al. (2020) the research employed ANN in conjunction with MOGA to optimise the variables of the age-hardening process for 6063 aluminium alloy. The optimisation goal was to maximise the UTS and %El of the material. The study collected a large dataset of experimental results and existing literature data, focusing on a few variables: solution temperature and time, quenching rate, pre-ageing time, ageing temperature and time. This data was utilised in training the ANN model to produce interrelationships between these input parameters and the resulting UTS and %El. The MOGA was then utilised to generate Pareto-optimal solutions, effectively balancing the conflicting objectives of maximising UTS and %El.

Hu et al. (2021) study aimed to use a machine learning (ML) approach to anticipate the mechanical properties of wrought aluminium alloys. The study combined both the alloying elements concentrations and the manufacturing processes as variables to improve the accuracy of the mechanical properties anticipated that were measured as the output, such as YTS, UTS, and elongation. The support vector regressor (SVR) model that was used is a machine-learning algorithm characterised by its robustness and capability to operate with high-dimensional data. The database from which this study was conducted consisted of nine hundred thirty samples from the aluminium alloy handbook and other peer-reviewed literature, including all the information on thermomechanical processes like rolling, extrusion, forging, and heat treatment methods. This paper describes how ML models can predict aluminium product properties with the support of an extensive data set.

In their study, Srinivas et al. (2022) studied the performance of aluminium and Titanium diboride composites. The objective of the paper was to build a model capable to estimate the aluminium composites

hardness utilising ANN. The model proposed in the paper consisted of seventeen input variables and one response output. The input variables included variables such as concentration of elements, ageing temperature, ageing time, and the weight percentage of Titanium diboride particles reinforcement, while the response variable was the hardness of the alloy composite. The data set that was used to train and develop the model consisted of ninety-six samples. These samples had different heat treatment processes, including single-stage and multistage solution heat treatments, and artificial ageing at different conditions. The large size and variability of the dataset made this model quite accurate in predicting hardness over large sets of conditions, further highlighting the role of comprehensive data gathering in developing a reliable predictive model. The results highlighted how ANN might be employed to optimise the performance of aluminium alloys.

2.4 Alloying, Ageing and Mechanical Properties

In their study, Ozturk et al. (2010), examined the change in the mechanical performance of 6061 aluminium with respect to the change in the ageing treatment conditions. The paper focused on observing how the ductility, hardness, YTS and UTS of the alloy were impacted across different age-hardening circumstances. Hardness and yield stress were shown to rise with ageing time and reached a maximum under peak-aged conditions after two hours of heat treatment at 200 °C, in such conditions, the paper noted that the yield stress and hardness are grossly increased by the development of solute clusters and following precipitation. In the peak-ageing conditions the small, beta precipitates were very noticeable. These precipitates acted as optimal barriers for dislocations, enhancing the material's strength. The study showed that ductility and strength have inverse relationships and behaviour. The study noted that over-ageing led

to a reduction in strain-hardening capability and ductility. The research highlighted the role of microstructural changes during ageing in influencing the mechanical properties of aluminium alloy 6061.

Han et al. (2014) study focused on researching aluminium alloys that contained different contents of Mg and assessed what effect the change in heat treatment variables would have on the tensile properties of these types of alloys. Aluminium alloys with three contents of Mg were studied. The solution heat treatment of the alloys was conducted at different temperatures for different periods under different cycles, ranging between single, double, and triple-step cycles. The investigation results showed that the addition of 0.3 wt% Mg increased YTS by 37% and UTS by 22% while decreasing the elongation by 21%. This observation indicates that Mg had a bigger impact on enhancing the yield strength compared to affecting the UTS. It was observed that higher solution temperatures and longer durations generally improved the tensile properties by promoting the dissolution of strengthening phases and the clustering of Si particles. The study also noted that Si particles can enhance ductility and tensile strength when they become finer and rounder either by heat treatment or by the addition of Strontium (Sr). Another insight the study noted is that Fe increases the hardness of the alloy but significantly reduces elongation. The paper noted that if it reached above the Cu eutectic temperature, the solution temperature leads to melting of the Cu-containing phases and reduction of mechanical properties.

Jha et al. (2015) performed an experimental investigation into the mechanical characteristics of 6060 and 6061 aluminium alloys, focusing on the impacts of concentration of elements on the tensile strength, hardness, and microstructure. One main observation in the paper was that the addition of Mg up to 0.65% led to grain refinement which led to the

enhancement of mechanical properties. The investigation also pointed to the influence of other alloying elements, where the more the Mn concentration the higher the tensile strength was observed, as Mn contributes to the formation of Al_2Mn precipitates, which enhance the YTS and UTS without reducing ductility. The study mentioned that Fe is generally found in the composition of aluminium alloys, however, this element has an adverse effect on castability and ductility. It was mentioned the increase in Fe level lowers the value of the tensile strength, the paper justified this because of the intermetallic present in the material.

Dey et al. (2016) presented an in-depth investigation into the use of computational intelligence techniques for the design of age-hardenable aluminium alloys. Their work focused on the effects of various temperature regimes on the mechanical properties of such alloys, which were prepared from 2000, 6000, and 7000 series alloys. Ageing temperature was established to be one of the major variables influencing such properties. This is explained by the observation that increasing the temperatures of ageing generally tends to increase tensile strength and hardness, and on the other hand the increase in temperature inversely impacted the ductility measured as the percentage of elongation. The study also established that the addition of certain alloying elements, including Si and Mg, improved the age-hardening effects on the alloy. The addition of such elements forms fine precipitates which enhance the strength and hardness of the material. The study highlighted the relationship between ageing conditions, alloy composition, and the mechanical properties of aluminium alloys. The study provides an example of how understanding the previously mentioned relationships could be utilised in optimising the alloy design to target specific combinations of mechanical characteristics according to specific applications.

Toschi (2018) paper examined how different heat treatment conditions affect the microstructure parameters, hardness, and tensile characteristics of the A354 aluminium alloy. The paper noted that the ageing process plays a main part in improving the mechanical properties of the alloy. It showed that the peak ageing conditions lead to a considerable increase in hardness and tensile strength due to the formation of fine precipitate. It also showed that over-ageing resulted in a coarser precipitate, which is responsible for the loss of hardness and tensile strength and the increased ductility. Evidence presented here indicates the importance of optimising ageing conditions to get a proper balance between strength and ductility for these two aluminium alloys.

Tsamroh et al. (2018) researched and investigated the heat treatment parameters optimisation in Al-Cu alloys using the Taguchi method, the heat treatment parameters that were investigated were the ageing temperature, ageing time, and the number of ageing stages. Then, a three-level factorial design was employed to vary the ageing parameters systematically. An experimental design was developed in pursuit of the improvement of hardness and toughness of the alloy measured by impact value, which are critical properties for application in both automotive and aircraft industries. The results obtained showed that for maximum hardness and toughness, the temperature should be 200°C, the holding time six hours, and the artificial ageing of two stages. The most influencing parameter for ageing was the ageing temperature, the second was ageing holding time, and the least influencing parameter was the number of ageing stages. This research underlines the possibility of making use of a systematic experimental design with the aim of fine-tuning the process of ageing and hence improving the properties of materials with a view to their industrial application.

Engler et al. (2019) performed a study on the Al-Mg-Si alloy 6016 to investigate the effects of different types of age-hardening process on the formation of the metallic precipitates and mechanical properties of the alloy. It showed that the alloy's mechanical performance, including YTS and UTS, was closely correlated with the size and density of the precipitates formed during ageing. It also noticed that artificial ageing at 185°C led to a peak hardness and strength after five hours of ageing time after which over-ageing started which reduced the strength.

In the study of optimisation of aluminium alloy 6063 ageing parameters conducted by Sekhar et al. (2020) it was observed that slow quenching after solution treatment and high pre-ageing time were critical for achieving a balance between strength and ductility. It was also found that higher ageing temperatures and longer ageing times improved ductility, while lower temperatures and shorter times resulted in higher tensile strength.

Chen et al. (2021) objective was to study the impact of the ageing process on the structural characteristics and mechanical performance of aluminium alloy 6061 sheets cast and rolled products. The sample solution treatment was performed for two hours at 550°C, after which it was quenched in water, and then finally it went under different artificial ageing cycles. The ageing temperature ranged between 160 to 200°C. While the holding time of the cycles was between zero and forty-eight hours. The maximum UTS was observed by six hours of artificial ageing at 200°C which was UTS 318 MPa, elongation 14%, and hardness 127 HV. The study showed that with the rise in ageing temperature, the time to attain peak ageing goes down, and for ageing temperatures of 160, 180, and 200°C, the peak ageing was attained in twenty-four, sixteen, and six hours, respectively. With an increase in ageing temperature, the strength of the

alloy improved, as for the highest ageing temperature of 200°C, the peak ageing strength was maximum. The microstructural analysis and detailed study explained these effects by stating that the ageing process leads to the formation of Mg_2Si inclusions and beta phase participates, which contributes to its enhanced mechanical properties.

In the research done by Aksoz et al. (2023) the primary objective was to examine how the ageing heat treatment impacts the mechanical properties and natural frequency of aluminium alloys 2024, 6061, and 7075. The study aimed to understand how the change in the heat treatment process influences hardness and natural frequency. This study showed that ageing heat treatments remarkably develop the hardness of the applied alloys, while it observed that the ageing did not result in notable changes in the natural frequency. The study described the observed influence that heating effects had, considering that an increase in hardness is associated with the formation of precipitates such as Al_2Cu , Mg_2Si , and Al_2CuMg during the ageing process. This formation of precipitates enhanced the material's strength by obstructing dislocation movement. Regardless of the microstructural changes, the natural frequency values remained largely unaffected, suggesting that the ageing process primarily influences hardness without altering the material's vibrational behaviour. This study provides valuable insights into the relationship between heat treatment variables and the mechanical performance of aluminium alloys.

Xiang et al. (2023) conducted a study to examine the influence of different ageing treatments on the mechanical properties and microstructure behaviour of aluminium alloy 7003. The primary objective was to illustrate how various ageing cycles affect the yield strength, elongation, and the microstructural features that develop in this alloy. It was realised in the study that ageing enhances yield strength, while

multiple-cycle ageing is associated with considerable reductions in elongation. These changes were attributed by the study to the evolution of the second phase, which participates within the grain structure. The study underlines the relationship between ageing treatments and the resultant mechanical characteristics, offering important views for the optimisation of aluminium alloy performance by means of controlled heat treatment processes.

Yin et al. (2023) explored the effects of varying the ageing treatments on the hardening characteristics of 6151 aluminium alloys. The heat treatment process in the experimental study started with solution treatment performed at 550°C then water quenching. Then the ageing treatments, pre-ageing was executed at temperatures of 80°C, 100°C, and 120°C, followed by artificial ageing at 160°C, 180°C, and 200°C with different ageing holding times. The primary variables studied included pre-ageing temperature, artificial ageing temperature, and ageing time, while the hardness was the response-measured mechanical property. Pre-ageing was observed to enhance the artificial ageing hardening response more than natural ageing. It was shown that the maximum hardness value obtained was 134 HV after pre-ageing at 120°C and artificial ageing at 200°C for forty minutes. It was found that hardness increased with the increase in artificial ageing holding time and temperature up to a certain point beyond which over-ageing occurred with a drop in hardness. This study's findings and observations provide a useful reference for future studies and industrial applications aiming to improve the performance of aluminium alloys through optimised ageing processes.

Singh et al. (2024) focused on examining the impact that heat treatment cycles have on the characteristics of 6082 aluminium alloy. The paper aimed at improving the mechanical performance of the aluminium

alloy through optimising the variables of different treatments, the paper addressed both the solution treatment stage and ageing. The study conducted experiments at different temperature ranges and various holding durations at both solution treatment and artificial ageing, in order to identify optimal conditions that can provide the desired tensile strength, hardness and ductility. The study observation revealed that the peak artificial ageing conditions were at 205 °C after six hours, which resulted in a notable increase in the material strength from 154 MPa before ageing to 280 MPa, and the hardness rose from 65 BHN to 102 BHN. The microstructural analysis showed that the improvement in tensile strength and hardness resulted from the precipitation of dissolved elements. It further showed that ductility was reduced, and this could be credited to enhanced brittleness from the fine-grained and precipitation-hardened structure. This study illustrates the possible role that optimisation of precise heat treatment parameters may play in managing the different mechanical properties of an aluminium alloy for specific industrial applications.

2.5 Literature Review Conclusion

The literature highlights that it is important to understand the effects of alloying elements levels, heat treatment conditions, and their interactions to ensure meeting the desired properties of aluminium alloys. It discusses the importance of alloying elements, including Mg and Si, which produce strengthening precipitates that undergo some changes during and after the heat treatment processes, which lead to property changes in the alloy.

The literature review reveals that controlling the heat treatment conditions, and the alloying elements levels is crucial for the optimisation of the mechanical properties to meet the desired criteria. Several methods

have been proven to be successful in studying and modelling the relationship between the aluminium alloy mechanical properties, alloying elements levels, and heat treatment conditions. Among the various methods are DoE, RSM, and the advanced approaches of artificial intelligence which include ANN. As for optimisation techniques utilised to optimise these relationships, the literature reveals that desirability methods and artificial intelligence approaches like GA have been shown to be effective in optimising the mechanical properties of aluminium alloys.

The review shows how the role of experimental approach and computational modelling approaches could be utilised to optimise the performance of aluminium alloy to desired applications. The methodology will utilise the experimental approaches and optimisation techniques identified in the literature for modelling and optimisation.

Chapter Three

Research Methodology

3.1 Introduction

3.2 Research Design

3.3 Material

3.4 Heat Treatment

3.5 Mechanical Testing

3.6 Numerical Modelling Using RSM

3.7 Optimisation Using Desirability and Genetic Algorithm

3.8 Assumptions

3.9 Methodology Conclusion

Chapter Three

Research Methodology

3.1 Introduction

Chapter three outlines the research methodology that was employed to explore of the impact of alloying elements and artificial ageing on the mechanical performance of 6063 aluminium alloy. The sub-sections in section 3.2 describe the research design which covers the factors, responses measured, and the experimental plan while section 3.3 covers the materials. Section 3.4 describes the heat treatment performed in the experimental work, while section 3.5 includes the mechanical testing procedures to be applied for tensile and hardness tests. The approach to numerical modelling is discussed in section 3.6. Section 3.7 discusses the optimisation techniques applied. Section 3.8 closes this chapter with the assumptions made in this study. Finally, the conclusion of the methodology is provided in section 3.9. While addressing these aspects, the chapter presents a view of experimental and analytical approaches toward the realisation of research objectives.

3.2 Research Design

The research objectives are to develop numerical models to predict and optimise the mechanical properties of the 6063 Al alloy after examining how the alloying elements levels and artificial ageing effects these properties.

3.2.1 Factors and Responses

The mechanical properties of the alloy that are measured in the research are the YTS, UTS, Modulus of Elasticity (ME), %El and H. The

YTS and UTS provide the necessary information on the alloy's performance under loads and the ability to withstand permanent deformation. While ME offers an indication of the alloy stiffness and elastic behaviour and %El provides an indication of the material ductility and ability to undergo plastic deformation. The H offers information on the resistance of the alloy to wear and surface deformation.

Artificial ageing is represented by the ageing temperature and the ageing time, which refers to the temperature at which the ageing is done and the duration of the holding at ageing respectively.

The alloying elements considered in the research are Fe, Si, Mg, and Mn. These four alloying elements had the biggest weight percentages and widest range, another two alloying elements were to be considered which are Cu and Cr however their ranges were very narrow in the alloy 6063 product family in the production facility so it would be very difficult to include in the experiment and control, because the experiments were to be designed according to the available alloys.

3.2.2 Experiment Plan

To develop an effective test plan or DoE the software Design Expert was utilised. This software can be used to produce the best DoE based on the user objective. Factorial designs can be used If the objective is screening to reduce the number of factors or study the cause-and-effect relationships. If the objective is to study and produce a formula of factors whose sum is always equal to one on a response property, then the mixture design is to be used. If the objective is to minimise, e or hit a target by finding the best combination of factors then the response surface designs are to be used.

The response surface method (RSM) is a suitable design for the research objective because the influence of the factors is to be studied on the responses while their sum is not equal to one and there are the ageing factors that cannot be summed with the alloying elements factors.

The RSM can be used with different types of design, to choose from the RSM different designs trial and error process was used. After trial and error, RSM based on CCD was chosen, it is flexible and enables the estimation of all interaction and quadratic terms, offering a thorough understanding of the response surface. (Chen et al., 2021). It provides a design that ensures reliable results across the space of the experiments as it is rotatable. (Xiang et al., 2023). Other designs had some advantages like the Box-Behnken Design (BBD) which does not include points at the extreme levels of the different factors which could limit the ability to study the full range and lead to less effectiveness than CCD. Also, Definitive Screening Designs (DSDs) could be used to study quadratic and interaction effects for up to numerical three factors but are not so efficient for more numerical factors and are not powerful in including the linear effects. There were also the Split-plot designs within the RSM that could be utilised to restrict the randomisation of certain factors by allowing them to be hard to change which is not what the research requires.

The CCD was used to produce an experimental design to study the influence of six factors, four of them are alloying elements weight percentage and two of them are the ageing cycle parameters as shown in Table 3.1, the factors varied over three levels the minimum and maximum are provided by the aluminium production company and the third is the mean as per the design.

Table 3.1: Different factors and their levels.

Parameter	Symbol	Unit	Level 1	Level 2	Level 3
Si	Si	wt%	0.40	0.60	0.80
Fe	Fe	wt%	0.12	0.16	0.20
Mn	Mn	wt%	0.01	0.04	0.07
Mg	Mg	wt%	0.45	0.55	0.65
Ageing temperature		° C	175	192.5	210
Ageing time		Hr	4	8	12

The DoE produced using the CCD composed of thirty-nine runs including five replicated points at the centre points to improve the accuracy near the centre. The DoE was evaluated considering the standard error, Variance Inflation Factor (VIF), R^2 , lack of fit, pure errors, and Fraction of Design Space (FDS) graph, then the DoE was compared with the aluminium production company product profile to ensure that all the runs can be performed using their 6063 alloy products.

The DoE met the criteria, where the standard errors were similar to each other and the lower the error the better design, the VIF values were close to one which is the ideal value and they did not reach the ten value which is the concern value, the R^2 that reflects the correlation between factors were acceptable and they were not high values which indicate that the factors are not too correlated. The lack of fit and pure error criteria suggested by the software to ensure an adequate model was met by having more than three lack of fit degrees of freedom and at least four pure error degrees of freedom. The FDS graphs used to evaluate the prediction error of the design by showing the volume of the design space that has a prediction variance less than or equal to the required value, for optimisation exploration the software guidelines suggest at least a score of 0.8 which was met by the proposed DoE. The last criterion was met by

ensuring that the product of the company providing the samples can cover the DoE.

The material used in this research to fabricate the samples for the tensile and hardness test was aluminium alloy 6063. The material was received as slices cut from extrusion ingots or billets as shown in Figure 3.1 below. The aluminium production company has already tested the material composition using atomic emission spectrometry.

Figure 3.1: Aluminium slices received before treatment.

Table 3.2: Alloy 6063 homogenisation parameters.

Alloy	Solution Temperature (° C)	Solution Time (min)	Quenching	Cooling
6063	540	45	Water	Natural Air

3.4 Heat treatment

Based on the DoE the aluminium slices are requested from an aluminium production company, the company provided the best match they can find in their product to the suggested based on the DoE. As mentioned before the sample slice goes through three stages:

First the solution treatment stage according to the parameters in Table 3.1.

The second stage is the cooling stage for twenty-four hours in natural flow air.

The third stage is the artificial ageing stage according to the temperature and time based on the DoE.

The heat treatment was done using an electric oven shown in Figure 3.2. To ensure following the heat treatment parameters several points need to be considered.

The first point is that the furnace needed one hour to reach the set temperature therefore that hour is not regarded in the time measurement.

The second point is the aluminium slice needed time to reach the set temperatures, as Figure 3.3 shows the difference in the furnace temperature and slice temperature, so a thermocouple was used to measure the slice's actual temperature, and the time was measured from the time that the slice reached the set temperature for both solution and ageing.



Figure 3.2: The electric furnace used in heat treatment.



Figure 3.3: Temperature readings for furnace and slice.

3.5 Mechanical Testing

After finishing the heat treatment of the aluminium slices based on the DoE three cuboids were cut from each slice using a bandsaw machine as shown in Figure 3.4. The cuboids were then machined using a lathe machine which is shown in Figure 3.5 to produce samples for both tensile and hardness testing as shown in Figure 3.4.

In order to evaluate the mechanical properties of the aluminium alloy tensile test and hardness test was performed.

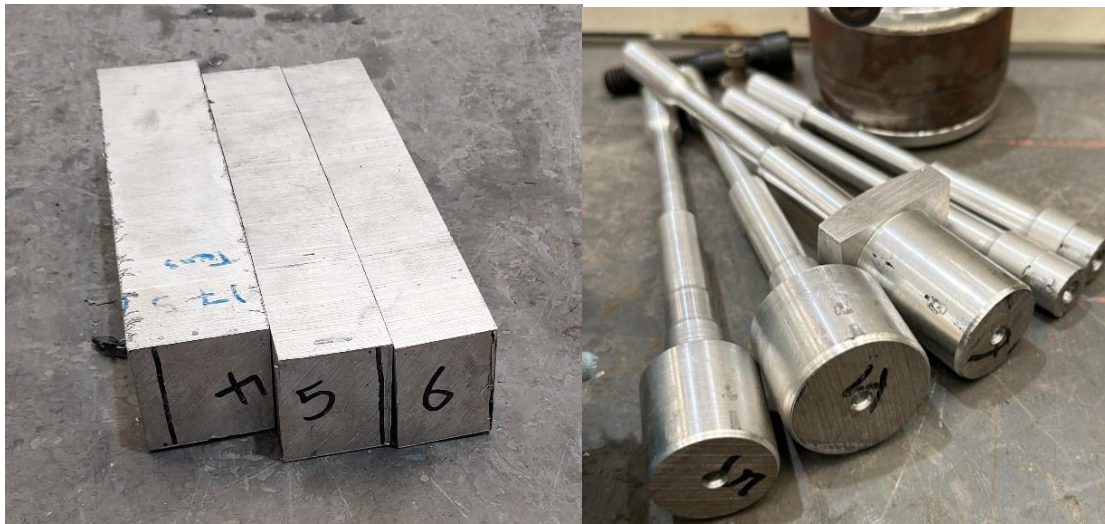


Figure 3.4: Aluminium cuboids after heat treatment, and machining.

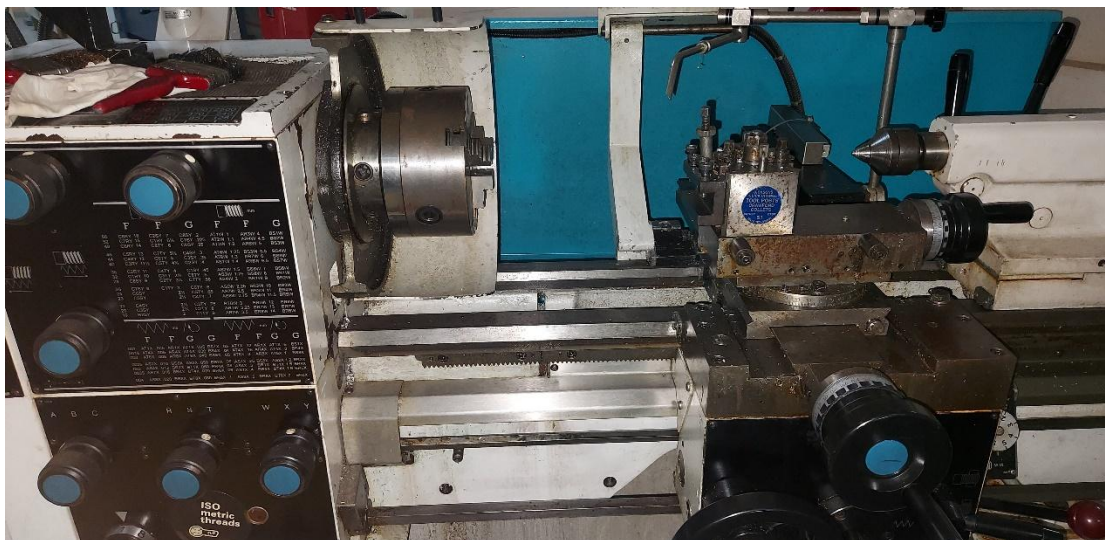


Figure 3.5: The lathe machine used for sample machining.

3.5.1 Tensile Test

The tensile test was executed on the specimen according to the ASTM-E8M standard which covers the procedure of uniaxial tensile test on metallic specimens at room temperature using SI units. The schematic and dimensions of the specimens that were used in the tensile test are shown in Figure 3.6 and Table 3.3. The specimens' tensile testing was conducted on the MTS Criterion Model 45 tensile testing machine which is shown in Figure 3.7. The tensile test was conducted at a constant crosshead speed of 0.2 mm/s and the load (KN)- displacement (F- δ) data was recorded. The load-displacement data was converted to stress-strain (σ - ϵ) data as shown in Equations 3.1 and 3.2.

$$\text{Stress} = \sigma = \frac{4 \times 1000 \times F}{\pi D^2} = \text{Mpa} \quad \text{Equation (3.1)}$$

$$\text{Strain} = \epsilon = \frac{\delta}{A} = \text{dimensionless} \quad \text{Equation (3.2)}$$

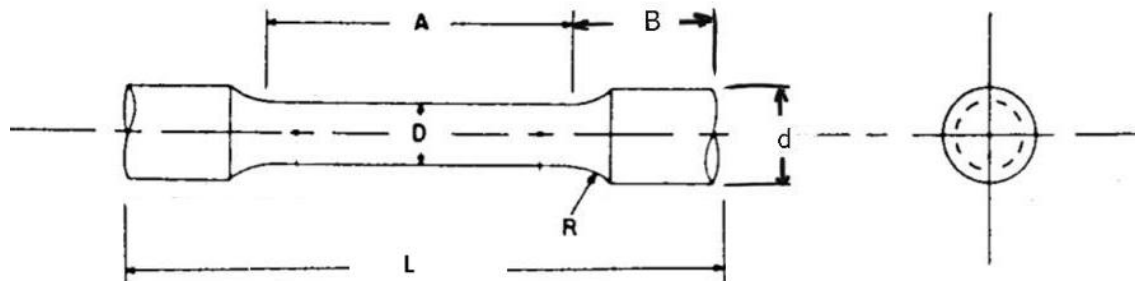


Figure 3.6: Round tensile test specimen schematic.

Table 3.3: Tensile specimen dimensions.

Section	Guage diameter	Grip diameter	Guage length	Grip length	Total length	Filet radius
Symbols	D	d	A	B	L	R
Dimension (mm)	9	14	54	38	130	8



Figure 3.7: MTS Criterion tensile testing machine.

The tensile test results data were used to evaluate the following properties: ME, YTS, UTS and the %El.

3.5.1.1 Tensile Strengths and Modulus of Elasticity

The stress and strain curve can be used to evaluate ME, YTS and UTS as shown in Figure 3.8. The ME can be evaluated by calculating the slope of the linear portion of the stress-strain curve. While the UTS is calculated by locating the maximum stress either from the plot or the data. The YTS can be evaluated using the 0.2% offset method, by plotting an offset line parallel to the linear region by 0.002 and finding its intersection with the stress-strain curve as shown in Figure 3.8 which shows an example of finding YTS in one of the samples. To evaluate the samples' ME, YTS and UTS properties a MATLAB code was built and used to plot the stress-strain

curve for each sample and evaluate the three properties, the code sample is available in Appendix 1.

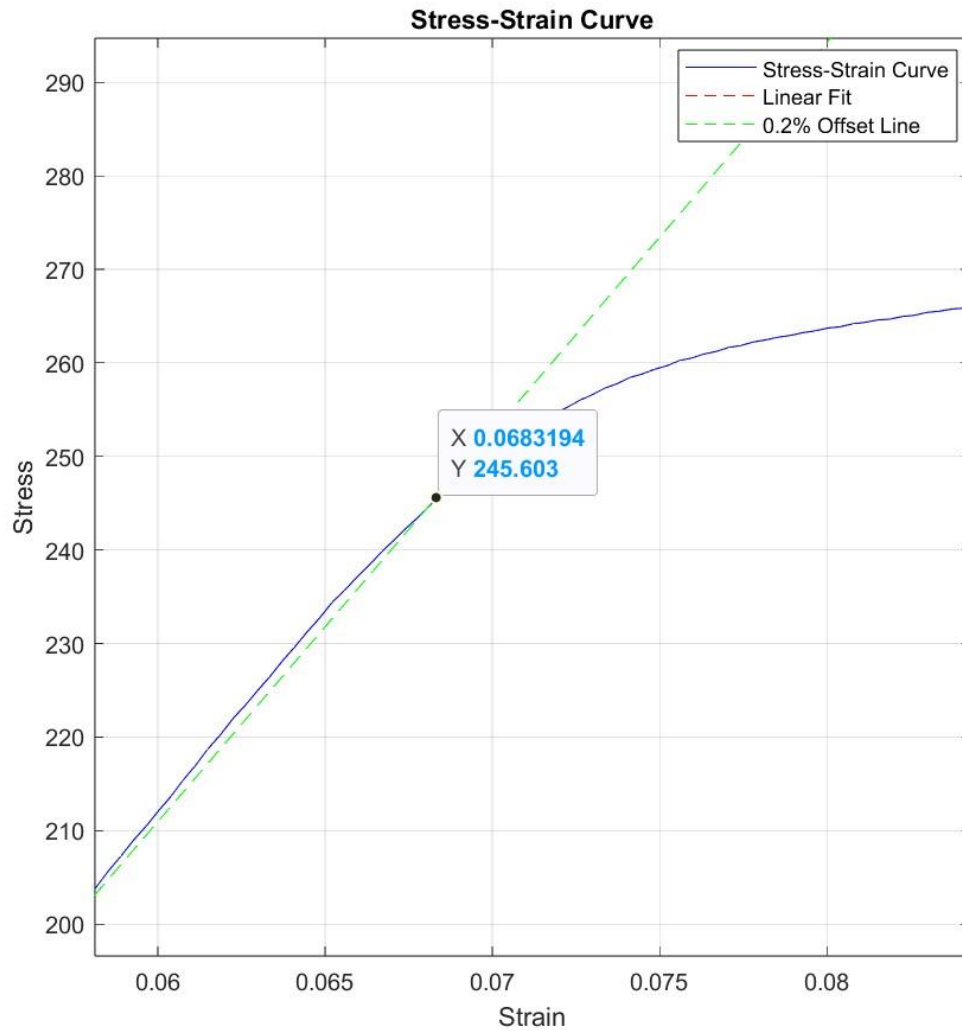


Figure 3.8: Sample 11 YTS evaluation using 0.2% offset method.

3.5.1.2 Elongation

The following formula evaluates %El:

$$\%El = \frac{L_f - L_0}{A} \times 100 \quad \text{Equation (3.3)}$$

Where the A is the gauge length and $L_f - L_0$ is the difference in length of the specimen before and after tensile testing.

The length of the specimen before the tensile test L_o and the length after the tensile test L_f were measured as presented in Figure 3.9.



Figure 3.9: Measurement of specimen length before and after the test.

3.5.2 Hardness Test

Vickers hardness test was performed using Matsuzawa Micro Hardness Tester (DVK-1) as shown in Figure 3.10 according to ASTM E92 standard for Vickers hardness test of metallic materials. The test was done using a load (P) of thirty Kg and the load holding time was fifteen seconds.

The Vickers Hardness could be evaluated by the following equation:

$$H_v = 1.845 \frac{P}{d^2} \quad \text{Equation (3.4)}$$

Where P is the testing load in Kg and d is the average of the two diagonals of the pyramid-shaped dent d_1 and d_2 as shown in Figure 3.11. The diagonal

measurements are done using the tester microscope and the hardness calculation can be done using the counter built in the machine or the equation provided above.



Figure 3.10: Vickers Hardness Tester (DVK-1).

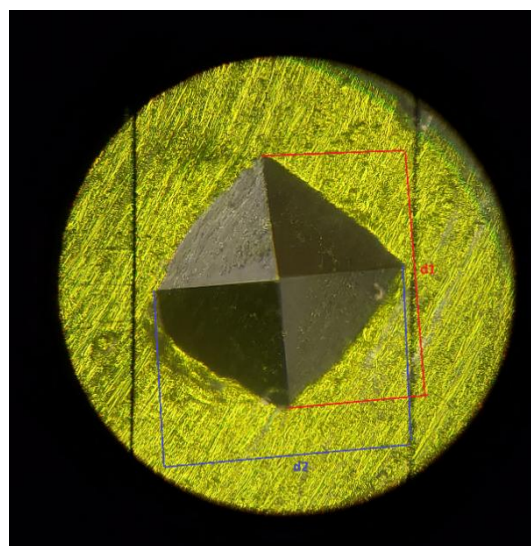


Figure 3.11: Hardness Test pyramid-shaped micro indentation.

3.6 Numerical Modelling Using RSM

RSM utilise statistical methods to build numerical relationships between the input variables and the different responses through a number of regression models. The general regression model based on RSM is represented in Equation 3.5 below:

$$\hat{Y} = \beta_0 + \sum_{i=1}^n \beta_i X_i + \sum_{i=1}^n \beta_{ii} X_i^2 + \sum_{i=1}^n \sum_{j=i+1}^n \beta_{ij} X_i X_j + \epsilon \quad \text{Equation (3.5)}$$

Considering :

$(\hat{Y})$: The forecasted value.

(β_0) : The intercept term.

$(\beta_i X_i)$: The single factor influences of the variable X_i .

$(\beta_{ii} X_i^2)$: The quadratic influence of the variable X_i .

$(\beta_{ij} X_i X_j)$: The influence of the interaction between the variables X_i and X_j .

(ϵ) : The error term.

ANOVA is used as an assessment tool for the validity of the numerical models developed to predict the different responses. ANOVA helps identify the significance and insignificance of the variables, determine the effectiveness of the investigated parameters' influence on the output, and calculate model coefficients. (Pouyafar and Meshkabadi, 2024).

One of the main outputs is the F-value which measures the distribution of the data, comparing the mean square of the source to that of residuals. A higher value shows a better fit in light of the model for each input parameter. Another is the p-value which denotes the importance of each variable inside the response. The p-value greater than 0.1 suggests the

variable is insignificant and if it is less than 0.05 it suggests that the variable is significant, and a. This analysis is important to ensure response validity, and it helps to confirm if a model really represents data and the relationship between variables (Montgomery, 2012).

Other parameters are presented by the ANOVA table include the Sum of Squares which simply the total of the squared deviation from the average. Degrees of Freedom refers to the number of variables estimated that were used to calculate the source's sum of squares. The Mean Square, also known as variance, is found by dividing the sum of squares by the degrees of freedom. The residuals indicate the volume of deviation in the output that remains unrepresented by the model. Lack of fit quantifies the discrepancy between the model's forecasts and the actual measured values. Pure error represents the variation observed between replicated runs. The corrected total (Cor Total) reflects the overall variation around the mean of the observations, with the model accounting for a portion of this variation and the residuals explaining the remainder (Montgomery, 2012).

Another part of the ANOVA tables contains the modelling statistics. It shows the mean which represents the overall average of all the responses. Another part is the standard deviation (Std Dev) which is the square root of the residual mean square and serves as a representation of the experiment's standard deviation. It also presents the coefficient of variation (C.V.) that shows the percentage of experiments' standard deviation from the mean, which is the standard deviation divided over the mean and multiplied by one hundred. While R^2 is a metric that quantifies the proportion of dispersion from the mean that is explained by the model, and Adjusted R^2 , on the other hand, adjusts this R^2 value according to the model level and terms, to quantify how many of the model terms are useful. Finally Adequate Precision is a signal to noise ratio that implies if the

model could be employed for prediction or not, with a value greater than four indicating sufficient model discrimination (Montgomery, 2012)

3.7 Optimisation Using Desirability Method and Genetic Algorithm

After the numerical models assessed, they can be used for optimisation, the models can be used for optimisation. The desirability method, as described by Myers et al. (2016), is a technique used to optimise multiple responses simultaneously. This method involves transforming each response into a desirability function (d_i). Which ranges between zero and one. The Zero is the least desirability and one is the highest desirability. Overall desirability, (D), is the mean of the individual desirability:

$$D = (d_1 \times d_2 \times \dots d_n)^{1/n} \quad \text{Equation (3.6)}$$

Each response is assigned a goal—maximum, minimum, target, or range. The (n) is the number of non-range desirability.

The goals determine the desirability function's shape for each response as follows, where L, U, T, and Y are the minimum, maximum, target, and response values, respectively. Where $L \leq T \leq U$.

If the goal is to maximise the response the individual desirability is represented as:

$$d_i \begin{cases} = 0 & Y < L \\ \left(\frac{y - L}{U - L} \right) & L < Y < U \\ = 1 & Y > U \end{cases} \quad \text{Equation (3.7)}$$

If the goal is to minimise the response the individual desirability is represented as:

$$d_i \begin{cases} = 0 & Y > U \\ = \left(\frac{U - Y}{U - L} \right) & L < Y < U \\ = 1 & Y < L \end{cases} \quad \text{Equation (3.8)}$$

If the goal is the response to be on target the individual desirability is as follows:

$$d_i \begin{cases} = 0 & Y < L \text{ or } Y > U \\ = \left(\frac{Y - L}{T - L} \right) & Y \leq T \\ = \left(\frac{U - Y}{U - T} \right) & T < Y \leq U \end{cases} \quad \text{Equation (3.9)}$$

If the goal is for the response to be in range the individual desirability is as follows:

$$d_i \begin{cases} = 0 & Y < L \text{ or } Y > U \\ = 1 & L \leq Y \leq U \end{cases} \quad \text{Equation (3.10)}$$

The desirability method can be used to include goals for the output variables and goals for the input variables. The optimisation of the desirability to find the best combination of the different variables can be done using different methods or tools. GA is one of those tools (Ozturk et al., 2015). GA could be used to optimise the desirability based on several numerical models, it can handle the different several nonlinear models of the different responses, and it can be used to find the different optimised conditions whether constrained or without constraints (Kuhn et al., 2019).

To perform the optimisation for different objectives and different conditions, some constrained and some not constrained, the desirability method was incorporated with the GA in MATLAB software. GAs work and the specific options used in our optimisation process. The GA goes through the following process for optimisation (Alhijawi et al., 2024; Sohail, 2023):

- **Initialisation:** The algorithm begins by creating a random initial population of possible solutions. In the population the single solution is called an individual, each individual consists of a set of parameters called genes. In the context of the study, it consists of the alloying elements' levels and ageing conditions.
- **Evaluation:** evaluate each single solution using a fitness function. The fitness function is used to determine how well an individual meets the desired objectives. In the study, the fitness function calculates the overall desirability based on the mechanical properties of aluminium alloy 6063 models.
- **Selection:** In this step, the individuals with the best fitness are selected to reproduce new individuals.
- **Crossover:** The selected individuals, which are called parents, are combined, and their genes are combined to produce offspring. This allows the exchange of genetic material and the creation of new solutions.
- **Mutation:** Some genes of the offspring solutions are randomly changed to maintain diversity in the genes; this process ensures the exploration of new areas of the search space and avoids local optimisation.
- **Replacement:** In this step, the newly generated individuals replace the old individuals, and the process continues. With more generations replacing the old, the population start to have better solutions.
- **Termination:** If one of the stopping criteria is met, such as meeting the maximum number of generations or reaching the set value fitness level the algorithm stops.

To integrate the desirability function with the GA for the optimisation process the following steps are executed, as summarised in Figure 3.12:

- Define the models for the mechanical properties as functions of the input variables, the mechanical properties would be the output responses of the different models' functions. These models' functions will be used to calculate the individual desirability of the different responses.
- Define the desirability function criteria as a function of the goals of the variables, output for the responses from the property model, the limits of the variables, and the target value if the goal for the variable is to be on target.
- Define the overall desirability function based on the desirability method criteria, this function inputs would be the outputs from the individual desirability function and the number of non-range desirability.
- Define the fitness function to be optimised, which is the overall desirability, this function is the function that will combine all the previous functions and will perform the connection between the functions, it will utilise the outputs from the previous functions to be inputs as required in the following functions, its final output would be optimised using the GA.
- Set the GA options and the stopping criteria for the GA. Including population size which represents the number of pairs in each generation with a higher population size, the GA searches more globally. The Maximum generations options specify the maximum number of generations at which GA should stop. The crossover fraction controls the reproduction of pairs. Mutation function options provide the ability to choose suitable functions for constrained or non-constrained optimisation. Function tolerance can be set to the value at which the GA if the average relative change in the best fitness reached the set value, the lower it is set the more accurate.

- Run the GA based on the number of parameters and their limits to optimise the fitness function for the overall desirability.
- The GA starts to generate a randomised population of possible solutions according to the limits of the alloying elements and the ageing conditions variables.
- The overall desirability is calculated and evaluated based on the fitness function of the different candidates in the population.
- The candidates with higher values of fitness to the overall desirability are selected for reproduction of candidates.
- The combination of different variables based on the selected candidates and crossing over of the candidates to exchange the genetics of the candidates to produce new candidates.
- Mutation of the reproduced candidates to ensure randomness and diversity in the reproduced candidates to avoid local optimisation.
- Replacement of the old candidates or population with the new reproduced and mutated candidates and population.
- After the new population is replaced, the GA's stopping criteria are checked. If none of the stopping criteria is met, then the new population is evaluated against the fitness function, and the GA repeats the process. If the stopping criteria are met, then the optimal variables and responses are selected based on the solution with the highest possible overall desirability.

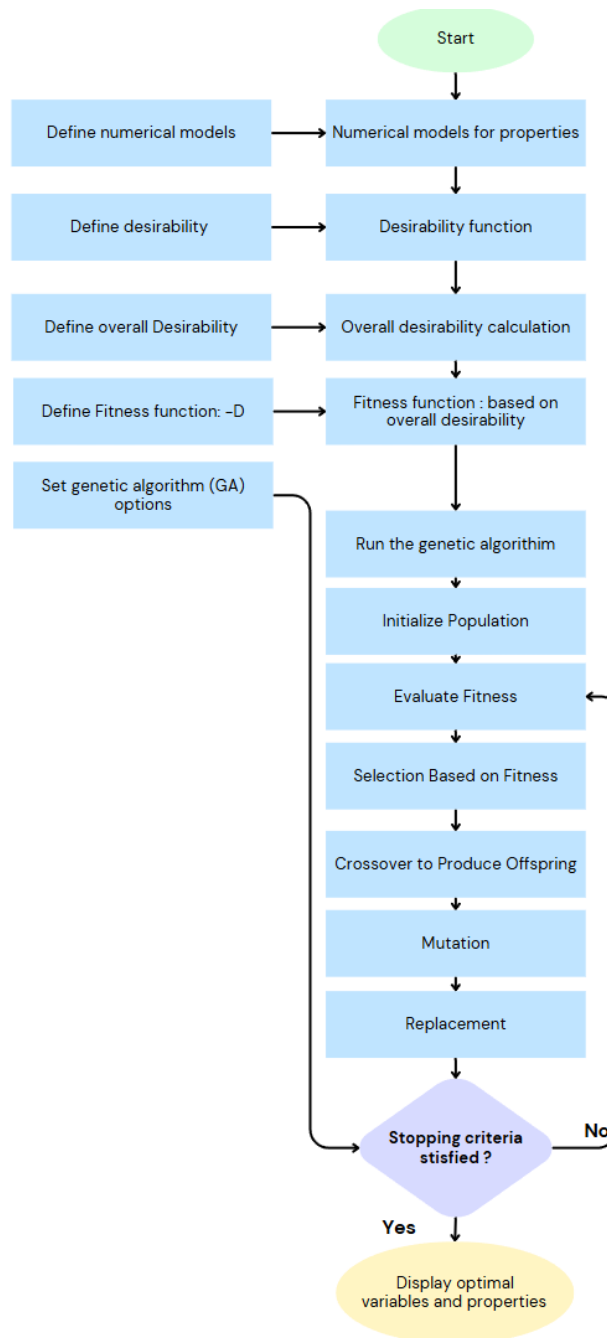


Figure 3.12: Desirability function and GA integration flow chart.

3.8 Assumptions

The main assumptions for the study can be summarised as follows:

1. Material uniformity: It is assumed that the compositions of the samples are uniform. The deviation in composition would suggest

that the results and conclusion will not reflect the influence of the input variables.

2. Controlled heat treatment: It is assumed that the ageing time and temperature are controlled. Controlled heat treatment conditions are needed to ensure that the correlations presented would present the effect of the ageing conditions on the mechanical properties.
3. Observations independence: The observations are assumed to be independent from each other. The independence of observations is required to ensure that the results are not biased due to common conditions or errors and to ensure ANOVA validity.
4. Normality: The residuals or differences between observed and predicted values by models are assumed to follow a normal distribution. This assumption is required as the ANOVA is based on normal distribution.

3.9 Methodology Conclusion

This chapter describes the methodology, which has formed the basis of the investigations conducted to study and optimise the relationship between the mechanical properties of aluminium alloy 6063 with alloying elements and artificial ageing conditions. The design of the experiment, sample preparations, mechanical testing, modelling and optimisation techniques employed were discussed.

The RSM with CCD was utilised to develop the relationship models between the mechanical properties of the alloys, with the alloying elements and ageing conditions. It was used because it allows for effective exploration of the influence of the different variables and their interaction in the experimental space.

A combination of numerical modelling and optimisation using the desirability method and GA has been employed in determining optimum alloying elements' levels and ageing conditions to achieve requirements for mechanical properties. This integrated approach, using different techniques, could provide insight into the complex variables and interactions involved that influence performance in aluminium alloy 6063.

The discussed methodological foundation would be built on to present the experimental data, data analysis, development and validation of numerical models, and the application of optimisation techniques to produce results that could be discussed and utilised to provide recommendations on the optimising of the mechanical performance of aluminium alloy 6063.

Chapter Four

Results and Discussion

4.1 Introduction

4.2 Experimental Results

4.3 Assumptions Validation

4.4 Ultimate Tensile Strength

4.5 Yield Tensile Strength

4.6 Hardness

4.7 Elongation

4.8 Modulus of Elasticity

4.9 Conformation

4.10 Optimisation

4.11 Results and Discussion Conclusion

Chapter Four

Results and Discussion

4.1 Introduction

Chapter four displays the experimental results and discusses the findings on the mechanical properties of the 6063 Al alloy.

The experimental results, which include measurements of the various mechanical characteristics, YTS, UTS, ME, %El, and H are presented in section 4.2 to begin the chapter. Section 4.3 is the validation of the assumptions.

The succeeding sections, from 4.4 to 4.8, discuss how the various variables influence the properties of the aluminium alloy by exploring which factors affect the properties and how different variables interact to impact the properties of the alloy. Section 4.4 focuses on the UTS, YTS in section 4.5, H of the alloy in section 4.6, Section 4.6 discusses the %El, and in section 4.8, the ME.

Then, section 4.9 is dedicated to the confirmation of the developed models by comparing the model forecasted values with the experimental measured values as a way of validating the accuracy of the developed models. Section 4.10 presents the optimisation of the properties of the alloy using the developed models by the desirability method coupled with GA. Finally, section 4.11 presents the conclusion on the results and discussion.

4.2 Experimental Results

The different experimental values of the mechanical properties values are shown in Table 4.1. The table shows the experimental values obtained for YTS, UTS, ME, %El and H that were obtained during the experiments. Each experimental run conditions are presented with the levels of Si, Fe, Mn, and Mg given in weight percentage of the alloy, along with the artificial ageing temperature in degrees Celsius and the artificial ageing time in hours. The presented experimental values for the mechanical properties are an average of three samples that were taken at each individual run. Some variations were observed in the duplicated centre points of the experimental plan. These could be the results of variations in microstructure caused by differences in quenching rate, temperature gradients in the furnace, casting effects, or traces of other alloying elements. Other causes may be related to human error or calibrations during the experiments.

The experimental data was utilised to produce predictive models for the five mechanical properties. The models developed will be presented in the following form in Equation 4.1:

$$\begin{aligned} \hat{P} = & c + a_A A + a_B B + a_C C + a_D D + a_E E + & \text{Equation (4.1)} \\ & a_F F + b_{AB} AB + b_{AC} AC + b_{AD} AD + b_{AE} AE + \\ & b_{AF} AF + b_{BC} BC + b_{BD} BD + b_{BE} BE + b_{BF} BF + \\ & b_{CD} CD + b_{CE} CE + b_{CF} CF + b_{DE} DE + b_{DF} DF + \\ & b_{EF} EF \end{aligned}$$

Where :

$\hat{P}$: the estimated mechanical property.

c : the intercept constant.

a_0 : the coefficient of individual terms

b_0 : the coefficient of interaction terms between two variables.

A: Si level in wt% ranging from 0.43 to 0.75.

B: Fe level in wt% ranging from 0.15 to 0.25.

C: Mn level in wt% ranging from 0.01 to 0.07.

D: Mg level in wt% ranging from 0.45 to 0.63.

E: Artificial ageing temperature in °C ranging from 175 to 210.

F: Artificial ageing time in Hours ranging from 4 to 12.

AB: Interaction between Si and Fe.

AC: Interaction between Si and Mn.

AD: Interaction between Si and Mg.

AE: Interaction between Si and temperature.

AF: Interaction between Si and time.

BC: Interaction between Fe and Mn.

BD: Interaction between Fe and Mg.

BE: Interaction between Fe and temperature.

BF: Interaction between Fe and time.

CD: Interaction between Mn and Mg.

CE: Interaction between Mn and temperature.

CF: Interaction between Mn and time.

DE: Interaction between Mg and temperature.

DF: Interaction between Mg and time.

EF: Interaction between temperature and time.

Table 4.1: Experimental results.

Variables (Alloy elements and Ageing parameters)							Mechanical Properties				
Run	Si % wt	Fe % wt	Mn % wt	Mg % wt	Temp °C	Time Hr	ME Gpa	UTS Mpa	YTS Mpa	El %	H
1	0.47	0.16	0.03	0.49	175	8	5.575	289.408	263.579	11.019	104.2
2	0.47	0.16	0.03	0.49	210	8	4.586	232.285	206.683	11.385	75.082
3	0.47	0.16	0.03	0.49	192.5	4	5.086	279.159	252.601	9.932	103.014
4	0.47	0.16	0.03	0.49	192.5	8	4.983	256.078	233.602	9.57407	92.4737
5	0.47	0.16	0.03	0.49	192.5	8	4.958	257.084	238.91	9.16667	92.4737
6	0.47	0.16	0.03	0.49	192.5	8	4.86	251.913	234.92	9.38889	92.4737
7	0.47	0.16	0.03	0.49	192.5	8	5.171	271.153	242.689	10	101.5
8	0.47	0.16	0.03	0.49	192.5	8	5.021	254.491	232.415	9.33	95.9
9	0.47	0.16	0.03	0.49	192.5	8	5.445	269.581	239.398	11.09	96.5
10	0.44	0.18	0.04	0.55	210	4	4.561	203.166	187.134	19.66	43.9237
11	0.44	0.18	0.04	0.55	175	12	5.233	275.622	245.98	9.821	98.3
12	0.44	0.18	0.04	0.55	210	12	4.122	202.691	166.268	15.409	76.733
13	0.75	0.18	0.03	0.51	192.5	8	5.648	311.724	284.961	9.883	68.042
14	0.54	0.15	0.01	0.63	210	12	4.462	228.827	198.306	11.228	79.833
15	0.51	0.19	0.013	0.47	175	4	4.46	234.948	174.665	16.142	141.921
16	0.51	0.19	0.013	0.47	210	12	4.306	218.122	183.534	12.716	74.267
17	0.59	0.19	0.07	0.5	192.5	8	5.504	284.414	265.25	7.777	102.8
18	0.59	0.19	0.07	0.5	210	12	4.637	239.38	213.868	8.414	92.033
19	0.54	0.15	0.01	0.63	210	4	5.234	273.086	251.172	6.741	92.2
20	0.59	0.19	0.07	0.5	175	4	5.851	298.423	273.703	8.985	106.217
21	0.59	0.19	0.07	0.5	210	4	5.289	273.589	252.652	7.383	89.659
22	0.46	0.19	0.03	0.48	192.5	12	5.074	250.891	230.658	11.235	86.833
23	0.59	0.19	0.07	0.5	175	12	5.381	289.822	262.129	9.105	110.646
24	0.46	0.19	0.03	0.48	192.5	8	5.221	261.543	243.943	11.735	88.467
25	0.54	0.15	0.01	0.63	175	12	5.536	296.853	258.294	10.304	104.367
26	0.44	0.17	0.024	0.51	175	4	5.313	282.256	253.972	12.37	99.033
27	0.43	0.16	0.05	0.46	192.5	8	4.91	257.776	230.747	9.932	95.033
28	0.47	0.18	0.04	0.48	210	12	4.306	213.579	181.901	12.056	76.567
29	0.47	0.18	0.04	0.48	192.5	8	5.024	271.672	245.29	9.512	91.653
30	0.44	0.17	0.022	0.51	210	11	4.336	217.986	183.216	11.759	68.767
31	0.44	0.17	0.022	0.51	210	4	4.609	239.018	207.209	12.537	76.338
32	0.44	0.17	0.022	0.51	192.5	8	5.153	273.961	245.069	10.636	87.635
33	0.47	0.18	0.04	0.48	175	4	4.815	264.363	230.474	12.117	102.886
34	0.44	0.17	0.022	0.51	175	12	5.228	275.9	247.499	10.5	98.823
35	0.44	0.16	0.04	0.51	210	4	4.861	224.408	197.273	12.36	72.265
36	0.44	0.16	0.04	0.51	175	12	5.602	291.052	264.852	6.983	118.096
37	0.44	0.16	0.04	0.51	192.5	8	4.862	250.305	222.610	9.16	97.845
38	0.59	0.19	0.06	0.50	175	4	5.852	285.572	271.703	9.985	95.325
39	0.54	0.25	0.01	0.60	210	4	5.186	279.390	260.095	8.48	94.452

4.3 Assumptions Validation

The validation of the assumptions made in the study can be summarised as follows:

1. The material uniformity was ensured by treating the samples under solution treatment conditions to ensure homogenisation, and the billet samples compositions were tested using atomic emission spectrometry.
2. The ageing heat treatment conditions were controlled by calculating the actual ageing time only without considering the preheating time and by monitoring the actual slice temperature using a thermocouple, as there was a difference between the furnace temperature and the slice temperature during preheating.
3. The independence of observations was ensured by following the CCD experimental plan according to the DoE to ensure no shared conditions, and each run samples were treated and tested separately to avoid common or shared errors.
4. The normality of data was validated through the visual inspection of normality plots of residuals for each of the models developed, as provided in Appendix 2, which showed that the residuals for the models are around the normal line and within the 95% confidence intervals.

4.4 Ultimate Tensile Strength

The ANOVA results for the UTS model, as shown in Table 4.2, show that the model has an F-value of 14.69 and a p-value of less than 0.0001. These values indicate that the model is statistically significant and that it provides a good fit for the data.

As for the different variables significance, Fe (B), Mn(C), Mg(D), Temperature (E) and Time (F) are significant parameters, with p-values of 0.0157, 0.358, 0.101, 0.0017 and 0.0041, respectively. All their p-values are less than 0.0500 which suggests that these factors have a substantial impact on the UTS. Interaction terms AB, AC, AD, AE, AF, BC, BE, CD, CE, and EF, all have p-values that are less than 0.0500, which shows that they are also significant terms. These significant interaction terms show the importance of the consideration of interactions between variables.

The p-value of the lack of fit test is 0.3621, this value indicates that the lack of fit is not significant. This implies that the model is adequate to explain variations in the data, and there are no significant differences between the model predictions and the actual observations.

The devolved model for the UTS equation expressed in terms of actual factors is represented in Equation 4.2.

$$\begin{aligned} \hat{UTS} = & 4.7872 \times 10^4 - 7.5945 \times 10^4 A - 1.4071 \times 10^5 B - \text{Equation (4.2)} \\ & 2.1641 \times 10^5 C - 5.0159 \times 10^4 D - 7.1296 E - 2.4076 F - \\ & 2.0620 \times 10^5 AB - 1.3881 \times 10^5 AC + 8.2939 \times 10^4 AD + \\ & 6.9304 AE - 35.0634 AF + 9.3273 \times 10^5 BC + 1.4064 \times \\ & 10^4 BD + 38.5927 BE + 104.5226 BF + 2.4695 \times 10^5 CE \\ & 32.5149 CE + 53.6286 CF - 4.4097 DE + 34.6407 DF - \\ & 0.1063 EF \end{aligned}$$

The model's R² value of 0.9536 and Adjusted R² of 0.8887, these values indicate that the explained variance by the model is very high, confirming the model's robustness. The Adequate Precision value of 15.3124 signifies a strong signal-to-noise ratio, further validating the model's reliability model to navigate the design space.

Table 4.2: ANOVA for UTS model.

Source	Sum of Squares	df	Mean Square	F-value	p-value
Model	26721.02	21	1272.43	14.69	< 0.0001
A-Si	11.80	1	11.80	0.1363	0.7172
B-Fe	643.06	1	643.06	7.42	0.0157
C-Mn	460.92	1	460.92	5.32	0.0358
D-Mg	749.82	1	749.82	8.66	0.0101
E-Temp	1201.92	1	1201.92	13.87	0.0020
F-Time	1247.19	1	1247.19	14.40	0.0018
AB	612.28	1	612.28	7.07	0.0179
AC	564.11	1	564.11	6.51	0.0221
AD	790.81	1	790.81	9.13	0.0086
AE	523.31	1	523.31	6.04	0.0266
AF	647.13	1	647.13	7.47	0.0154
BC	627.42	1	627.42	7.24	0.0168
BD	296.89	1	296.89	3.43	0.0839
BE	501.52	1	501.52	5.79	0.0295
BF	188.57	1	188.57	2.18	0.1608
CD	657.94	1	657.94	7.60	0.0147
CE	778.15	1	778.15	8.98	0.0090
CF	113.47	1	113.47	1.31	0.2704
DE	85.82	1	85.82	0.99	0.3354
DF	216.81	1	216.81	2.50	0.1345
EF	552.30	1	552.30	6.38	0.0233
Residual	1299.41	15	86.63		
Lack of Fit	963.61	10	96.36	1.43	0.3621
Pure Error	335.80	5	67.16		
Cor Total	28020.43	36			
Std. Dev.	9.31			R²	0.9536
Mean	258.550			Adjusted R²	0.8887
C.V. %	3.60			Adeq Precision	15.312

4.4.1 Variables Influence on UTS

Figure 4.1 illustrates the influence of varying the amount of Fe in the aluminium alloy on the UTS. The figure shows that as the level of Fe increases the UTS increases, these results coincide with the results found by Tokuda et al. (2006), which studied the impact of Fe and the

solidification process on the mechanical performance of a 6000 series aluminium alloy and found that increasing the Fe content increases the strength of the alloy.

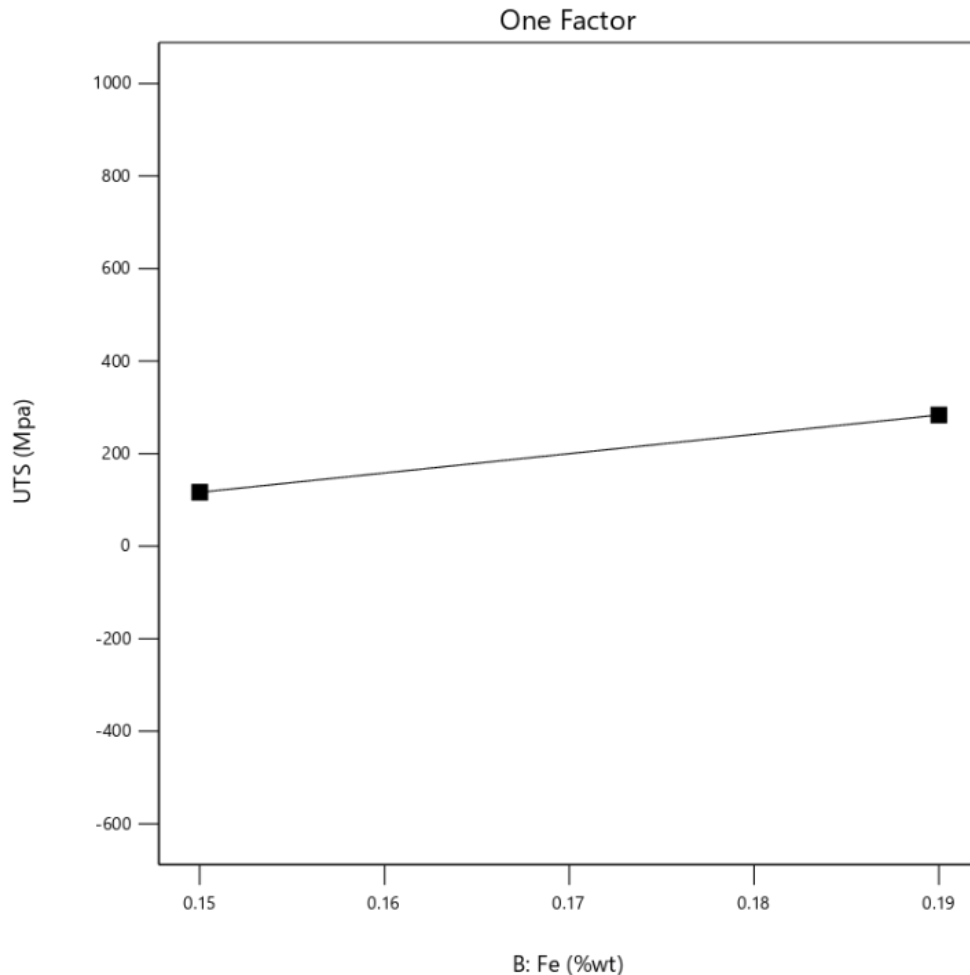


Figure 4.1: Fe single factor effect on UTS.

Figure 4.2 shows the influence of the Mn level on the UTS of the aluminium alloy. The figure illustrates how the increase in the Mn level increases the UTS of the aluminium alloy. These results are in line with the results found by Lee et al. (2012), during the study of the effect of Mn addition on the tensile properties of cold-rolled aluminium alloy sheets, where it was observed that alloys with higher Mn levels exhibited higher strengths.

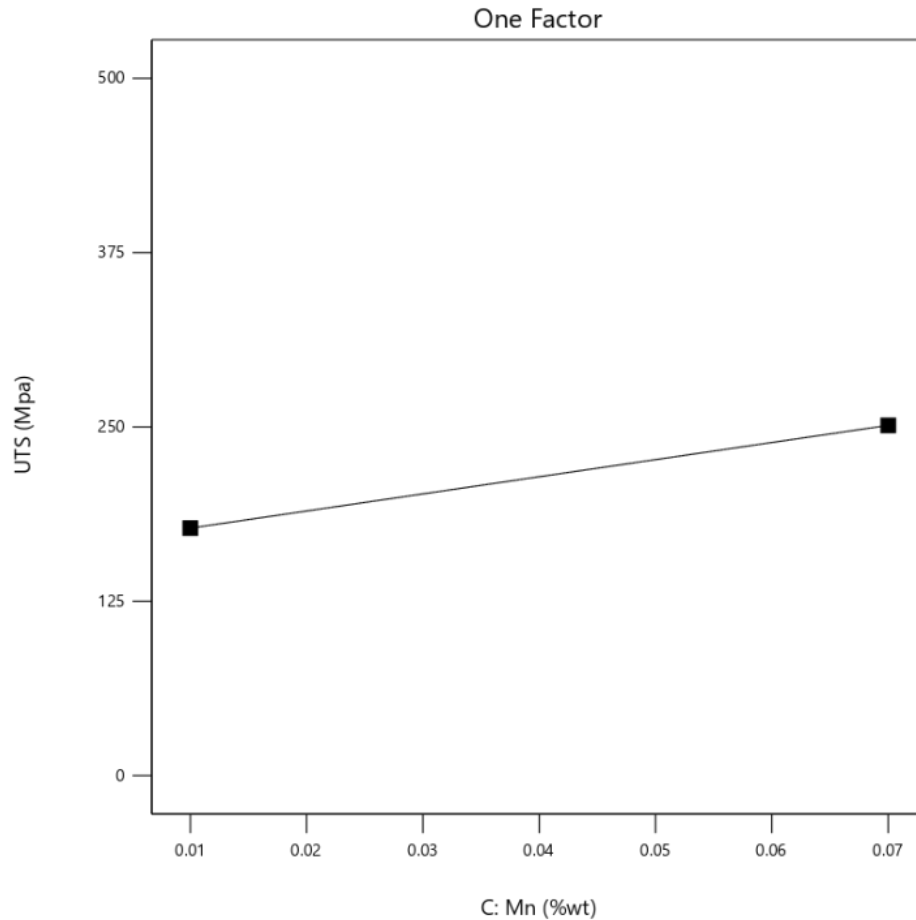


Figure 4.2: Mn single factor effect on UTS.

Figure 4.3 demonstrates the influence of changing the level of Mg on the UTS of aluminium alloy. It can be seen in the figure that increasing the Mg level increases the UTS of the aluminium alloy. The results concluded from the graph are the same results that Han et al. (2014) found, during the study of the influence of Mg level and heat treatment parameters on the tensile properties of Al-Si-Mg alloys, where it was found that adding Mg to the aluminium alloy increased its strength.

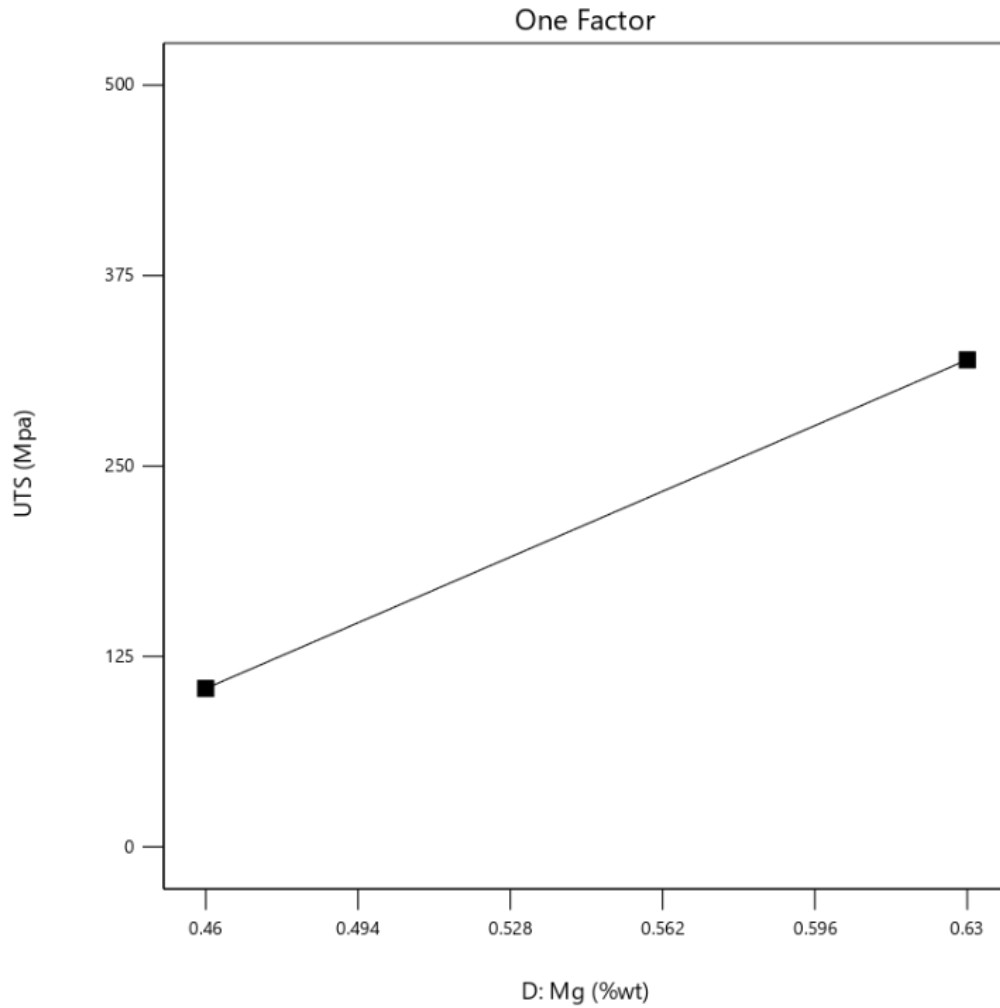


Figure 4.3: Mg single factor effect on UTS.

The effect of the interaction (BC), between the Fe and Mn levels, on the aluminium alloy's UTS can be seen in Figures 4.4 and 4.5 below. It can be observed from the figures that as the Fe level increases the alloy UTS decreases, and the figures also show that as the Mn to Fe ratio increases the UTS of the alloy increases. These observations are in coherence with the results of Seifeddine et al. (2008) study, in which the effect of Mn and cooling rate on intermetallic formations and mechanical properties of Al-Si alloys was studied, the study results indicated that a higher Mn to Fe ratio in the alloy results in higher strength values.

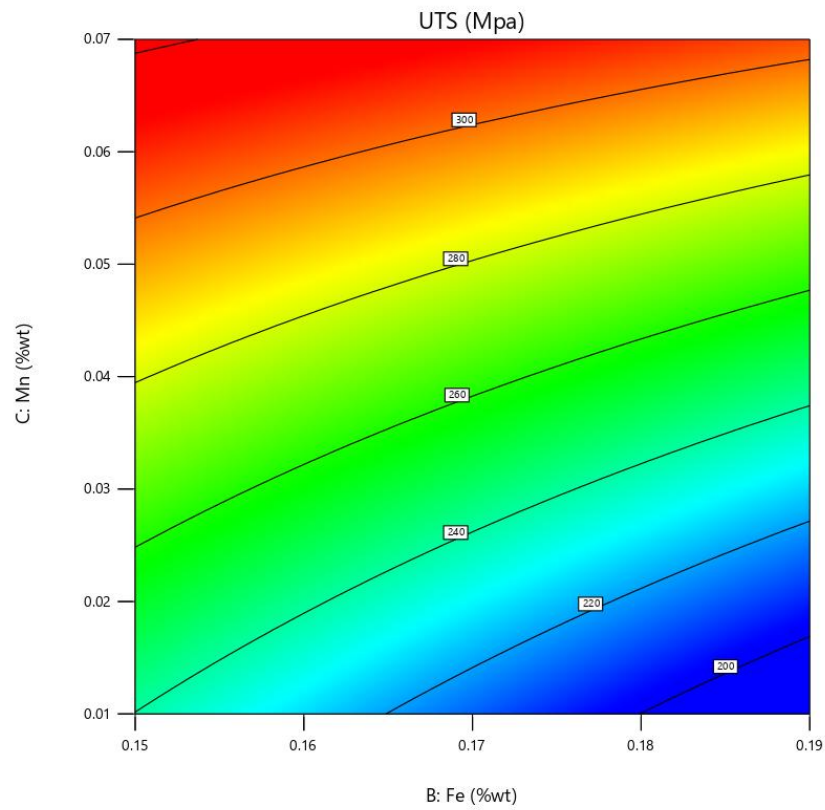


Figure 4.4: Interaction of Fe and Mn influence on UTS.

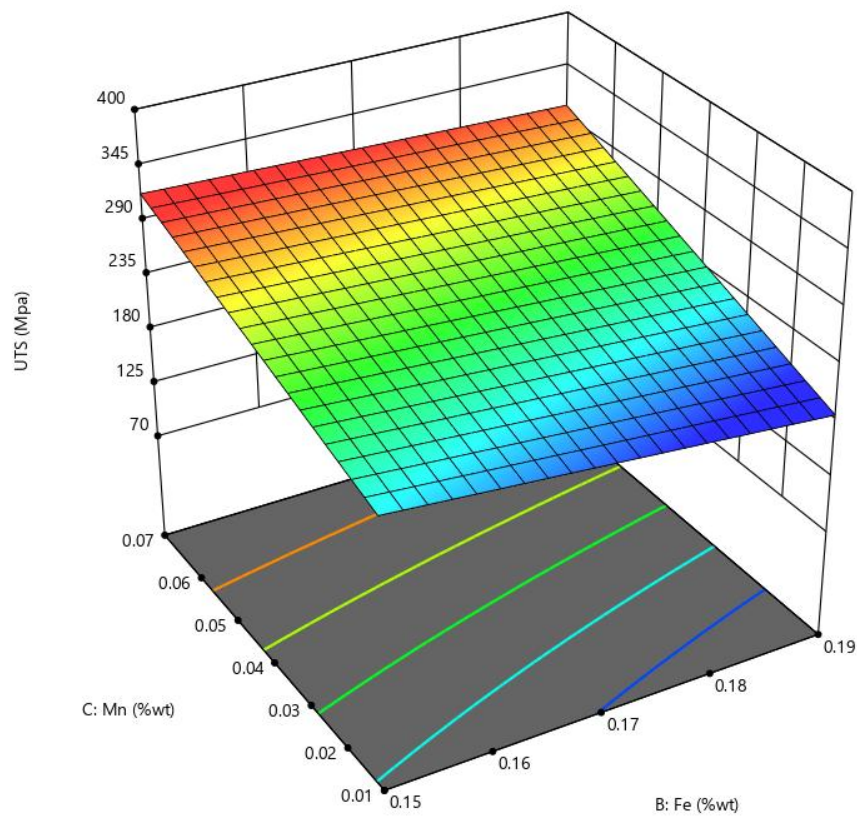


Figure 4.5: Interaction of Fe and Mn influence on UTS 3D.

Figures 4.6 and 4.7 show the influence of the interaction factor EF, between the ageing temperature and time, on the alloy UTS. The figures show that the influence at lower ageing temperatures as the ageing time increases the UTS increase, it can be observed also at the medium temperature range and the higher temperature range that the UTS value at each temperature reaches a maximum value then at the ageing time is increased the UTS starts to decrease. It can be observed from the figures that the time to reach the maximum UTS value decreases as the ageing temperature decreases while the maximum UTS obtained increases as the ageing temperature increases, this indicates that for different ageing temperatures, there is a maximum ageing time after which over ageing starts. These results are in line with the results of Ozturk et al. (2010), in the study of the ageing treatment effect on Al-Si-Mg alloy mechanical properties, where it was found the UTS of the aluminium alloy studied increased with the increase of ageing time up to a peak ageing time of four hours at 200 °C ageing temperature and reached 321 MPa then the UTS starts decreasing. The observations of Chen et al. (2021) on the influence of ageing treatment on the strength of Al-Si-Mg alloy showed the same effect, and it illustrated that for a lower ageing temperature of 180° C the time needed to reach peak ageing was sixteen hours of ageing, while at 200° C ageing temperature, the ageing time needed to reach the peak was 6 hours.

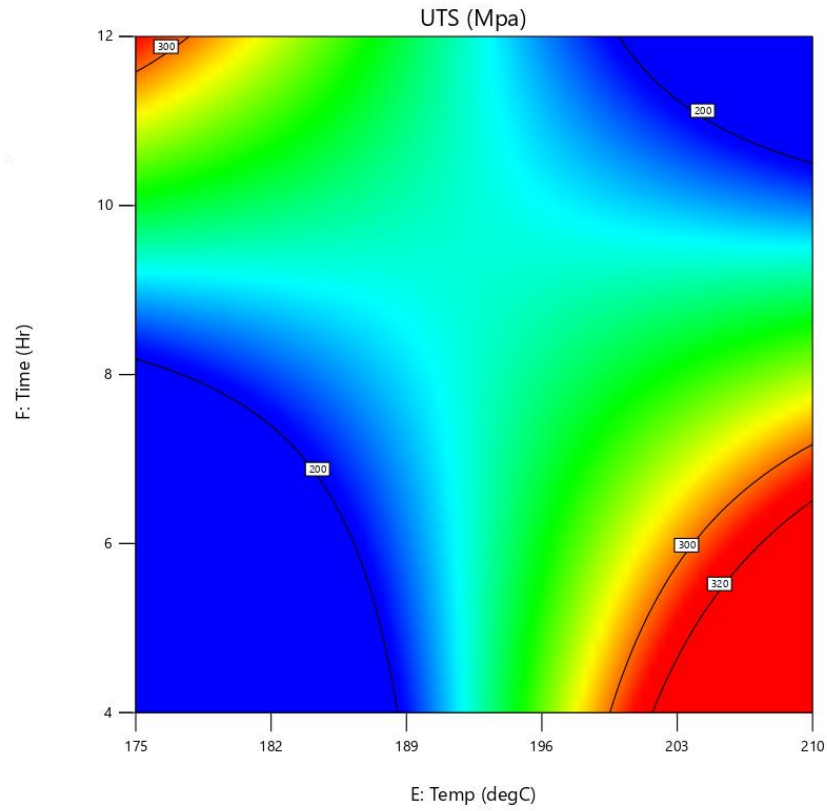


Figure 4.6: Temperature and time influence on UTS.

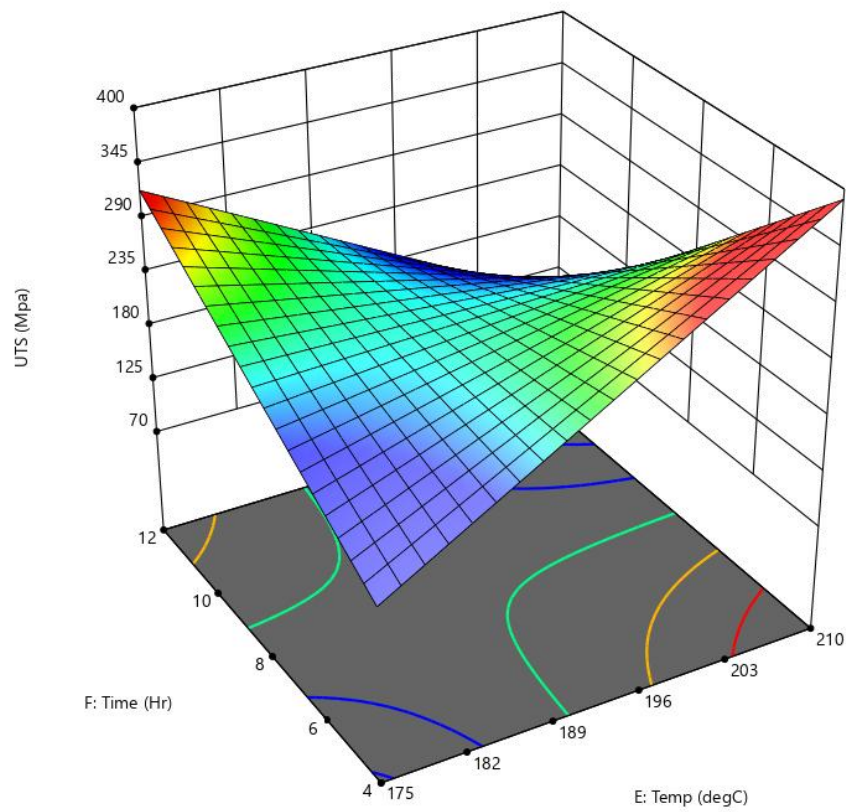


Figure 4.7: Temperature and time influence on UTS 3D.

Figures 4.8 and 4.9 below show the influence of the interaction between the Si level and ageing time on the aluminium alloy UTS. The figures illustrate that as the level of the Si increases the UTS of the alloy increases, and they also show for a fixed Si level as the ageing time increases the UTS increases, but the figures also show that as the Si level increases the influence of the ageing time decreases. The findings from the figures are corresponding with the findings of Dwivedi et al. (2006), where during studying change in mechanical properties of Al-Si-Mg alloy with respect to the change in Si content and heat treatment variables, it was found that the alloy strength increases with the increase in the Si content, and it was found higher ageing variables resulted in higher strength and hardness values.

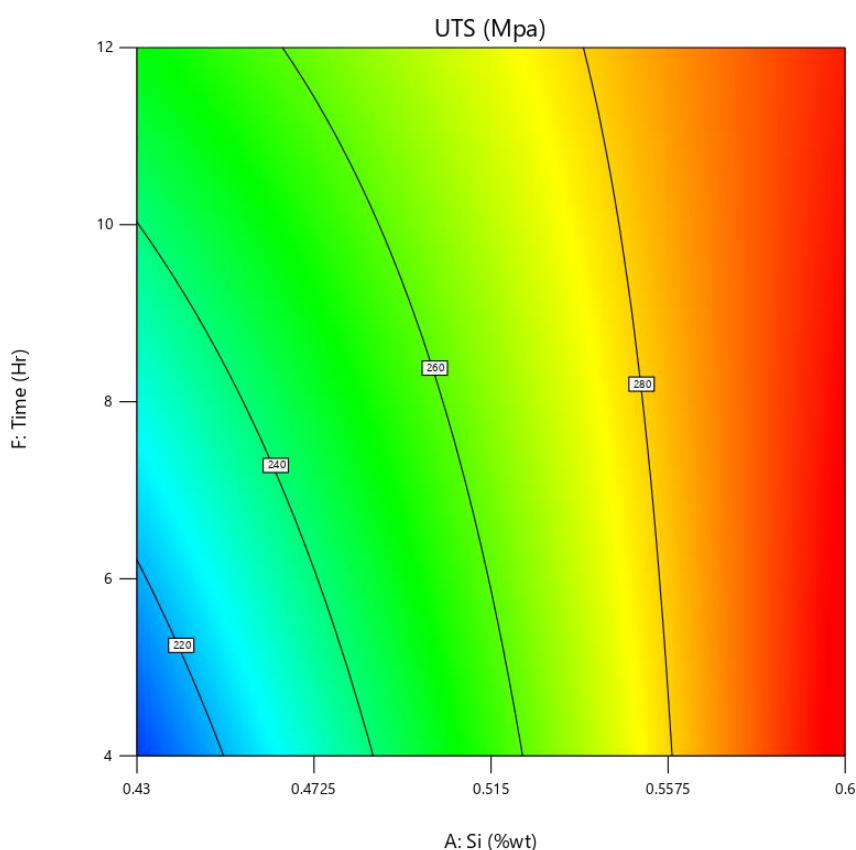


Figure 4.8: Interaction of Si and ageing time influence on UTS.

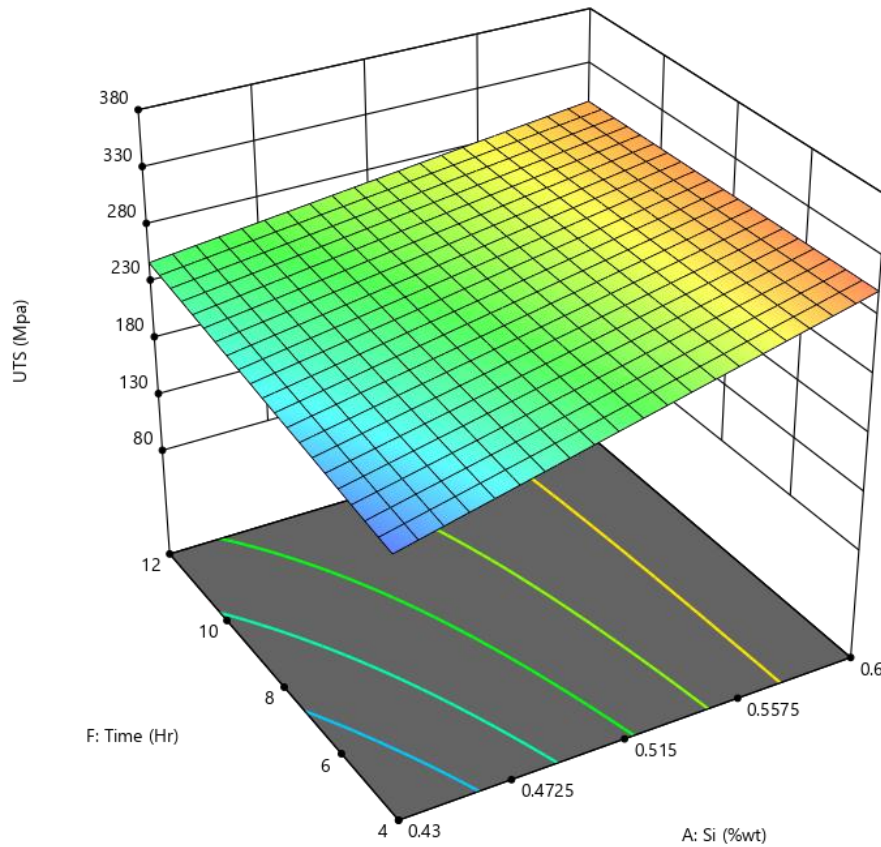


Figure 4.9: Interaction of Si and ageing time influence on UTS 3D.

4.5 Yield Tensile Strength

The ANOVA of the YTS model, as presented in Table 4.3, provides insights into its performance and reliability. The model's F-value of 14.64 and a p-value of less than 0.0001 indicate a highly significant effect of the independent variables on the YTS, suggesting that the model is a good fit for the data and covers and the low p-value indicates that the relationships represented by the models are unlikely to be caused randomly.

As for the significance of the variables, the p-values for Fe (B), Mn (C), Mg (D), Temperature (E) and Time (F), are all less than 0.500, indicating that all of these variables are significant. There are also interaction terms with p-values less than 0.0500, which are AB, AC, AD, AE, BC, BD, BE, CD, CE, and EF, indicating a highly significant effect on YTS. The interaction terms BF and DE are also significant to YTS in

moderate to considerable extent, having p-values 0.3423 and 0.3457, respectively, less than 0.5.

Table 4.3: ANOVA for YTS model.

Source	Sum of Squares	df	Mean Square	F-value	p-value
Model	31486.42	21	1499.35	14.64	< 0.0001
A-Si	30.91	1	30.91	0.3017	0.5909
B-Fe	963.70	1	963.70	9.41	0.0078
C-Mn	484.12	1	484.12	4.73	0.0461
D-Mg	1524.93	1	1524.93	14.88	0.0015
E-Temp	667.24	1	667.24	6.51	0.0221
F-Time	1092.11	1	1092.11	10.66	0.0052
AB	880.70	1	880.70	8.60	0.0103
AC	834.64	1	834.64	8.15	0.0121
AD	1558.97	1	1558.97	15.22	0.0014
AE	1053.20	1	1053.20	10.28	0.0059
AF	212.27	1	212.27	2.07	0.1706
BC	971.62	1	971.62	9.48	0.0076
BD	939.38	1	939.38	9.17	0.0085
BE	522.34	1	522.34	5.10	0.0393
BF	98.54	1	98.54	0.9619	0.3423
CD	1283.94	1	1283.94	12.53	0.0030
CE	1105.93	1	1105.93	10.79	0.0050
CF	0.4801	1	0.4801	0.0047	0.9463
DE	97.12	1	97.12	0.9479	0.3457
DF	4.27	1	4.27	0.0417	0.8410
EF	710.59	1	710.59	6.94	0.0188
Residual	1536.73	15	102.45		
Lack of Fit	1458.08	10	145.81	9.27	0.0120
Pure Error	78.66	5	15.73		
Cor Total	33023.16	36			
Std. Dev.	10.12			R²	0.9535
Mean	231.01			Adjusted R²	0.8883
C.V. %	4.38			Adeq Precision	15.3913

The model has an R^2 value of 0.9535, which indicates that approximately 95.35% of the variability in YTS can be explained by the model, while the adjusted R^2 value of 0.8883 suggests a good fit. The model's adequate precision is 15.3913, indicating that it has a strong signal-to-noise ratio.

The coefficient of variation (C.V.) of 4.38% shows a relatively low level of dispersion around the mean, further supporting the model's robustness. These results indicate that the YTS model is robust and accurate and can constitute an effective tool for understanding and predicting the mechanical properties of the aluminium alloy 6063.

The resultant numerical equation from the devolved model for YTS expressed in terms of actual factors is represented in Equation 4.3.

$$\begin{aligned} Y\hat{T}S = & 6.2876 \times 10^4 - 1.0018 \times 10^5 A - 1.7231 \times 10^5 B - \quad \text{Equation (4.3)} \\ & 2.8954 \times 10^5 C - 7.0960 \times 10^4 D - 8.1951 E + 14.9684 F + \\ & 2.4730 \times 10^5 AB - 1.6885 \times 10^5 AC + 1.1645 \times 10^5 AD + \\ & 9.8319 AE - 20.0817 AF + 1.1607 \times 10^6 BC + 2.5017 \times \\ & 10^4 BD + 39.3856 BE + 75.5598 BF + 3.4498 \times 10^5 CD - \\ & 38.7628 CE + 3.4883 CF - 4.6910 DE + 4.8600 DF - \\ & 0.1206 EF \end{aligned}$$

4.5.1 Variables Influence on YTS

Figure 4.10 below displays the single-factor effect of the Fe level on the YTS of the aluminium alloy. It can be observed from the figure that as the Fe level increases in the aluminium alloy the YTS value of the alloy decreases. The observations based on the figure are coherent with the observations of Tunçay et al. (2017), that investigated the tensile strength and microstructural properties of Al-Si-Mg alloy with different Fe levels and observed that the strength of the alloy decreased as the Fe levels in the alloy increased.

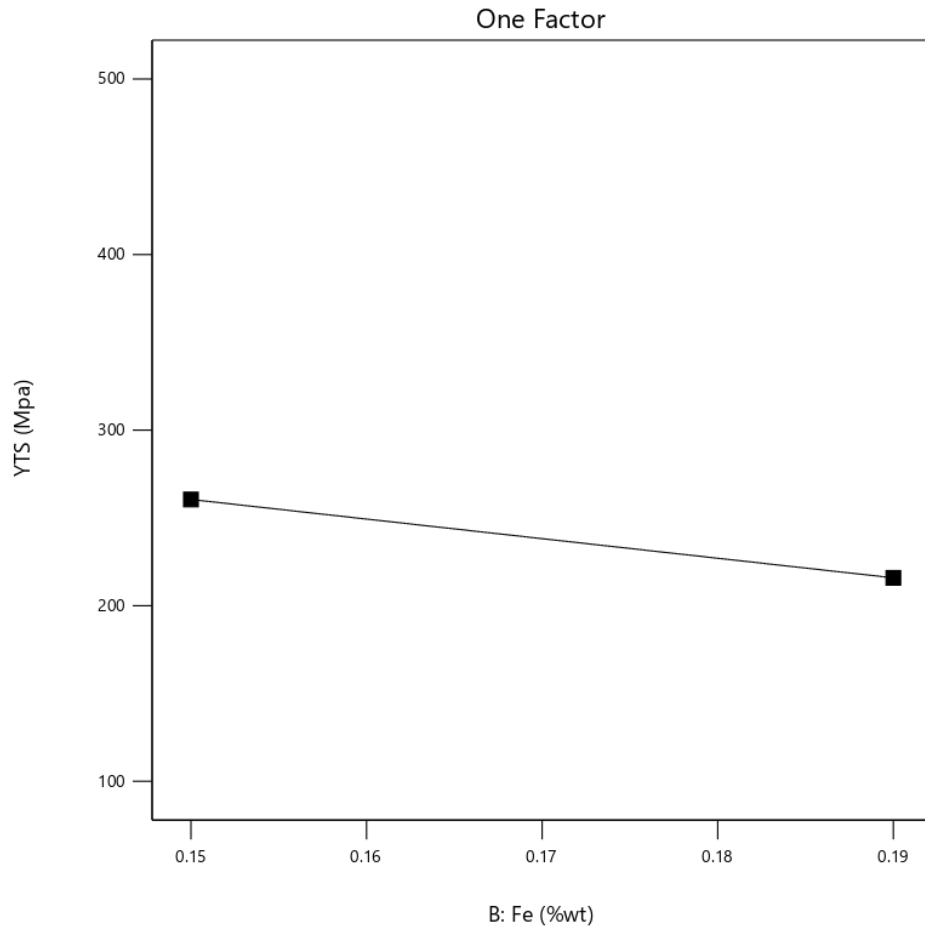


Figure 4.10: Fe single factor effect on YTS.

The single factor influence of the Mn level on the aluminium alloy YTS is shown in Figure 4.11 below. The figure illustrates that the increase in the Mn level leads to higher YTS values for the aluminium alloy. These observations are consistent with the observations of Qian et al. (2021) study, the study on the influence of Mn levels on the mechanical properties and microstructure of Al-Si alloys observed that increasing the Mn levels in the aluminium alloy resulted in an increase in the alloy yield strength.

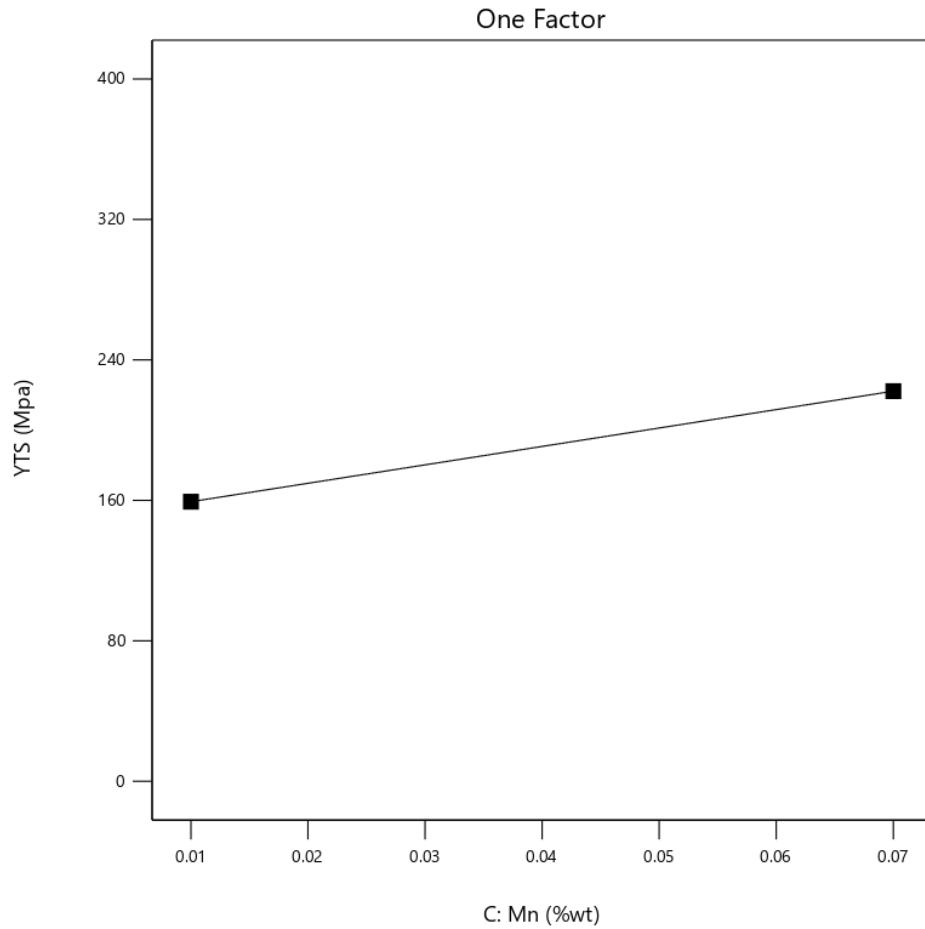


Figure 4.11: Mn single factor effect on YTS.

The single factor influence of Mg level on the YTS of the aluminium alloy can be seen in Figure 4.12 below. The figure shows that the increase of the Mg level in the aluminium alloy results in the increase of the YTS values of the alloy. These observations are in coherence with the results of Yamamoto et al. (2020) study, that investigated the influence of Mg levels in AL-Si-Mg alloys on the tensile properties, age-hardening response, and microstructural properties of the alloys, the study results showed increasing the Mg levels in the Al-Si-Mg alloy increased the yield strength of the alloy.

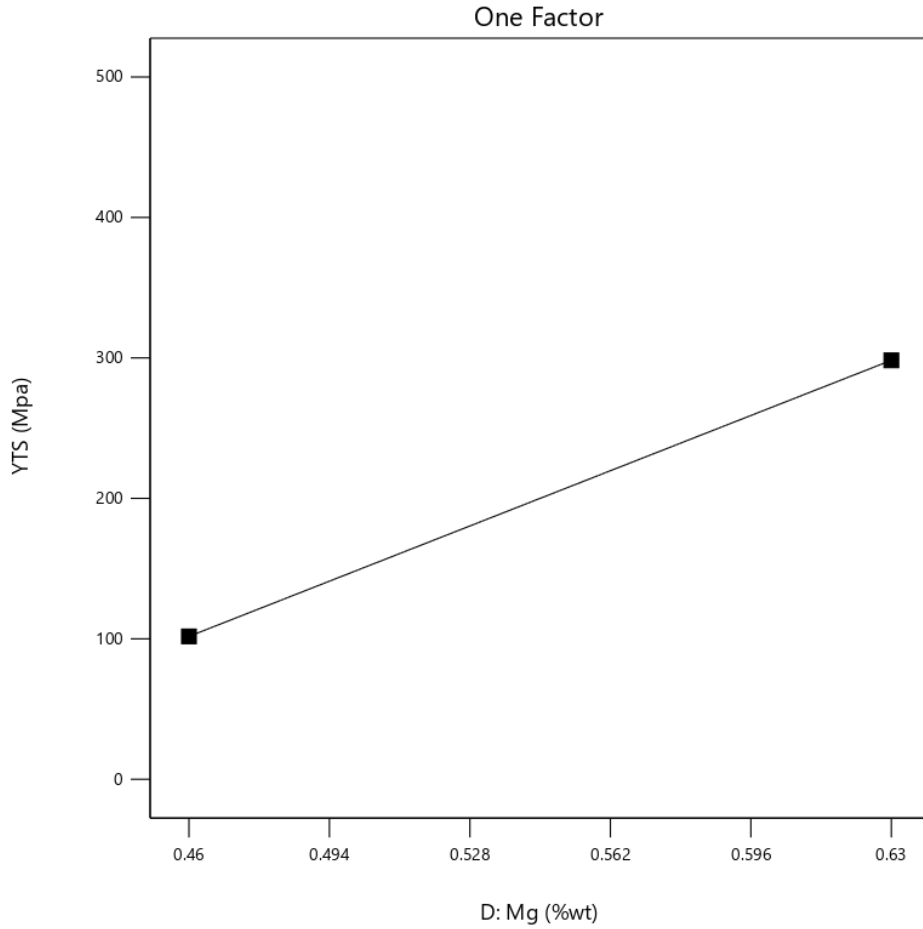


Figure 4.12: Mg single factor effect on YTS.

The influence of the interaction (AB) between the Si and Fe levels on the YTS of the aluminium alloy is shown in Figures 4.13 and 4.14. It can be observed from the figures that as the ratio of Si to Fe increases the YTS value of the aluminium alloy increase. This observation is consistent with the Gorny et al. (2013) observation, in the study of the influence of the cooling rate, Si level, and Fe on the development of Fe-based intermetallic in Al-Si alloys, the study observed that as the level of Si is reduced, and the level of Fe is increased the development of the Fe based intermetallic increase. The development of these Fe-based intermetallic degrades the aluminium alloy strength (Gorny et al., 2013; Pancho et al., 2018).

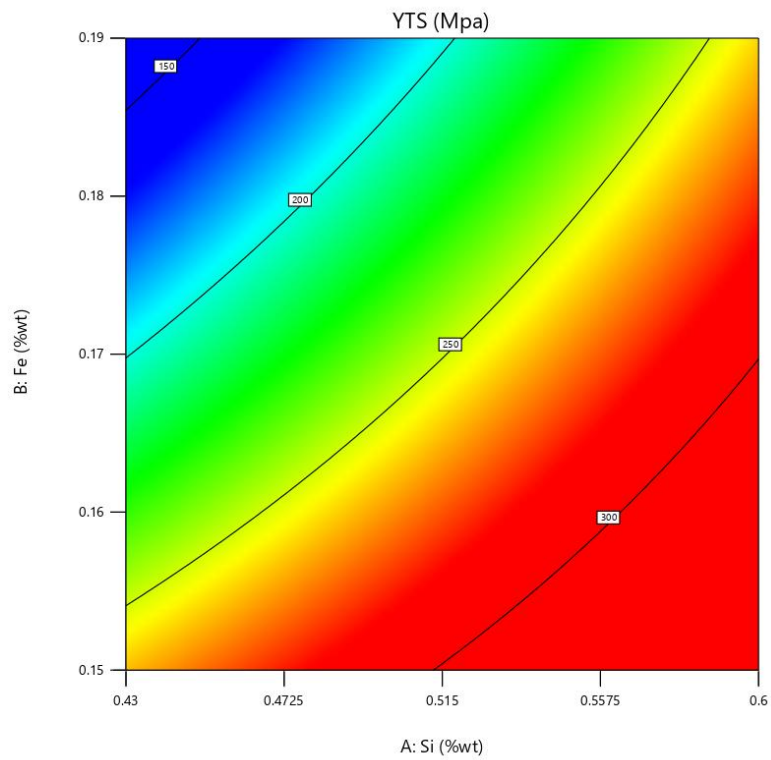


Figure 4.13: Interaction of Si and Fe influence on YTS.

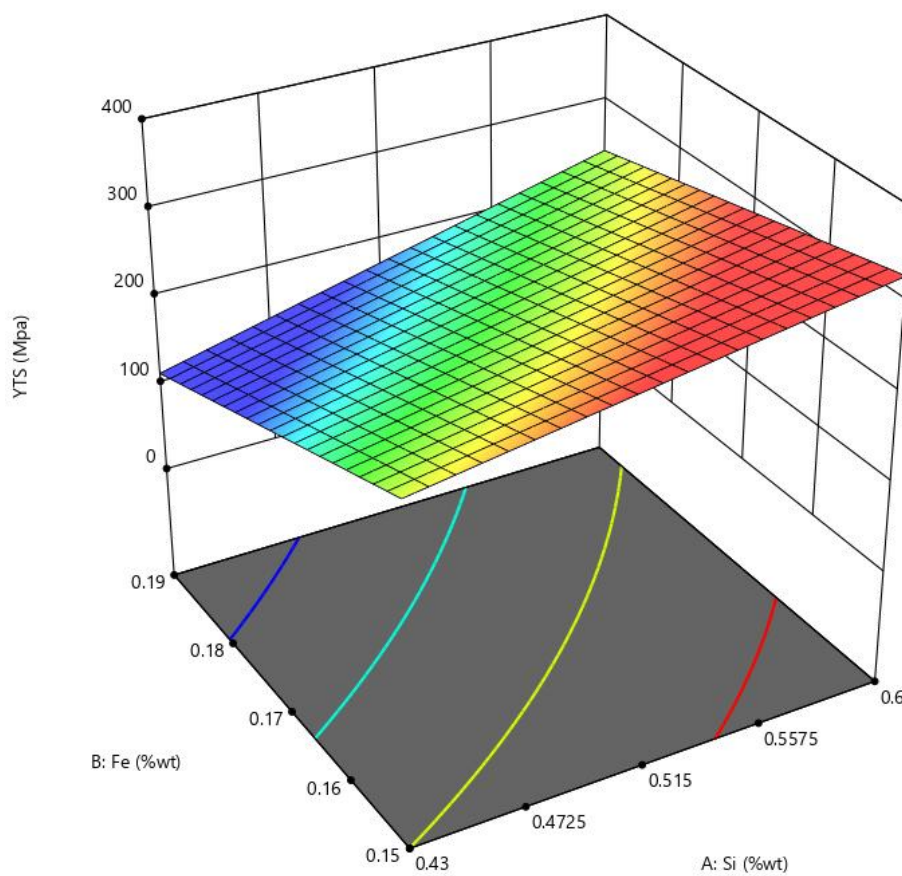


Figure 4.14: Interaction of Si and Fe influence on YTS 3D.

Figures 4.15 and 4.16 below illustrate the influence of the interaction between ageing temperature and ageing time on the aluminium alloy YTS. The figures show that ageing temperature of 175 °C as the ageing time increases the YTS increases, but for an ageing temperature of 203 °C the YTS values reach a maximum value then as the ageing time increases the YTS value decreases, this shows for each ageing temperature there is a maximum YTS value that is reached and after that over ageing which increasing the ageing time further reduces the strength. The ageing time to reach maximum value at lower ageing temperatures is observed to be higher than the ageing time needed at higher ageing temperatures. These observations are consistent with the observations made by Chen et al. (2021), after studying the change in microstructure and mechanical properties of Al-Si-Mg alloys after ageing heat treatment, the study results showed the alloy under study reached a maximum tensile strength of 304 MPa at 180 °C ageing temperature after sixteen hours of ageing, and at 200 °C the tensile strength reached a maximum of 318 MPa after six hours of ageing time and after the alloy reaches the maximum strength the increase of ageing time lead to decreasing the alloy strength.

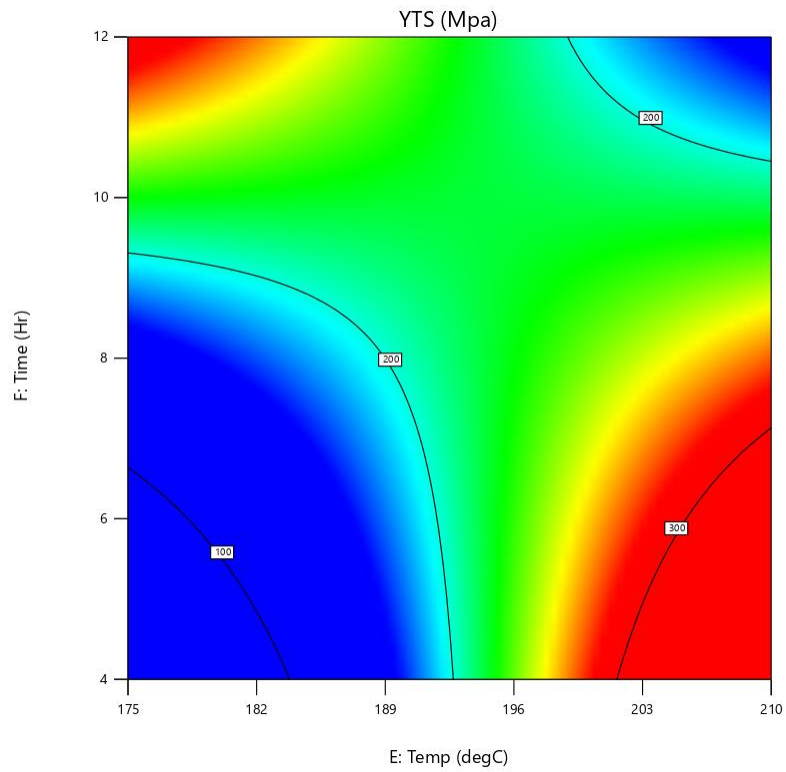


Figure 4.15: Temperature and time influence on YTS.

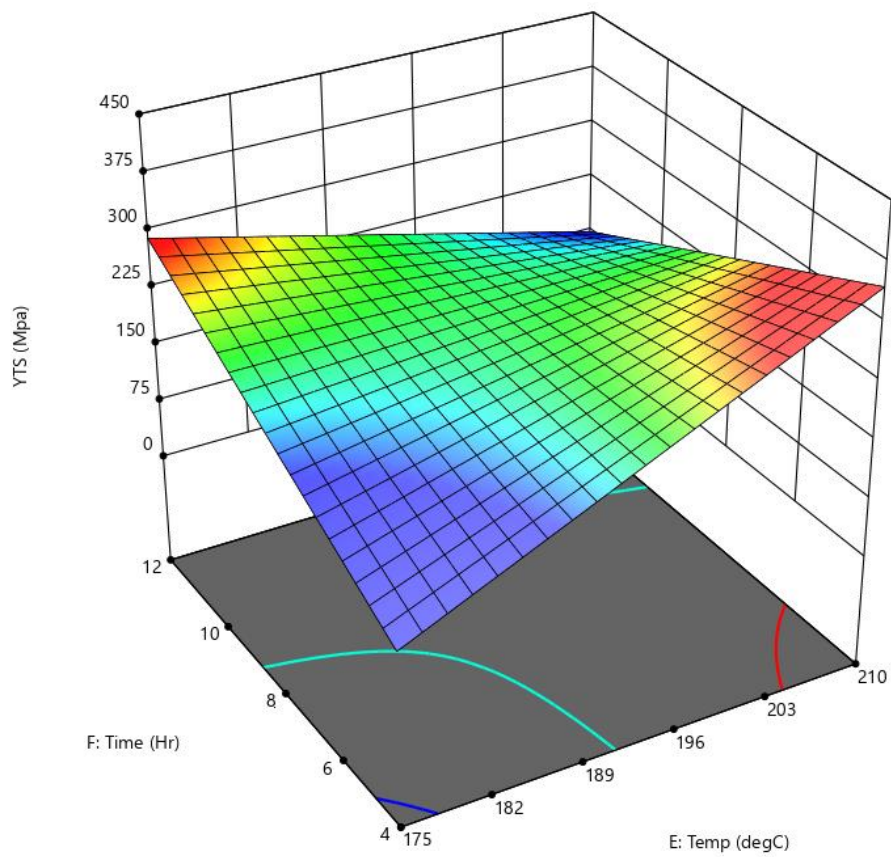


Figure 4.16: Temperature and time influence on YTS 3D.

4.6 Hardness

The ANOVA results of the Hardness model, as seen in Table 4.4, indicate how well the model performs, with an F-value of 49.91 and a p-value of less than 0.0001. As the high F-value along with this low p-value suggests that relationships represented by the model are statistically significant and it covers a significant portion of the variability in the data.

Examining the different parameters, highly significant parameters are Temperature (E) and Time (F); both of their p-values are less than 0.0001, showing a major effect on hardness. Likewise, significant interaction terms AF, BD, CF, and DF p-values are less than 0.0500, highlighting the significance and importance of these interactions in the model determining the hardness. Parameters such as Fe (B), Mn(C), Mg, (D), interaction terms, AC, AD, AE, BC, BE, BF, CE, DE, and EF are found to have p-values less than 0.1, which indicate that they do not have a significant influence on the model however they still contribute to the model.

The lack of fit test, with a p-value of 0.7273, indicates that the model fits the data well, as there is no significant lack of fit. This suggests that the model's predictions are consistent with the observed data.

Other indicators further support the model's robustness. The R^2 value of 0.9810 and Adjusted R^2 of 0.9525 demonstrate that the model explains a high proportion of the variance in hardness. The coefficient of variation (C.V.) is 3.52%, indicating low variability relative to the mean. The Adequate Precision value of 30.1469, well above the threshold of four, confirms the model's strong signal-to-noise ratio, ensuring reliable predictions. Overall, the ANOVA results affirm the Hardness model's validity and reliability, with significant parameters and interactions, a good fit to the data, and strong statistical indicators.

Table 4.4: ANOVA for Hardness model.

Source	Sum of Squares	df	Mean Square	F-value	p-value
Model	7299.63	21	347.60	34.40	< 0.0001
A-Si	27.23	1	27.23	2.69	0.1229
B-Fe	41.88	1	41.88	4.14	0.0612
C-Mn	45.95	1	45.95	4.55	0.0512
D-Mg	37.62	1	37.62	3.72	0.0742
E-Temp	301.94	1	301.94	29.88	< 0.0001
F-Time	281.81	1	281.81	27.89	0.0001
AB	37.26	1	37.26	3.69	0.0754
AC	40.27	1	40.27	3.98	0.0657
AD	36.21	1	36.21	3.58	0.0792
AE	3.34	1	3.34	0.3309	0.5743
AF	420.82	1	420.82	41.64	< 0.0001
BC	37.10	1	37.10	3.67	0.0760
BD	200.19	1	200.19	19.81	0.0005
BE	13.63	1	13.63	1.35	0.2648
BF	9.97	1	9.97	0.9866	0.3374
CD	34.68	1	34.68	3.43	0.0851
CE	0.1542	1	0.1542	0.0153	0.9034
CF	193.05	1	193.05	19.10	0.0006
DE	10.55	1	10.55	1.04	0.3242
DF	379.58	1	379.58	37.56	< 0.0001
EF	2.99	1	2.99	0.2956	0.5952
Residual	141.47	14	10.11		
Lack of Fit	77.31	9	8.59	0.6693	0.7173
Pure Error	64.17	5	12.83		
Cor Total	7441.10	35			
Std. Dev.	3.18			R²	0.9810
Mean	90.36			Adjusted R²	0.9525
C.V. %	3.52			Adeq Precision	30.1469

The numerical equation representing the devolved model for Hardness expressed in terms of actual factors is represented in Equation 4.4.

$$\begin{aligned}
 \hat{H} = & -2.6453 \times 10^4 + 4.2460 \times 10^4 A + 8.3915 \times 10^4 B + \quad \text{Equation (4.4)} \\
 & 1.2656 \times 10^5 C + 2.9729 \times 10^4 D - 3.7877 E - 14.675 F - \\
 & 1.2255 \times 10^5 AB + 9.1169 \times 10^4 AC - 4.5332 \times 10^4 AD + \\
 & 0.8787 AE - 40.7572 AF - 5.7028 \times 10^5 BC - 2.3636 \times \\
 & 10^4 BD + 10.7645 BE + 37.1489 BF - 1.4030 \times 10^5 CD - \\
 & 1.0795 CE + 143.3848 CF + 1.7371 DE + 47.1628 DF - \\
 & 0.0078 EF
 \end{aligned}$$

4.6.1 Variables Influence on Hardness

Figure 4.17 below displays the influence of the ageing time on the hardness of the aluminium alloy. It can be observed from the figure that the increase in ageing time results in higher alloy hardness values. These observations are in accordance with the observations made by Ozturk et al. (2010), during the study to examine the relationship between the change in the heat treatment parameters and the mechanical properties of Al-Mg-Si alloy 6061, where the study observed that the hardness value of the alloy increased with the increase in the ageing time.

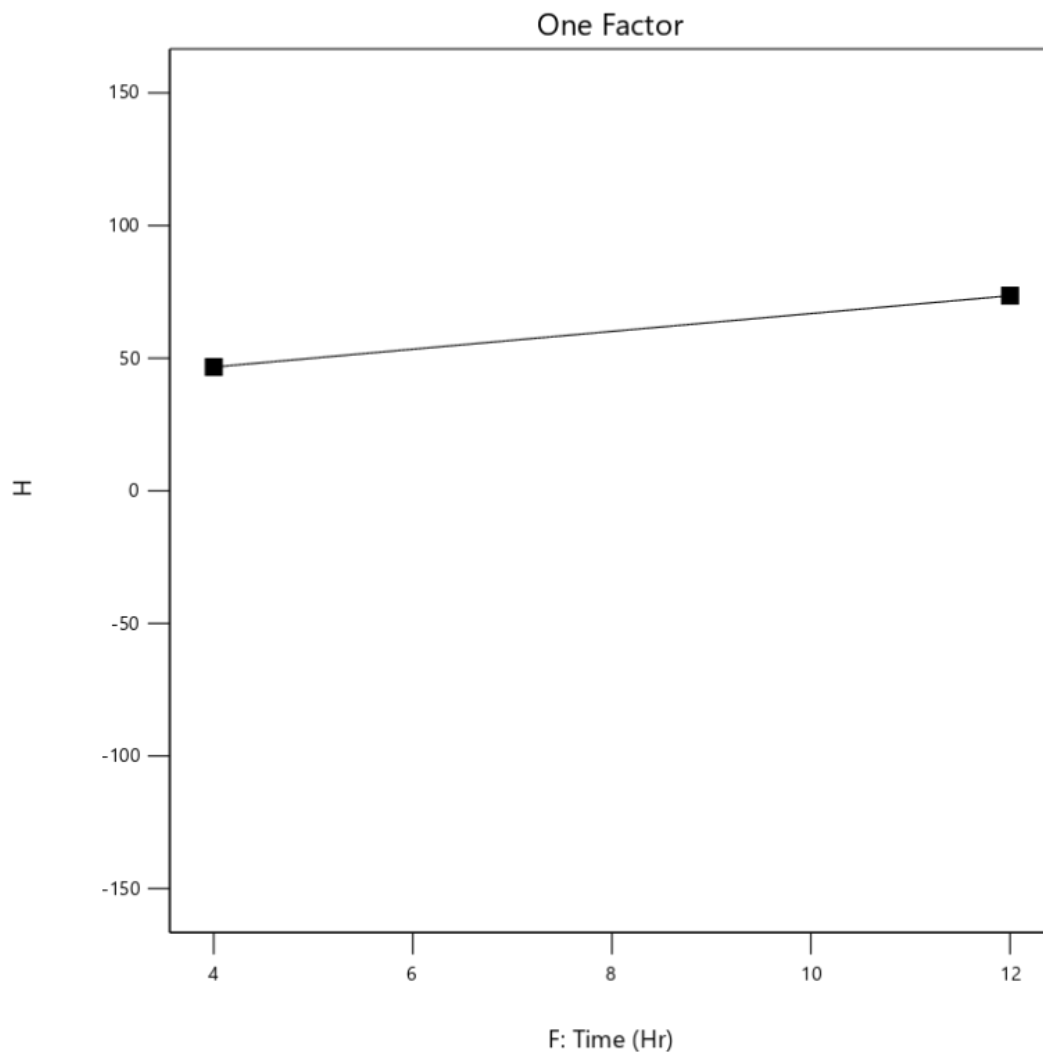


Figure 4.17: Ageing time single factor effect on hardness.

Figure 4.18 below shows the single factor influence of the ageing temperature on the hardness of the aluminium alloy. The figure demonstrates that for this range of ageing temperature as the ageing temperature increases the hardness of the aluminium alloy decreases. These observations are consistent with the observations made by Ibrahim et al. (2011), as part of a study on the effects of Mg level and ageing variables on the hardness and microstructural properties of Al-Si-Mg alloys, where it was observed that the increase of the ageing temperature up to 180° C and higher caused the hardness of the aluminium alloy to decrease.

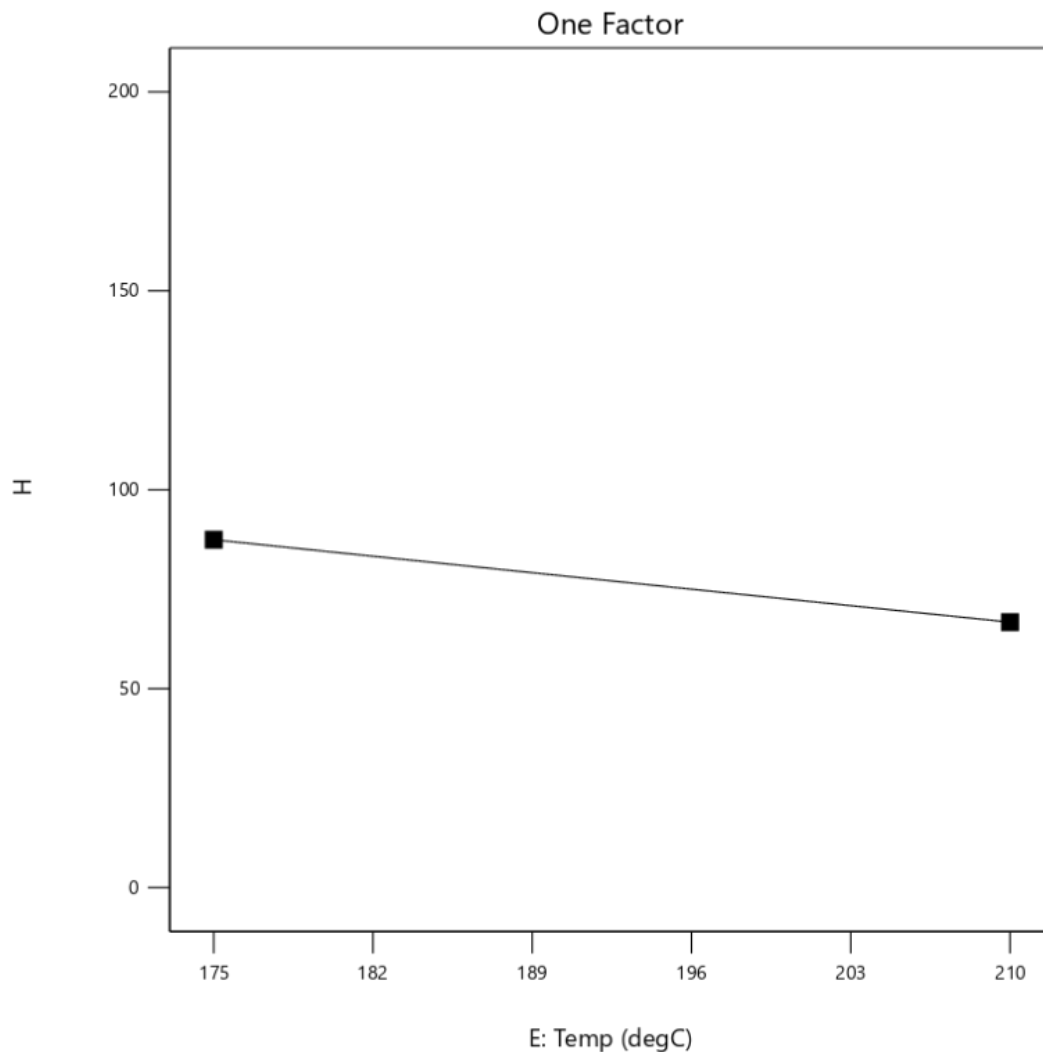


Figure 4.18: Ageing temperature single factor effect on hardness.

Figures 4.19 and 4.29 below illustrate the influence on the alloy hardness due to the interaction (AF) between the Si level and the ageing time. As it can be observed from the figures the increase in both or either one of the Si level and ageing time results in an increase in the alloy hardness. These findings are consistent with the results found by Dwivedi et al. (2006), during the study of the effect of Si level and heat treatment variables on the mechanical characteristics of Al-Si-Mg alloy, found that the increase in the Fe level increases the alloy hardness and for higher ageing conditions the hardness increased to further higher levels.

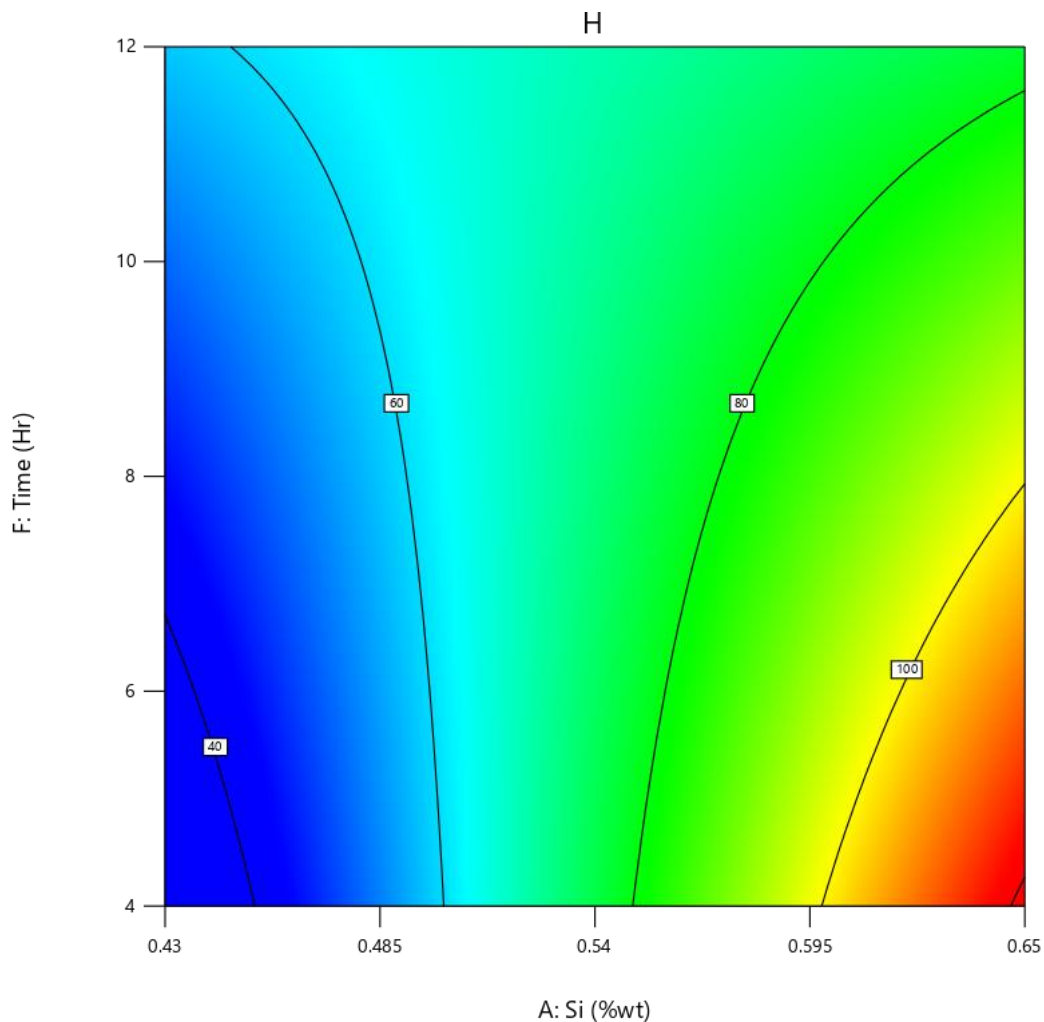


Figure 4.19: Si and time combined impact on hardness.

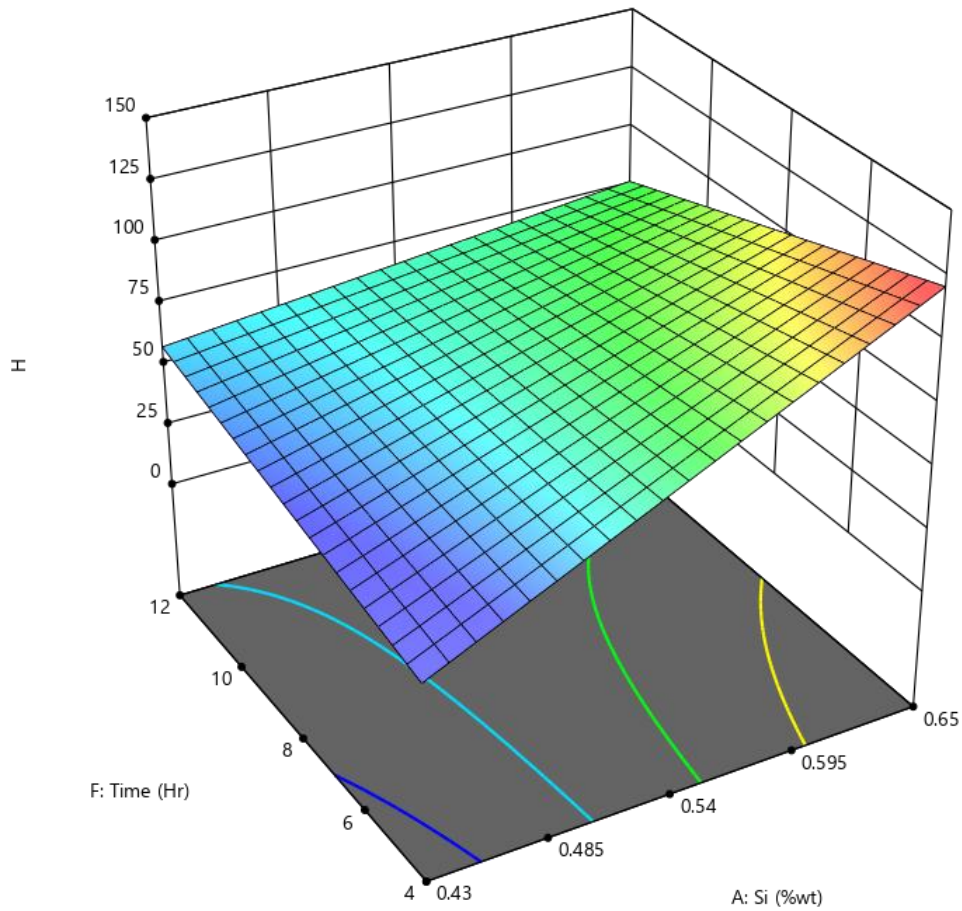


Figure 4.20: Si and time combined impact on hardness 3D.

Figures 4.21 and 4.22 represent how the interaction factor (BD), between the Si and Mg levels, affects the hardness of the aluminium alloy. The figures show that as the Mg level increases the hardness value of the alloy increases, however, the Si level has the opposite effect on the hardness as it is observed that the increase in Si level leads to a reduction in the hardness value of the alloy. The figures also show that as the level of Fe increases the influence of Mg reduces. These observations from the figures are concurrent with the observations made by Ibrahim et al. (2015) in the study of the role played by different additives on the mechanical properties and microstructure of the Al-Si-Mg alloys, where the study observed that an increase of the Mg level led to an increase in the alloys mechanical properties and the increase of Fe addition led to a decrease in those properties.

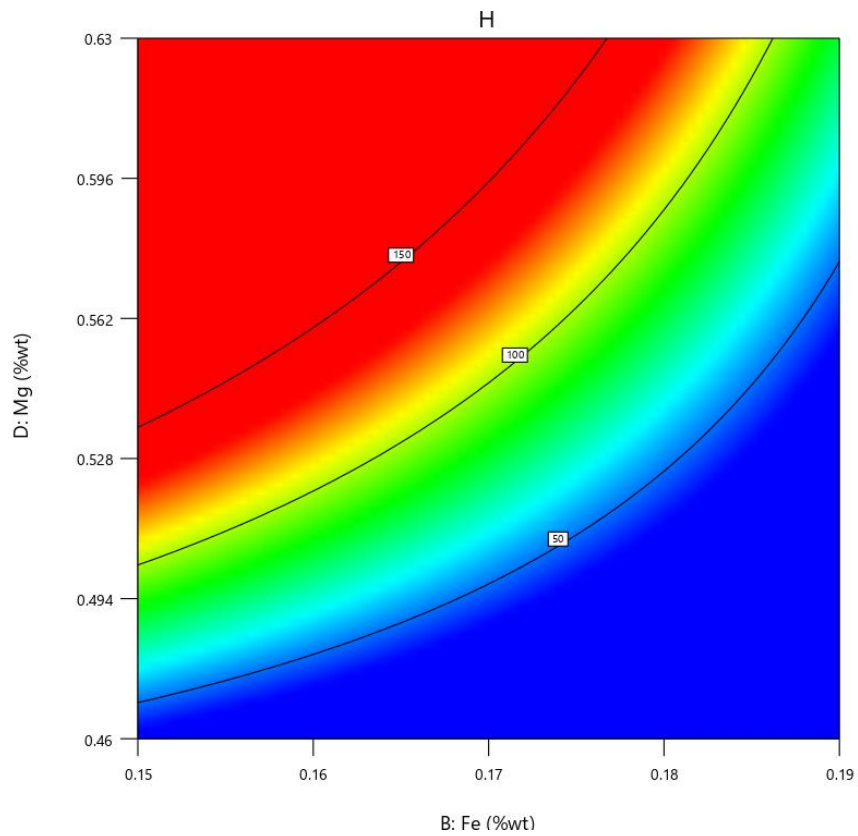


Figure 4.21: Interaction of Fe and Mg influence on hardness.

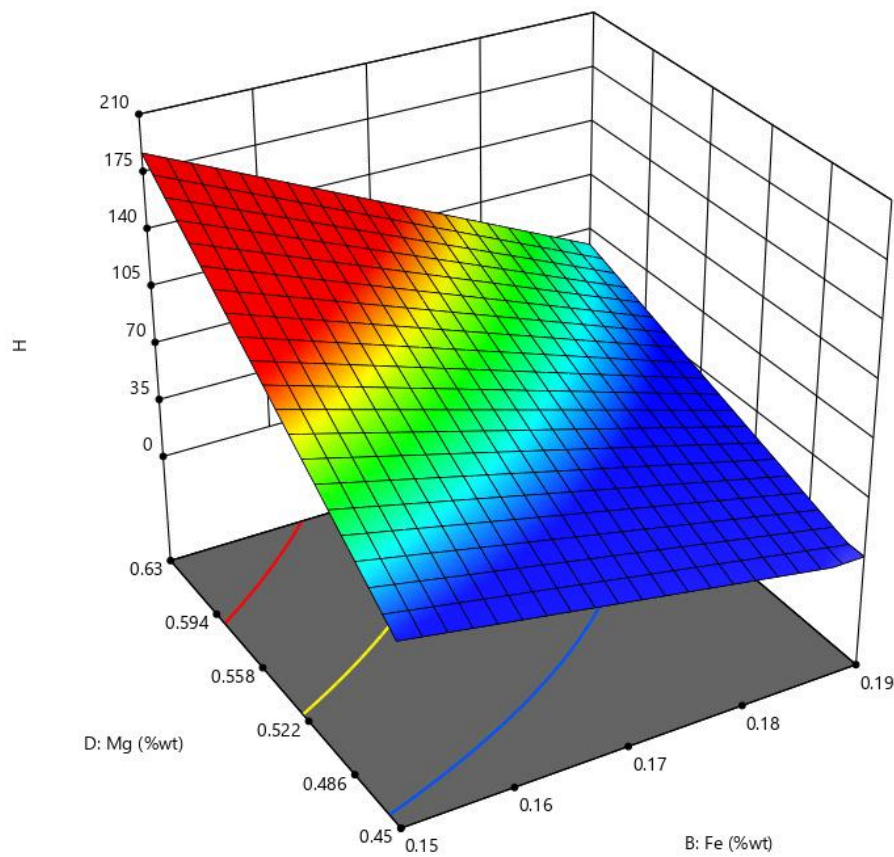


Figure 4.22: Interaction of Fe and Mg influence on hardness 3D.

Figures 4.23 and 4.24 show the influence of the interaction (CF), between Mn level and ageing time, on the hardness of the aluminium alloy. The figures illustrate that as the level of Mn increases the hardness value increases, it also shows that for the same level of Mn, the hardness value increases with the increase of ageing time in the high range of the Mn levels but decreases slightly in the low range of Mn levels. The figures show that as the level of Mn increases the influence of ageing time increases. These results coincide with the results found by Tareq et al. (2021), where it was found that with the addition of higher levels of Mn, the hardness of the aluminium alloy increased.

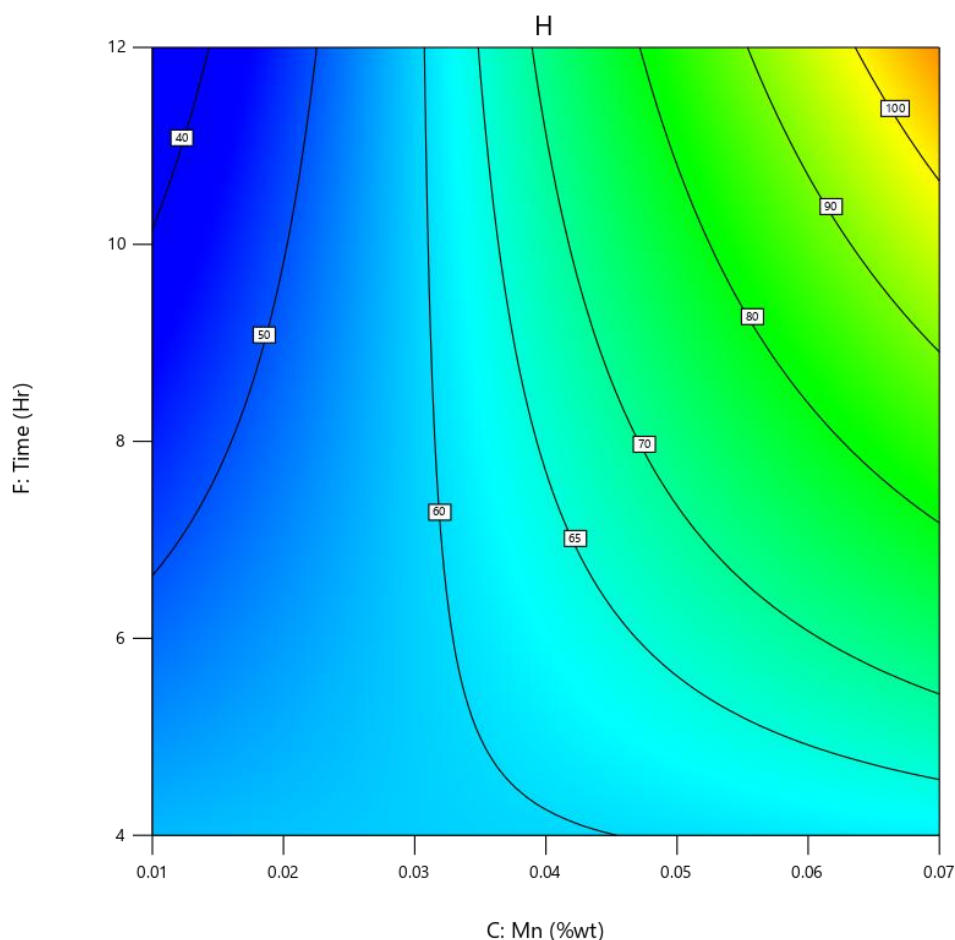


Figure 4.23: Mn and time combined influence on hardness.

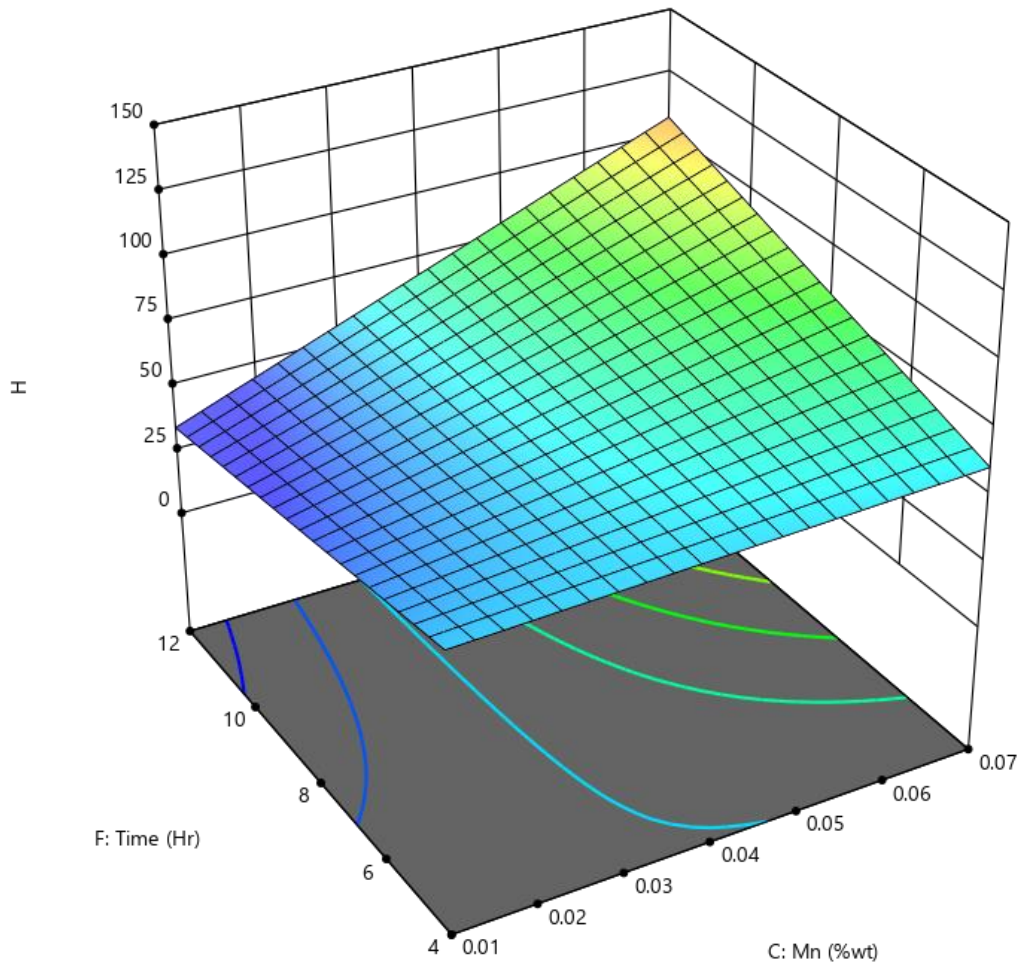


Figure 4.24: Mn and time combined influence on hardness 3D.

Figures 4.25 and 4.26 show the influence of the interaction (DF) between the Mg level and ageing time on the hardness of the aluminium alloy. It can be observed from the figures that as Mg level in the aluminium alloy and the ageing time increases the hardness of the aluminium alloy increases. These findings on the influence of Mg and ageing time on the hardness of the alloy are coherent with the findings of Tash et al. (2007) that found, during the study of the heat treatment and metallurgical variables influence on the hardness and microstructure of Al-Si-Mg alloys, that a remarkable increase in hardness was obtained after the addition of higher Mg levels and ageing heat treatment.

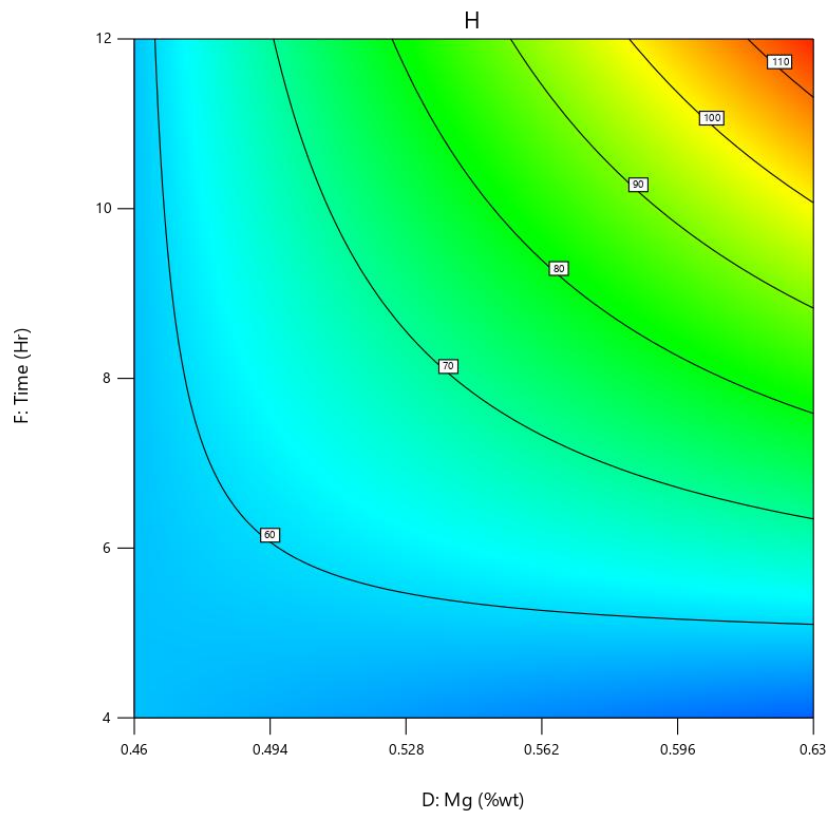


Figure 4.25: Mg and time combined effect on hardness.

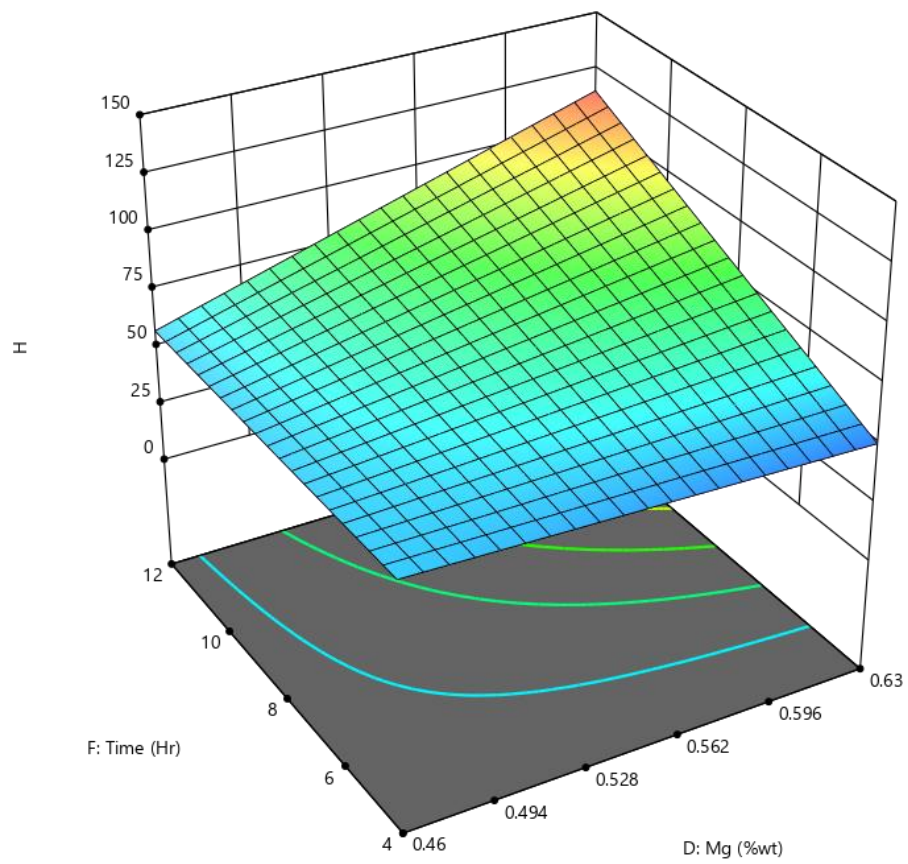


Figure 4.26: Mg and time combined effect on hardness 3D.

4.7 Elongation

The ANOVA of the Elongation model, as shown in Table 4.5, shows its performance and reliability. The model's F-value of 12.53 and a p-value of less than 0.0001 indicate that the model is highly significant¹. Where the F-value suggests that the relationships represented by the model in regard to the influence of the different variables on the El% are significant, while the low p-value indicates that this representation of significant relationships is statistically significant and not by chance.

As for the variables' significance. The Time (F), and the interaction parameters AE and AF are all highly significant as they all have p-values less than 0.01. Additionally, factors with p-values less than 0.05 include Fe (B), Mg (D), Temperature (E), and several interactions such as AB, AC, AD, BC, CD, CE, and CF. These factors are also significant and contribute meaningfully to the model, though to a lesser extent than those with p-values less than 0.01. Parameters with p-values less than 0.1, including Mn (C) with a p-value of 0.0516 and BD interaction with a p-value of 0.0848, further contribute to the model's predictive capability.

The lack of fit test, with a p-value of 0.2466, indicates that the model does not show a significant lack of fit, implying that the model captures the relationship between the variables and the response effectively.

The R^2 value of 0.9461 and Adjusted R^2 of 0.8706 indicate that a large part of the variability in elongation is explained by the model. The Adequate Precision of 18.6620, well above the threshold of four, signifies a strong signal-to-noise ratio, ensuring the model's predictive capability. The C.V. % of 8.40 provides a normalised measure of dispersion, further validating the model's robustness. In summary, the lack of fit tests and other statistical indicators affirm the model's robustness and reliability,

making it a valuable tool for predicting the elongation of aluminium alloy 6063.

Table 4.5: ANOVA for Elongation model.

Source	Sum of Squares	df	Mean Square	F-value	p-value
Model	214.17	21	10.20	12.53	< 0.0001
A-Si	0.8653	1	0.8653	1.06	0.3189
B-Fe	5.02	1	5.02	6.17	0.0253
C-Mn	3.64	1	3.64	4.47	0.0516
D-Mg	5.36	1	5.36	6.59	0.0215
E-Temp	6.39	1	6.39	7.85	0.0134
F-Time	13.14	1	13.14	16.14	0.0011
AB	5.54	1	5.54	6.81	0.0197
AC	4.90	1	4.90	6.02	0.0269
AD	5.83	1	5.83	7.17	0.0172
AE	21.70	1	21.70	26.66	0.0001
AF	22.50	1	22.50	27.64	< 0.0001
BC	5.50	1	5.50	6.75	0.0201
BD	2.77	1	2.77	3.41	0.0848
BE	0.3171	1	0.3171	0.3896	0.5419
BF	2.30	1	2.30	2.83	0.1134
CD	5.54	1	5.54	6.81	0.0197
CE	11.23	1	11.23	13.80	0.0021
CF	5.22	1	5.22	6.41	0.0230
DE	5.66	1	5.66	6.95	0.0187
DF	2.67	1	2.67	3.28	0.0901
EF	1.98	1	1.98	2.44	0.1393
Residual	12.21	15	0.8139		
Lack of Fit	9.67	10	0.9673	1.91	0.2466
Pure Error	2.54	5	0.5071		
Cor Total	226.38	36			
Std. Dev.	0.9022			R²	0.9461
Mean	10.74			Adjusted R²	0.8706
C.V. %	8.40			Adeq Precision	18.6620

The numerical equation representing the devolved model for % Elongation with respect to actual factors is represented in Equation 4.5.

$$\begin{aligned} \hat{El}\% = & -3993.2711 + 6970.0889 A + 1.1584 \times 10^4 B + 1.9884 \times 10^4 C + 3805.9148 D + \\ & 0.0980 E - 0.0756 F - 1.9616 \times 10^4 AB + 1.2933 \times 10^4 AC - 7123.7453 AD - 1.4111 AE + 6.5380 AF - \\ & 8.7314 \times 10^4 BC + 1359.1340 BD - 0.9704 BE - 11.5474 BF - 2.2669 \times 10^4 CD + 3.9059 CE - \\ & 11.5028 CF + 1.1320 DE - 3.8453 DF + 0.0064 EF \end{aligned} \quad \text{Equation (4.5)}$$

4.7.1 Variables Influence on Elongation

Figure 4.27 below shows the influence of ageing time on the aluminium alloy elongation. It can be observed from the figure that as the ageing time increases the aluminium alloy elongation decreases. Alexopoulos et al. (2022) study on the response of aluminium alloy 6156 to ageing conditions concluded the same results, where it was observed that artificial ageing decreases the alloy elongation and increases the yield stress

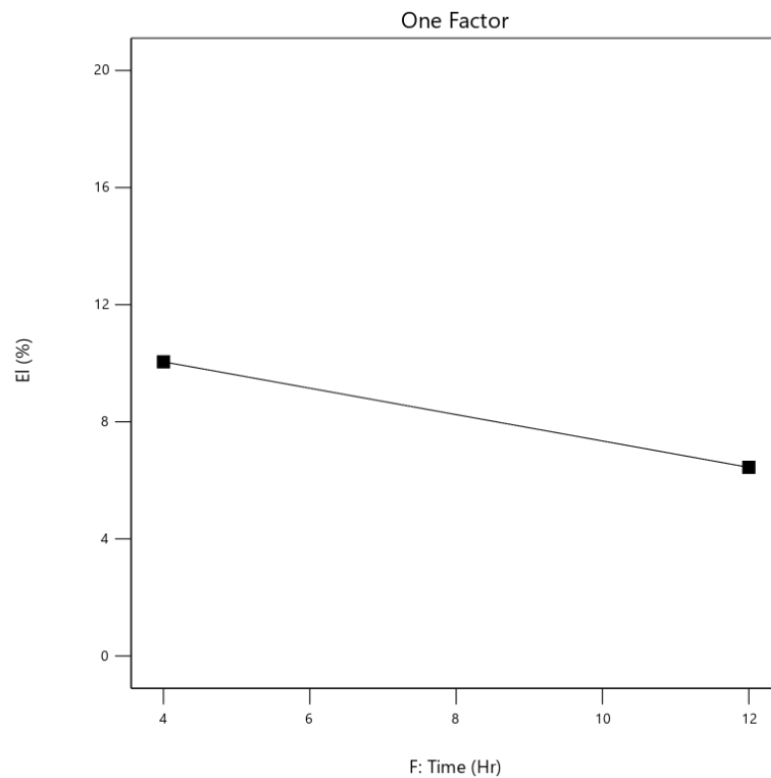


Figure 4.27 : Ageing time single factor effect on elongation.

Figure 4.28 shows the single-factor effect of the addition of Fe on the elongation of the aluminium alloy. It can be observed from the figure below that as the level of Fe increases the elongation of the aluminium alloy decreases. These results are in line with the results of Sarkar et al. (2004), that was found during the study of the effect of Fe level on the tensile properties of aluminium alloy 6111, where it was found that the ductility of the aluminium alloy reduced as the level of Fe addition increased.

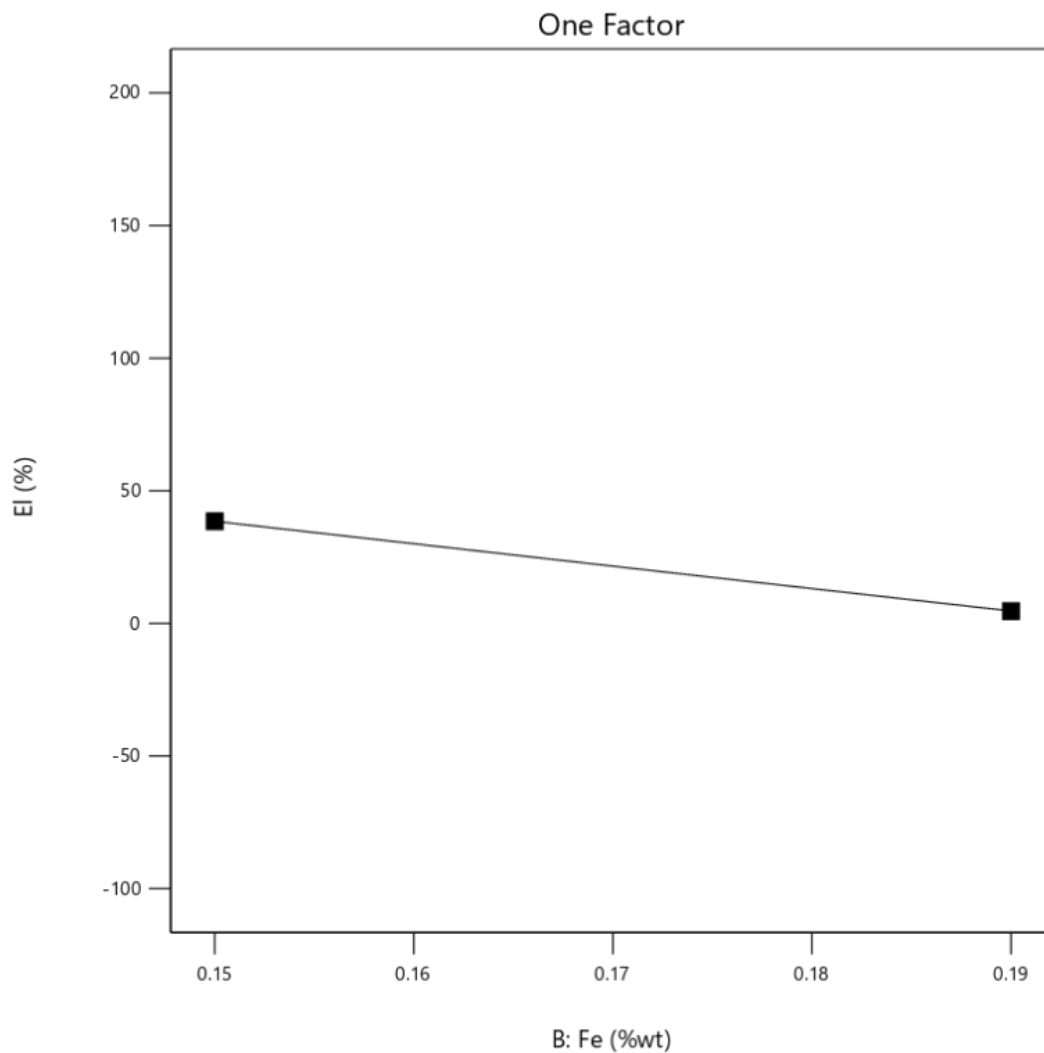


Figure 4.28: Fe single factor effect on elongation.

Figure 4.29 demonstrates the single factor influence of the Mg level on the alloy elongation percentage. The figure shows that as the Mg levels increase a decrease in the alloy elongation percentage is observed. This observation in regard to the Mg influence on the alloy elongation percentage lines up with observed results in Han et al. (2014) study on the influence of ageing heat treatment and various Mg levels on the tensile properties of Al-Si-Mg alloys, where the study results stated that the increase in Mg levels led to improvements in the alloy strengths but at the expense of reduction in the elongation percentage of the alloys.

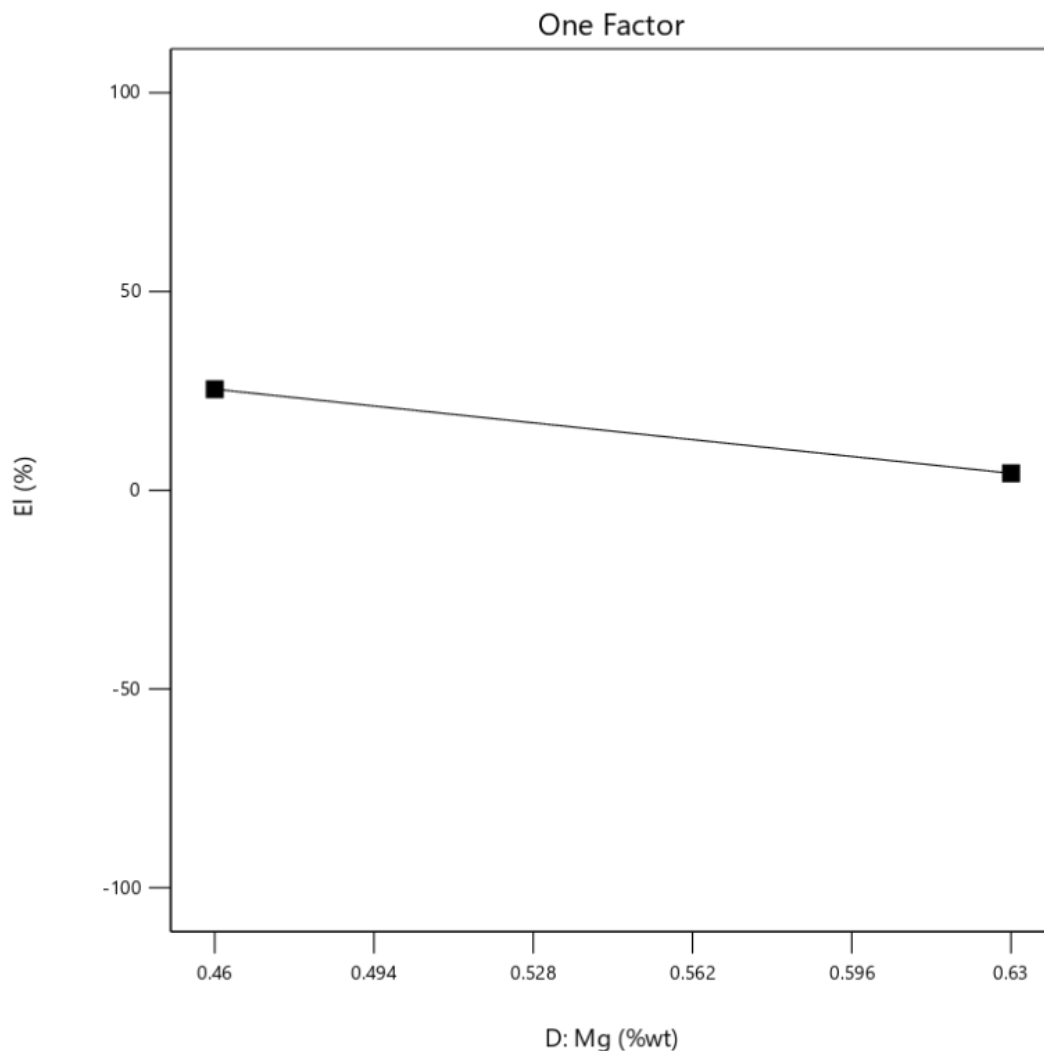


Figure 4.29: Mg single factor effect on elongation.

Figures 4.30 and 4.31 show the effect of the interaction factor (AE), between the Si level and the ageing temperature, on the elongation percentage of the aluminium alloy. It can be observed from the figures that as the Si level increases a reduction in the elongation percentage is observed, while it can be observed that the increase in the ageing temperature results in a higher value of the elongation percentage of the alloy. These observations are compatible with the observations observed during Dwivedi et al. (2006) study on the effects of ageing conditions and Si concentration on the microstructure and mechanical properties of Al-Si-Mg alloys, in which it was observed that increasing the ageing temperature from 150 to 230 °C increased the elongation percentage of the alloy, however, the increase of the Si level in the alloy resulted in a reduction in the elongation percentage.

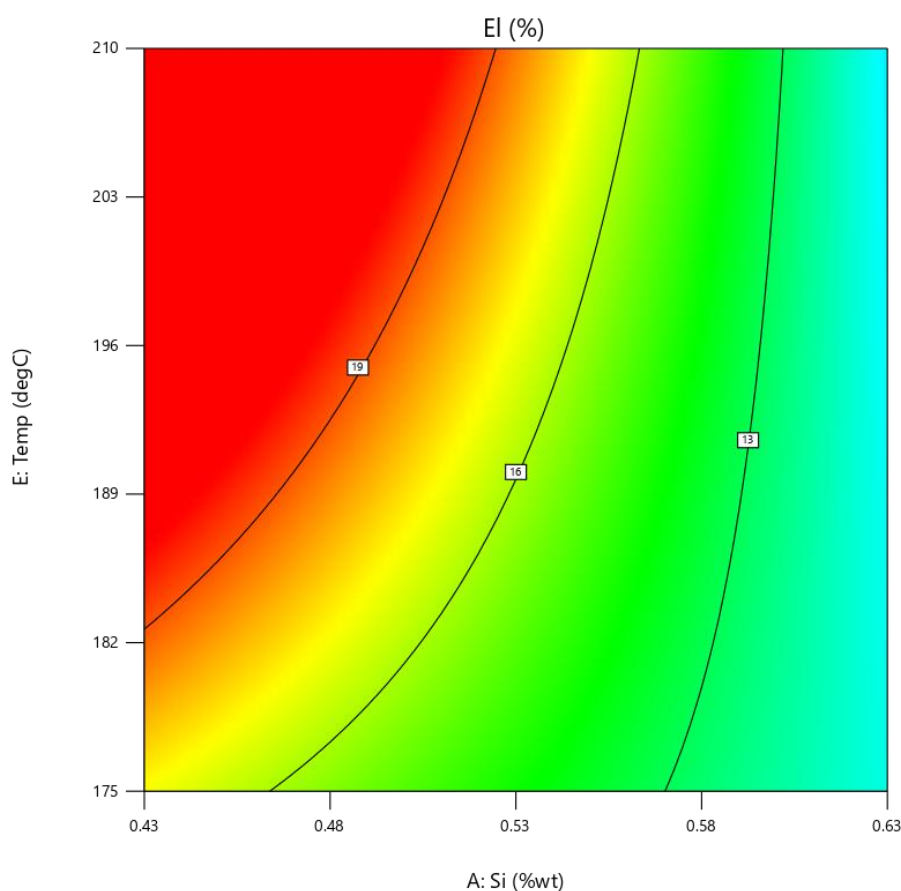


Figure 4.30: Interaction factor AE influence on elongation.

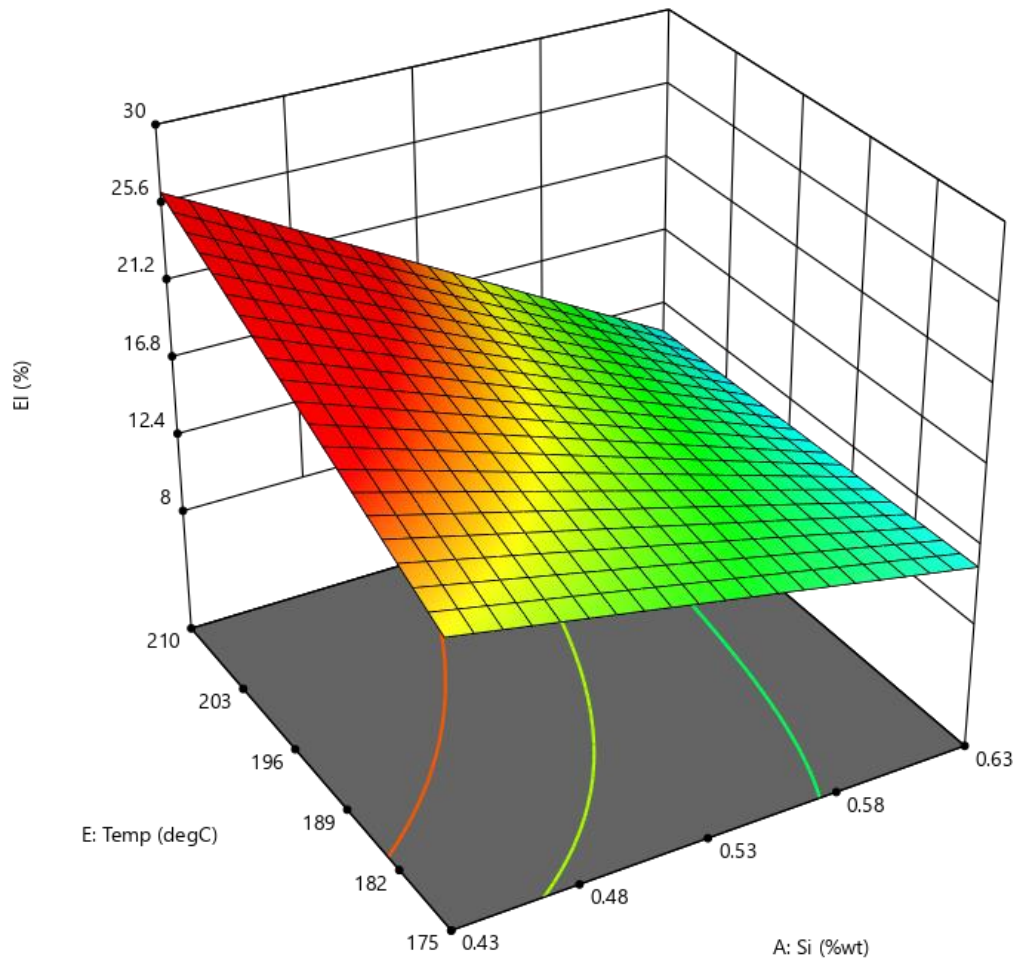


Figure 4.31: Interaction factor AE influence on elongation 3D.

The effect of the interaction (AF), between the Si level and ageing time, on the aluminium alloy elongation is shown in Figures 4.32 and 4.33. The figures illustrate that the increase in the Si level and the ageing time results in a reduction in the alloy elongation. These observations are consistent with the observations of Dwivedi et al. (2006) study, which focused on the effect of the Si level and heat treatment on the mechanical properties of Al-Si-Mg alloys, the results indicated that as the Si content increased in the alloy and the ageing time increased the alloy elongation percentage decreased.

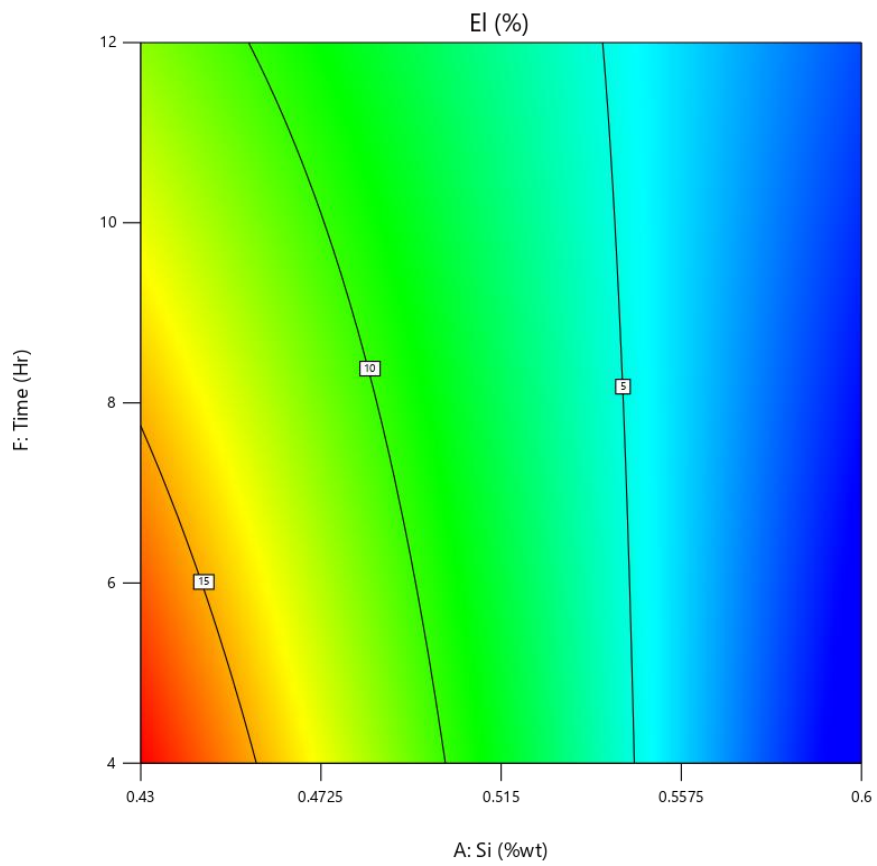


Figure 4.32: Interaction factor AF influence on elongation.

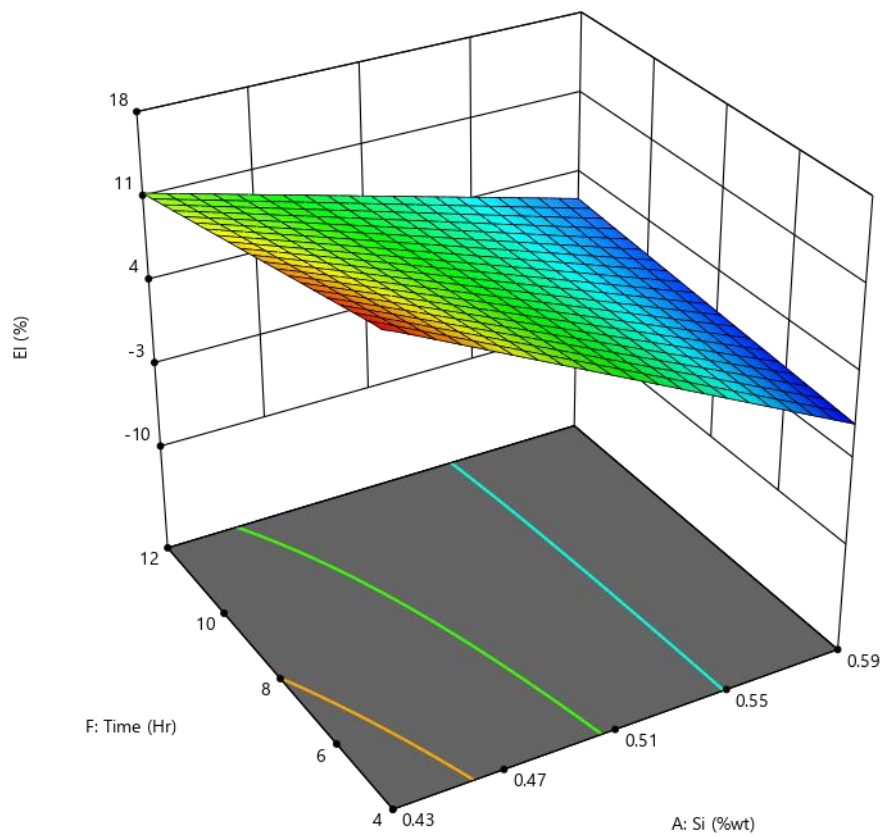


Figure 4.33: Interaction factor AF influence on elongation 3D.

The influence of the interaction factor (CF), between the Mn level and the ageing time, on the alloy elongation percentage is shown in Figures 4.34 and 4.35. It can be observed from the figures that as the level of Mn increases higher elongation percentages are obtained, and it can be observed that increasing the ageing time leads to obtaining higher elongation percentages. These observations coincide with the observations made by Qian et al. (2021), during the study of the influence of Mn levels on the mechanical properties and the microstructure of cast and heat-treated Al-Si-Mg alloys, that study observed that increasing the Mn level in the alloy to up to 0.5% led to an increase in the elongation percentage, and it was also observed that the alloys that went under ageing treatment exhibited higher elongation values.

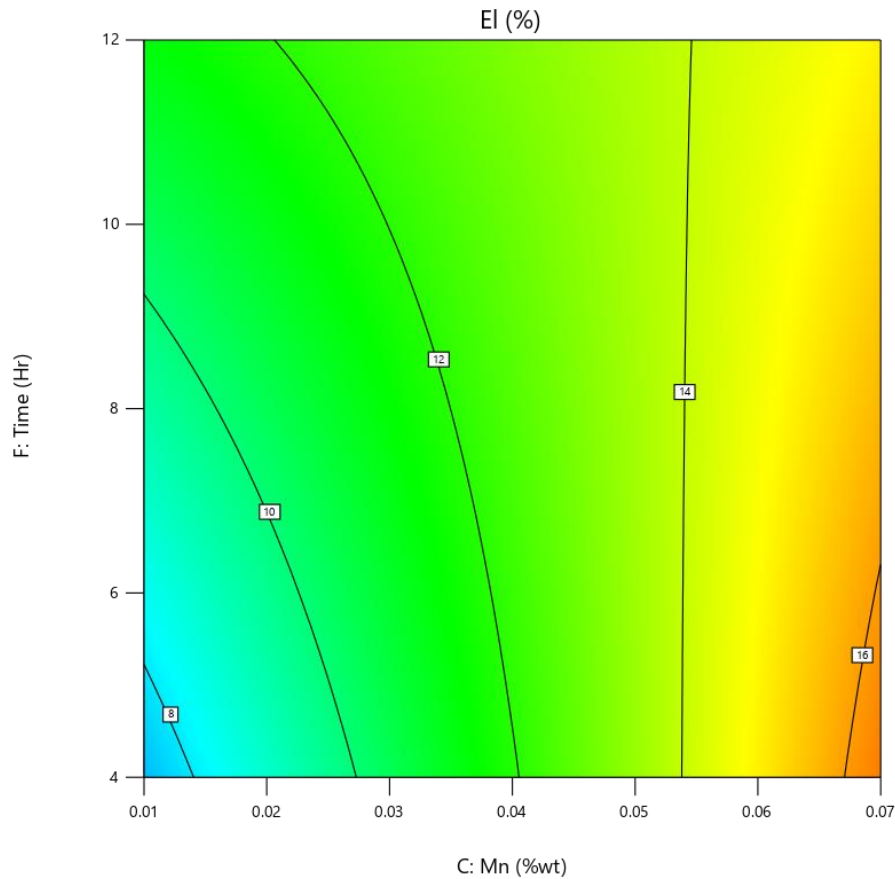


Figure 4.34: Interaction factor CF influence on elongation.

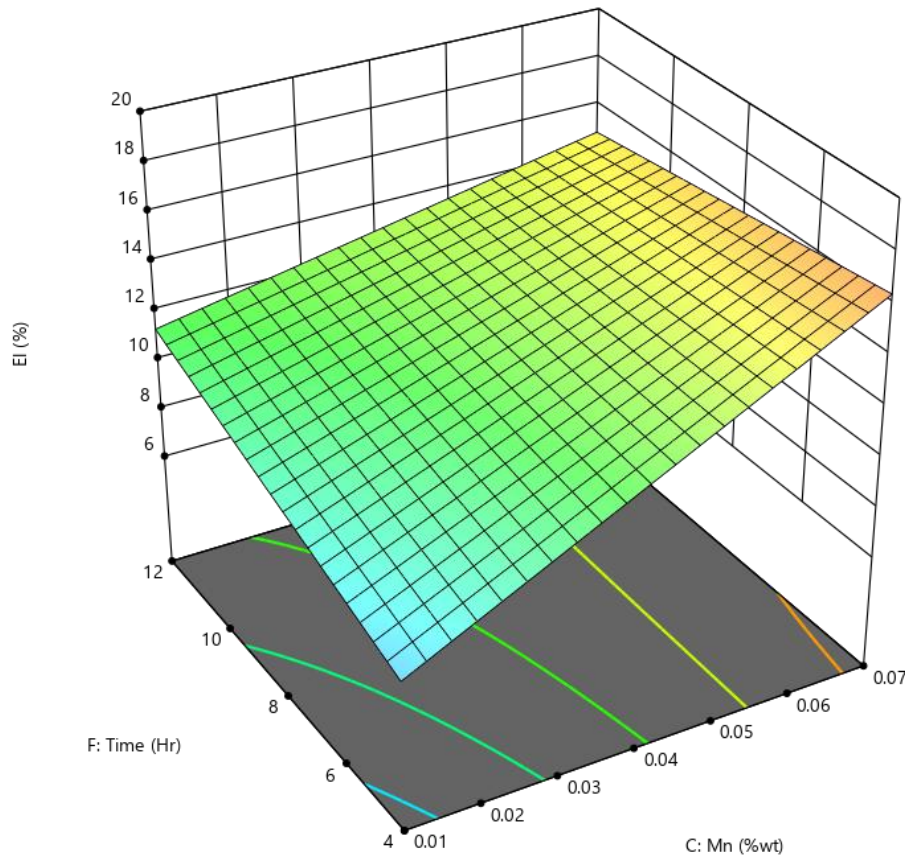


Figure 4.35: Interaction factor CF influence on elongation 3D.

4.8 Modulus of Elasticity

The ANOVA results for the ME model, shown in Table 4.6, provide a comprehensive assessment of the model's performance and the significance of various factors. The model's F-value of 7.83 is notably high, and the p-value of 0.0007 enforces the model's overall significance.

As for the significance of the different parameters, Temperature (E), Time (F), Mg (D), and the interaction term AD, all have p-values less than 0.05, which shows that these variables have a significant influence on the model. Other variables with a p-value of less than 0.1, which indicates moderate significance on the model are Fe (B) and the interaction term CD.

The model's Lack of Fit, with a p-value of 0.6523, indicates that there is no significant lack of fit, implying that the model accurately describes

the connection between the components and the response variable. The model has a good degree of fit with the R^2 of 0.9164, explaining 91.64% of the variability in ME, and the Adjusted R^2 of 0.7993, indicates a strong model fit.

The model signal-to-noise ratio is good, as the adequate precision ratio is 11.239, indicating the model's reliability in covering the design space. The Coefficient of Variation (C.V.) is 3.86%, which implies that the dispersion around the mean is low, which also validates the model precision.

The ME model shows strong statistical significance and reliability, it can serve as a useful tool in understanding the mechanical properties of aluminium alloy 6063.

The devolved model numerical equation expressed in terms of actual factors is represented in Equation 4.6.

$$\begin{aligned} \hat{ME} = & 785.4155 - 1278.2692 A - 1960.0674 B - \quad \text{Equation (4.6)} \\ & 3735.5685 C - 935.4017 D - 0.0582 E + \\ & 0.5163 F + 2913.2191 AB - 1881.3358 AC + \\ & 1581.6993 AD + 0.0534 AE - 0.2496 AF + \\ & 1.3268 \times 10^4 BC + 222.2444 BD + 0.3696 BE + \\ & 0.3818 BF + 4696.7594 CD - 0.2732 CE - \\ & 0.6411 CF - 0.0614 DE - 0.3681 DF - 0.0014 EF \end{aligned}$$

Table 4.6: ANOVA for Modulus of Elasticity model.

Source	Sum of Squares	df	Mean Square	F-value	p-value
Model	6.13	21	0.2917	7.83	< 0.0001
A-Si	0.0484	1	0.0484	1.30	0.2724
B-Fe	0.1293	1	0.1293	3.47	0.0822
C-Mn	0.0296	1	0.0296	0.7929	0.3873
D-Mg	0.2978	1	0.2978	7.99	0.0128
E-Temp	0.4413	1	0.4413	11.84	0.0036
F-Time	0.2751	1	0.2751	7.38	0.0159
AB	0.1222	1	0.1222	3.28	0.0902
AC	0.1036	1	0.1036	2.78	0.1162
AD	0.2876	1	0.2876	7.72	0.0141
AE	0.0311	1	0.0311	0.8333	0.3758
AF	0.0328	1	0.0328	0.8796	0.3632
BC	0.1270	1	0.1270	3.41	0.0848
BD	0.0741	1	0.0741	1.99	0.1788
BE	0.0460	1	0.0460	1.23	0.2841
BF	0.0025	1	0.0025	0.0675	0.7986
CD	0.2380	1	0.2380	6.39	0.0232
CE	0.0549	1	0.0549	1.47	0.2435
CF	0.0162	1	0.0162	0.4351	0.5195
DE	0.0166	1	0.0166	0.4462	0.5143
DF	0.0245	1	0.0245	0.6569	0.4303
EF	0.1023	1	0.1023	2.74	0.1184
Residual	0.5591	15	0.0373		
Lack of Fit	0.3417	10	0.0342	0.7859	0.6523
Pure Error	0.2174	5	0.0435		
Cor Total	6.69	36			
Std. Dev.	0.1931			R²	0.9164
Mean	5.01			Adjusted R²	0.7993
C.V. %	3.86			Adeq Precision	11.2391

4.8.1 Variables influence on Modulus of elasticity

The single-factor effect of the ageing temperature on the aluminium alloy ME is shown in Figure 4.36 below. The figure illustrates that the increase in the ageing temperature results in obtaining lower values of the ME of the aluminium alloy. These observations based on the figure are consistent with the observations made by Radutoiu et al. (2013), during the study performed to analyse the effect of artificial ageing on the

microstructure and properties of aluminium alloy, the study observations indicated that a reduction in the ME was observed as the artificial ageing temperature was increased.

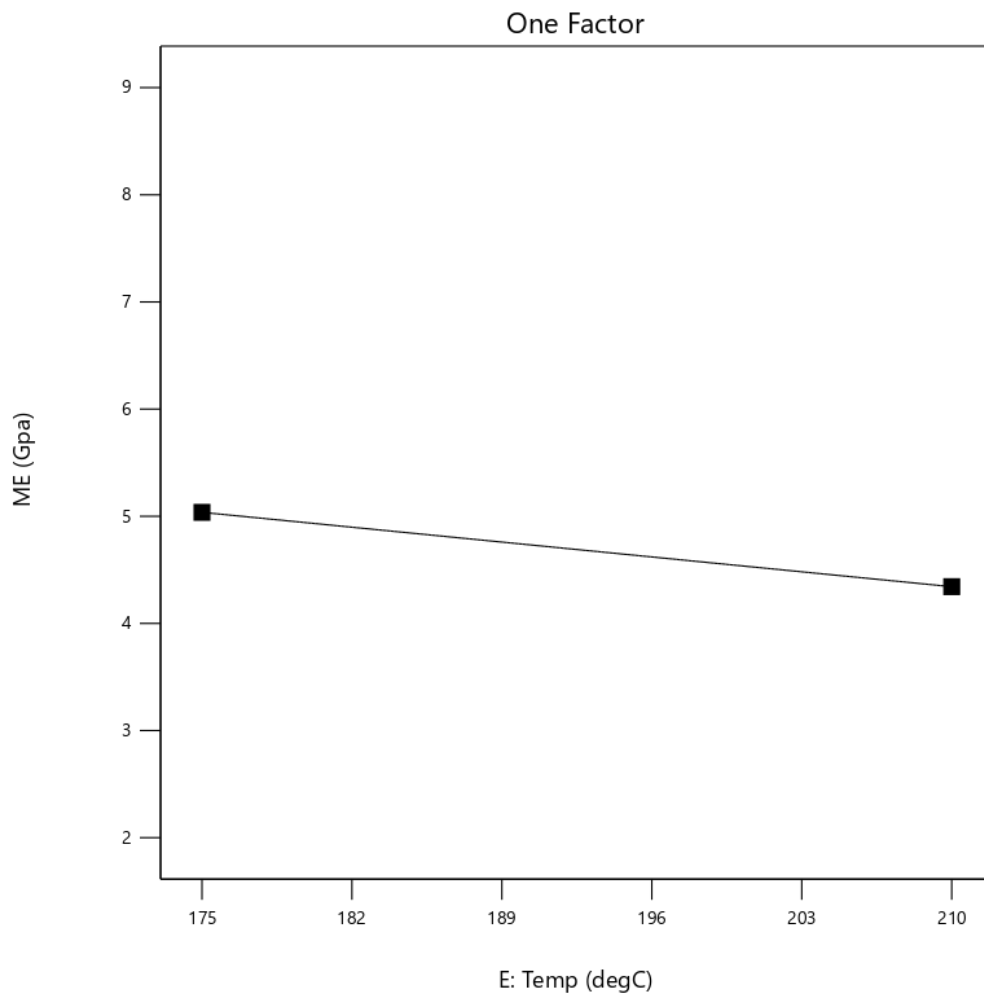


Figure 4.36: Ageing temperature single factor effect on ME.

The single factor influence of the ageing time on the aluminium alloy ME is shown in Figure 4.37. It can be observed from the figure that the increase in the ageing time of the aluminium alloy leads to a reduction in the alloy ME. These observations are coherent with the observations of Alexopoulos (2009) study on the degradation of the artificially aged aluminium alloy under corrosion, the study results indicated that as the

artificial ageing time increases the aluminium alloy experiences a reduction in the ME.

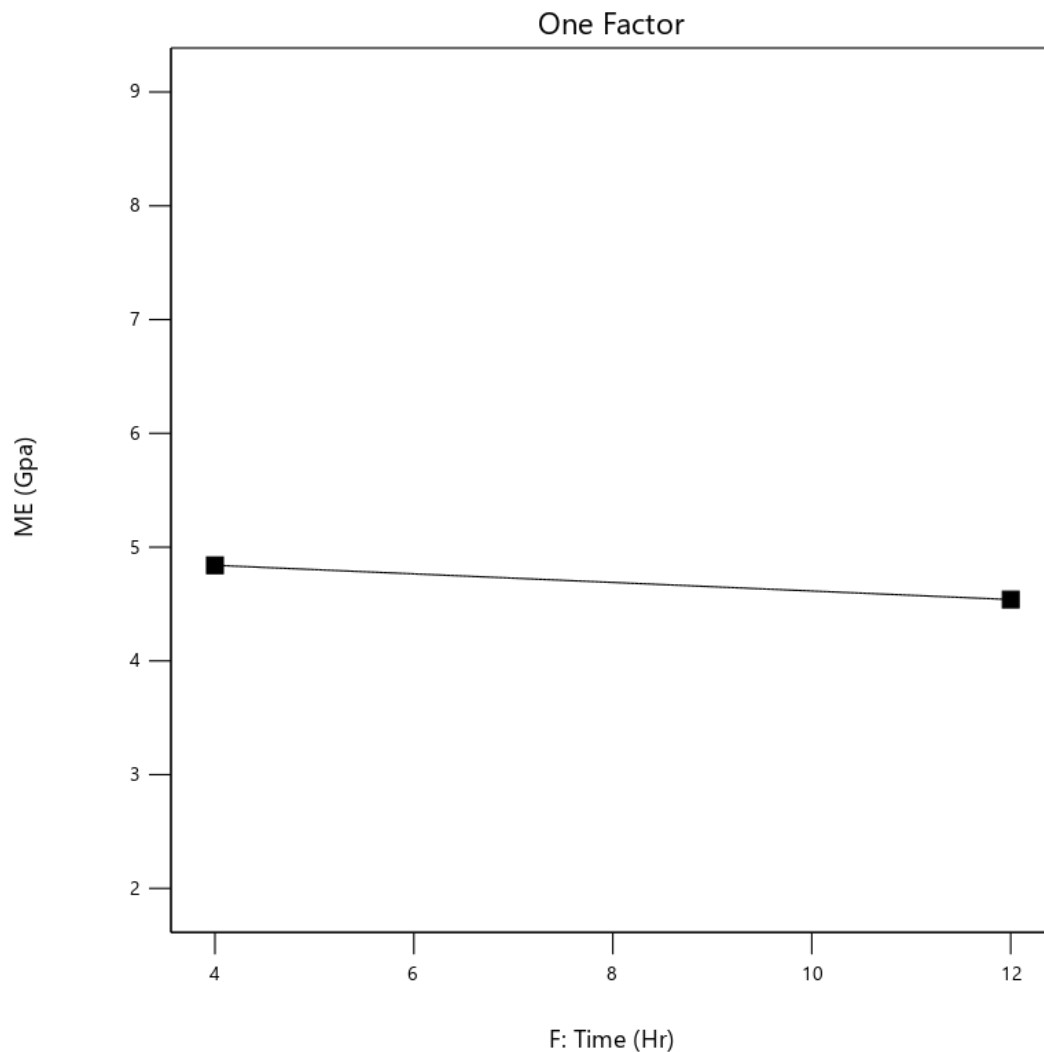


Figure 4.37: Ageing time single factor effect on ME.

Figure 4.38 below displays the single-factor effect of Mg level on the ME of the aluminium alloy. The figure indicates that the increase in the Mg level in the aluminium alloy results in a reduction in the ME. The observed influence of the Mg level on the aluminium alloy ME is in coherence with the observation made by S. Ren et al. (2007), in the study of the influence of Si and Mg on thermal and mechanical properties of Al-Si alloys

manufactured by the pressure less infiltration route, it was observed that the increase of Mg levels resulted in a reduction in the ME of the alloy.

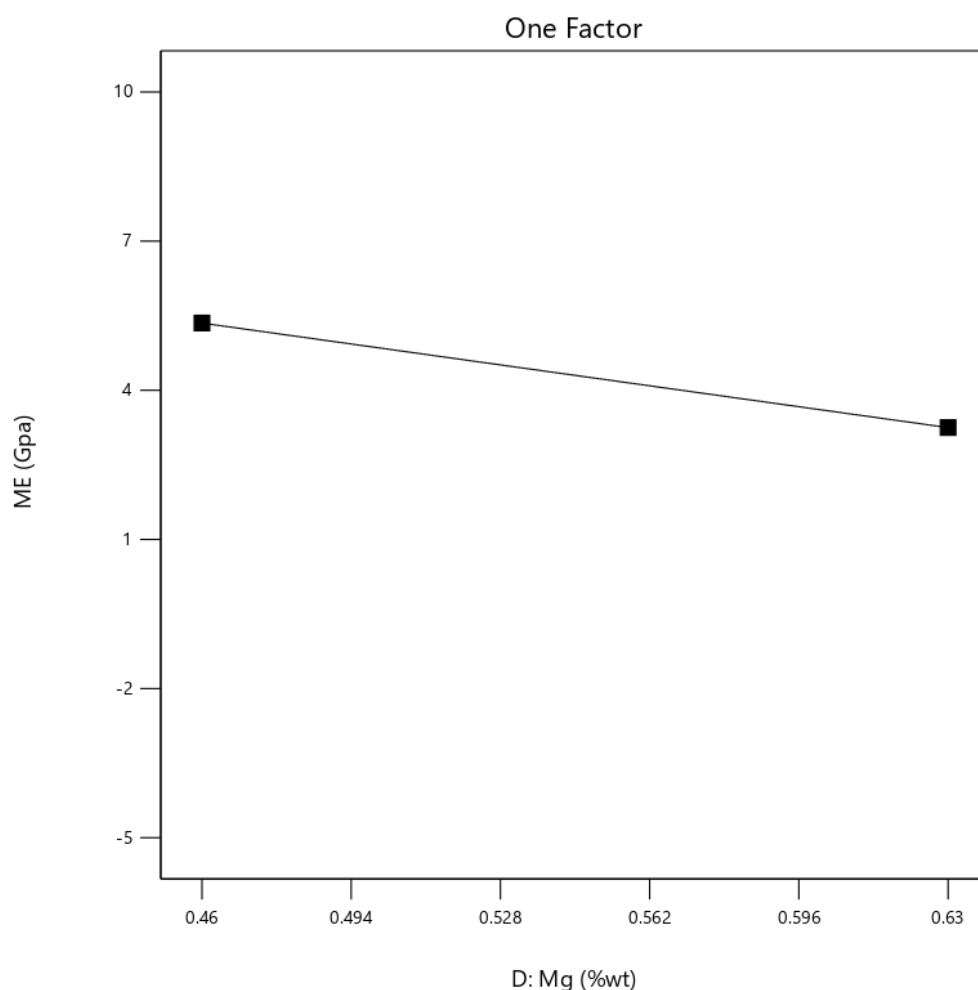


Figure 4.38: Mg single factor effect on ME.

Figures 4.39 and 4.40 below show the influence of the interaction between Si and Mg on the ME. It can be observed that for each level of Mg with an increase in the Si level a reduction in the level of ME. These results are consistent with the observation of Pius et al. (2023), where during the study of the influence of the Mg-Si ratio on the mechanical properties of Al-Mg-Si alloys it was observed that ME is inversely related to the Mg-Si ratio.

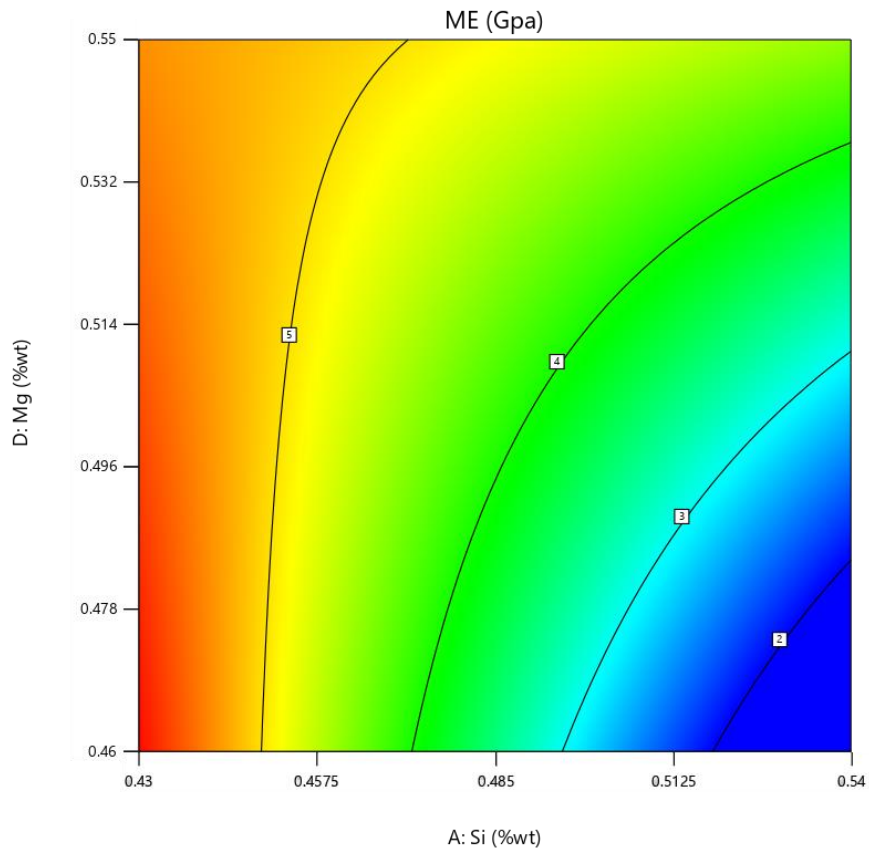


Figure 4.39: Interaction factor AD influence on ME.

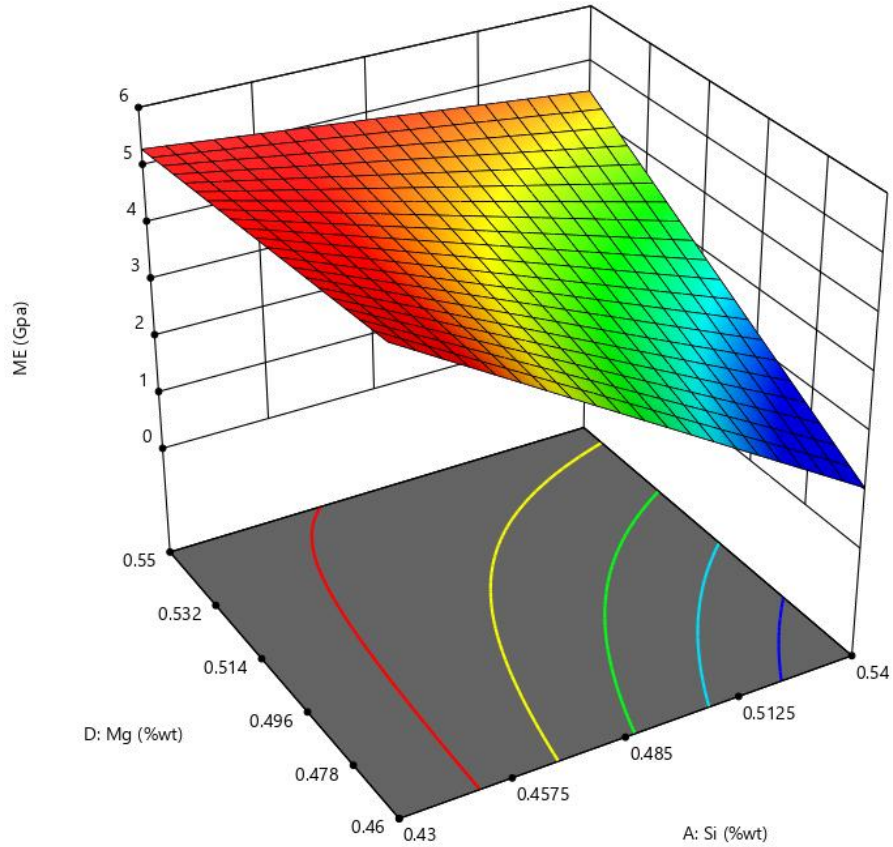


Figure 4.40: Interaction factor AD influence on ME 3D.

4.9 Confirmation

Confirmation of the model was done by comparing the model prediction for the alloy properties with the experimental results of an extra experiment that was performed as part of the research. Three samples were taken from the experiment and their results were compared with the model predicted results as shown in Table 4.7. Comparing the values of the confirmation experiments with the forecasted results by the model for ME, UTS, YTS, EL% and H shows that the %Errors of the model predictions for the different values is less than 5% and around 1% which indicates the validity of the prediction of the developed numerical models, all the experimental properties mean fall within the model predictions confidence level of 95%.

Table 4.7: Conformation experiments results and errors.

Variables Conditions					
Si wt %	Fe wt%	Mn wt%	Mg wt%	Time	Temp
0.44	0.15	0.04	0.49	192.5	8
Model Estimations					
Properties	ME (GPa)	UTS (MPa)	YTS (MPa)	EL%	H
Model	5.302	267.690	244.571	7.969	94.017
95% low	4.902	248.400	223.602	6.100	85.513
95% high	5.702	286.970	265.540	9.838	102.520
Experimental Values of Properties and Errors					
Exp 1	5.251	273.750	252.120	8.463	94.000
Pred Error (%)	0.982	2.214	2.994	5.838	0.017
Exp 2	5.026	261.0300	233.975	8.129	91.500
Pred Error (%)	5.503	2.549	4.528	1.978	2.750
Exp 3	5.2121	268.42	247.203	8.1111	97.8
Pred Error (%)	1.7356	0.272	1.065	1.754	3.869
Mean	5.199	267.730	244.433	8.234	94.433
Pred Error (%)	1.985	0.0168	0.0564	3.227	0.441

4.10 Optimisation

After the evaluation and confirmation of the developed models for the different mechanical properties, the different models can be utilised in the optimisation of the properties of the aluminium alloy. The optimisation was done using the desirability method. To cross validate the optimisation results GA was used. The codes used to perform and utilise the GA are shown in Appendix 3.

The formulation of the optimisation based on the desirability method as

$$\text{Objective: Maximise } D = (d_1 \times d_2 \times d_3 \times d_4)^{1/4} \quad \text{Equation (4.7)}$$

Subject to:

$$d_1 \begin{cases} = 0 & U\hat{T}S < 202.69 \\ \left(\frac{U\hat{T}S - 202.69}{311.72 - 202.69} \right) & 202.69 < U\hat{T}S < 311.72 \\ = 1 & U\hat{T}S > 311.72 \end{cases} \quad \text{Equation (4.8)}$$

$$d_2 \begin{cases} = 0 & Y\hat{T}S < 164.67 \\ \left(\frac{Y\hat{T}S - 164.67}{284.96 - 164.67} \right) & 164.67 < Y\hat{T}S < 284.96 \\ = 1 & Y\hat{T}S > 284.96 \end{cases} \quad \text{Equation (4.9)}$$

$$d_3 \begin{cases} = 0 & \widehat{EL}\% < 6.741 \\ \left(\frac{\widehat{EL}\% - 6.741}{19.66 - 6.741} \right) & 6.741 < \widehat{EL}\% < 19.66 \\ = 1 & \widehat{EL}\% > 19.66 \end{cases} \quad \text{Equation (4.10)}$$

$$d_4 \begin{cases} = 0 & \hat{H} < 43.92 \\ \left(\frac{\hat{H} - 43.92}{118.09 - 43.92} \right) & 43.92 < \hat{H} < 118.09 \\ = 1 & \hat{H} > 118.09 \end{cases} \quad \text{Equation (4.11)}$$

$$U\hat{T}S, Y\hat{T}S, \widehat{EL}\%, \text{ and } \hat{H} = \text{functions}(A, B, C, D, E \text{ and } F) \quad \text{Equation (4.12)}$$

Based on the models of estimated models

$$Si\ LR \leq A \leq Si\ HR \quad \text{Equation (4.13)}$$

$$Fe\ LR \leq B \leq Fe\ HR \quad \text{Equation (4.14)}$$

$$Mn\ LR \leq C \leq Mn\ HR \quad \text{Equation (4.15)}$$

$$Mg\ LR \leq D \leq Mg\ HR \quad \text{Equation (4.16)}$$

$$Temperature\ LR \leq E \leq Temperature\ HR \quad \text{Equation (4.17)}$$

$$Time\ LR \leq F \leq Time\ HR \quad \text{Equation (4.18)}$$

The equations 4.13 to 4.18 represent the constraints of the levels of the four alloying elements and the ageing conditions. The lower range (LR) and Higher range (HR) of the four alloying elements can be based either on the entire range of Al alloy 6063 alloying elements levels, or it can be based on the levels of a specific variation of the 6063 Al alloy in the cases of targeting specific alloy variations. The LR and HR for E and F are based on the artificial ageing conditions, which in this research are 175°C and 210°C for temperature, while for the time they are 4 hours and 12 hours.

The first optimisation aimed to maximise the alloy strength, hardness and ductility based on the limits of the Al alloy 6063 family. The optimum variable values for alloying elements' weight percentages for Si, Fe, Mn, and Mg were found to be (0.5596, 0.100, 0.0122, 0.4531) respectively. The optimum ageing temperature and time were found to be 175°C and 5.8129 hours. The optimum mechanical properties were a UTS of 303.339 MPa, YTS of 288.1529 MPa, %El of 16.3703% and Hardness of 118.096. These optimisation results can be compared with the results obtained by Sui et al. (2024) who found that for 6063 Al alloy optimum ageing conditions were at 170°C for 8 hours to maximise hardness to 95.70 HV and UTS of 226.24 MPa, noting that the paper did not consider conflicting objectives. In a different study by Alza (2021) on 6063 Al alloy ageing treatment the study

considered the optimising of the ageing conditions to maximise both the ductility and strength, the results of the study found that ageing of alloy at 230°C for 4 hours with the optimal combination that resulted in 15 El% and 200.45 MPa UTS, the study however did not consider the alloying elements effect were it was conducted using a fixed composition.

The models and the optimisation method could be utilised to optimise the mechanical properties for specified alloys by optimising the ageing conditions. The desirability method is utilised in this case to optimise the mechanical properties and to optimise the variables by assigning the goals for the alloying element to be on target or in range and optimise the ageing conditions.

Optimisation was used to optimise the ageing conditions of the alloy 6063.32 as shown in Appendix 4, which is one of the commonly requested alloys by the customers of the aluminium facility that produced the samples in this study. The values for the alloying elements of this alloy were used as the range values of the variables A, B, C, and D in the models corresponding to the levels of Si, Fe, Mn and Mg. The optimisation results for the alloy elements variables were (0.47, 0.171, 0.0483, 0.5303), and for the ageing temperature and time of 175°C and 6.61 hours. The optimised mechanical properties were a UTS of 264.0604 MPa, YTS of 256.4907 MPa, %El of 12.4459% and Hardness of 106.0364 with an overall desirability of 0.6383.

Another optimisation was to optimise the ageing conditions of the alloy 6063.10 as shown in in Appendix 5, which is another commonly requested. The values for the alloying elements of this alloy were used as the range values of the variables A, B, C, and D in the models corresponding to the levels of Si, Fe, Mn and Mg. The optimisation results

for the alloy elements variables were (0.4774, 0.140, 0.030, 0.460), and for the ageing temperature and time of 175.001°C and 7.9629 hours. The optimised mechanical properties were a UTS of 295.6578 MPa, YTS of 276.6682 MPa, %El of 11.5161% and Hardness of 118.0961 with an overall desirability of 0.736.

The summary of the optimisations that were performed is presented in Table 4.8 below.

Table 4.8: Summary of the optimisations done on 6063 alloys.

First Optimisation						
Variable	Si wt %	Fe wt%	Mn wt%	Mg wt%	Temp	Time
LR	0.35	0.10	0.01	0.45	175	4
HR	0.64	0.25	0.06	0.65	210	12
Output	0.559	0.100	0.012	0.453	175	5.813
Overall D= 0.909						
Property	UTS (MPa)		YTS (MPa)		EL%	
Goal	Max		Max		Max	
Output	303.334		288.153		16.370	

6063.32 Optimisation						
Variable	Si wt %	Fe wt%	Mn wt%	Mg wt%	Temp	Time
LR	0.41	0.14	0.03	0.53	175	4
HR	0.47	0.19	0.05	0.57	210	12
Output	0.470	0.171	0.048	0.530	175	5.831
Overall D= 0.638						
Property	UTS (MPa)		YTS (MPa)		EL%	
Goal	Max		Max		Max	
Output	264.060		256.490		12.445	

6063.10 Optimisation						
Variable	Si wt %	Fe wt%	Mn wt%	Mg wt%	Temp	Time
LR	0.42	0.14	0.03	0.46	175	4
HR	0.48	0.19	0.06	0.51	210	12
Output	0.477	0.140	0.030	0.460	175.001	7.963
Overall D= 0.720						
Property	UTS (MPa)		YTS (MPa)		EL%	
Goal	Max		Max		Max	
Output	295.657		276.668		11.516	

The comparison between the optimisation results obtained using the GA coincides with the results from the commercial package for optimisation using the desirability method as Table 4.9 shows.

Table 4.9: Results comparison between GA and commercial software.

First Optimisation						
Variable	Si wt %	Fe wt%	Mn wt%	Mg wt%	Temp	Time
GA	0.5596	0.1000	0.0122	0.4531	175.000	5.8129
Software	0.5585	0.1400	0.0100	0.1240	175.238	5.1809
Property	UTS (MPa)	YTS (MPa)	EL%	H	Desirability	
GA	303.3339	288.1529	16.3703	118.0960	0.9107	
Software	302.6630	287.4780	16.3790	118.0960	0.9090	

6063.32 Optimisation						
Variable	Si wt %	Fe wt%	Mn wt%	Mg wt%	Temp	Time
GA	0.4700	0.1710	0.0483	0.5303	175.000	5.8316
Software	0.4700	0.1710	0.0465	0.5332	175.000	5.8141
Property	UTS (MPa)	YTS (MPa)	EL%	H	Desirability	
GA	264.0604	256.4907	12.4459	106.0364	0.6383	
Software	262.8140	259.456	12.6966	105.3300	0.6380	

6063.10 Optimisation						
Variable	Si wt %	Fe wt%	Mn wt%	Mg wt%	Temp	Time
GA	0.4774	0.1400	0.0300	0.4600	175.001	7.9629
Software	0.4776	0.1400	0.0300	0.4620	175.000	7.5250
Property	UTS (MPa)	YTS (MPa)	EL%	H	Desirability	
GA	295.6578	276.6682	11.5161	118.0961	0.7360	
Software	293.9610	272.4070	11.5100	118.0961	0.7300	

4.11 Results and Discussion Conclusion

The chapter's detailed analysis of the results of the study revealed that the approach of integration of RSM with CCD, the desirability method and the GA utilised through the study showed success in investigating the complex relationship between the mechanical properties of the aluminium alloy, ageing conditions and alloying levels, and the approach was shown

to be successful in determining the optimum combination of variables to meet required alloys performance.

The models developed for predicting the mechanical properties of UTS, YTS, Hardness, %EL, and the ME were shown to be statistically significant based on the ANOVA results, and their validity was confirmed by utilising experimental results comparison.

The study findings and results indicated the significance of the effects that the alloying elements (Si, Fe, Mn and Mg), and ageing time and temperature on the mechanical performance of the aluminium alloy 6063, which affirms the need to optimise these parameters in order to reach the required alloy performance. This study's results indicated how important the combined impact of the different alloying concentrations and ageing conditions on the alloy performance, which indicates the complexity level of the relationship between these variables and the alloy's mechanical performance.

The integrated approach of utilising the desirability method and GA was shown to be able to find the optimal combination of parameter values to have improved mechanical properties for alloy 6063 and for specific alloy variations.

The findings in the chapter affirm the requirement for controlling the heat treatment conditions and alloying elements in order to optimise the mechanical performance of aluminium alloy 6063. This chapter presents an approach for utilising statistical modelling and optimisation techniques in future works on targeted optimisation of aluminium alloy performance.

Chapter Five

Conclusion and Recommendations

5.1 Conclusions

5.2 Recommendations and Future Work

Chapter Five

Conclusion and Recommendations

With an emphasis on the impacts of alloying materials and artificial ageing circumstances, the study provided an investigation of the mechanical properties of aluminium alloy 6063. Numerical models were derived to predict the aluminium alloy YTS, UTS, ME, %El, and H. Experimental results were used to validate the numerical models, the models showed excellent accuracy and dependability.

The impact of alloying elements including Si, Fe, Mn, and Mg on the alloy's mechanical properties was discussed in the study. The study also emphasised how important ageing time and temperature are to control mechanical properties.

The models and optimisation techniques used in the study, the desirability method combined with GA, were found to be successful in finding optimal conditions for enhancing the alloy's mechanical performance.

The conclusions and recommended suggestions for future studies as summarised in the next two sections.

5.1 Conclusions

The use of DoE and RSM appeared to be an effective method to study how different variables influence the mechanical properties of aluminium alloy 6063. This approach made it possible to develop numerical models that could explain the influence of alloying elements, and ageing treatment parameters on aluminium alloy mechanical properties. Employing GAs and desirability functions optimisation approaches was instrumental in

recognising the ideal alloying and ageing conditions for the different requirements of properties. These techniques allowed for the alloying elements and ageing treatment to be customised to meet desired goals for strength, hardness, and ductility.

The percentages of the alloying components Si, Mg, Mn, and Fe were shown to have an important effect on the mechanical characteristics of the aluminium alloy. Higher concentrations of Si and Mg were shown to improve tensile strength and hardness, where higher Mn levels improved ductility and increased Fe levels decreased ductility.

Ageing conditions significantly affected the mechanical characteristics of the aluminium alloy. It was noticed that the optimum ageing conditions varied according to the targeted property goals. Higher ageing temperatures and longer durations generally were observed to lead to higher strength and hardness but increasing them more could degrade the mechanical properties if over-ageing conditions were reached.

The developed models shown in the equations 5.1 to 5.5 below were confirmed using additional experiments, to confirm the developed models' accuracy. The models exhibited a high degree of correlation with experimental results, indicating the model's reliability in modelling the mechanical properties of aluminium alloy 6063 under different conditions.

$$\begin{aligned}
 \hat{U\hat{T}S} = & 4.7872 \times 10^4 - 7.5945 \times 10^4 A - 1.4071 \times 10^5 B - & \text{Equation (5.1)} \\
 & 2.1641 \times 10^5 C - 5.0159 \times 10^4 D - 7.1296 E - 2.4076 F + \\
 & 2.0620 \times 10^5 AB - 1.3881 \times 10^5 AC + 8.2939 \times 10^4 AD + \\
 & 6.9304 AE - 35.0634 AF + 9.3273 \times 10^5 BC + 1.4064 \times \\
 & 10^4 BD + 38.5927 BE + 104.5226 BF + 2.4695 \times 10^5 CD - \\
 & 32.5149 CE + 53.6286 CF - 4.4097 DE + 34.6407 DF - \\
 & 0.1063 EF
 \end{aligned}$$

$$\begin{aligned} \hat{YTS} = & 6.2876 \times 10^4 - 1.0018 \times 10^5 A - 1.7231 \times 10^5 B - & \text{Equation (5.2)} \\ & 2.8954 \times 10^5 C - 7.0960 \times 10^4 D - 8.1951 E + 14.9684 F + \\ & 2.4730 \times 10^5 AB - 1.6885 \times 10^5 AC + 1.1645 \times 10^5 AD + \\ & 9.8319 AE - 20.0817 AF + 1.1607 \times 10^6 BC + 2.5017 \times \\ & 10^4 BD + 39.3856 BE + 75.5598 BF + 3.4498 \times 10^5 CD - \\ & 38.7628 CE + 3.4883 CF - 4.6910 DE + 4.8600 DF - \\ & 0.1206 EF \end{aligned}$$

$$\begin{aligned} \hat{H} = & -2.6453 \times 10^4 + 4.2460 \times 10^4 A + 8.3915 \times 10^4 B + & \text{Equation (5.3)} \\ & 1.2656 \times 10^5 C + 2.9729 \times 10^4 D - 3.7877 E - 14.675 F - \\ & 1.2255 \times 10^5 AB + 9.1169 \times 10^4 AC - 4.5332 \times 10^4 AD + \\ & 0.8787 AE - 40.7572 AF - 5.7028 \times 10^5 BC - 2.3636 \times \\ & 10^4 BD + 10.7645 BE + 37.1489 BF - 1.4030 \times 10^5 CD - \\ & 1.0795 CE + 143.3848 CF + 1.7371 DE + 47.1628 DF - \\ & 0.0078 EF \end{aligned}$$

$$\begin{aligned} \hat{El}\% = & -3993.2711 + 6970.0889 A + 1.1584 \times 10^4 B + & \text{Equation (5.4)} \\ & 1.9884 \times 10^4 C + 3805.9148 D + 0.0980 E - 0.0756 F - \\ & 1.9616 \times 10^4 AB + 1.2933 \times 10^4 AC - 7123.7453 AD - \\ & 1.4111 AE + 6.5380 AF - 8.7314 \times 10^4 BC + \\ & 1359.1340 BD - 0.9704 BE - 11.5474 BF - 2.2669 \times \\ & 10^4 CD + 3.9059 CE - 11.5028 CF + 1.1320 DE - \\ & 3.8453 DF + 0.0064 EF \end{aligned}$$

$$\begin{aligned} \hat{ME} = & 785.4155 - 1278.2692 A - 1960.0674 B - & \text{Equation (5.5)} \\ & 3735.5685 C - 935.4017 D - 0.0582 E + 0.5163 F + \\ & 2913.2191 AB - 1881.3358 AC + 1581.6993 AD + \\ & 0.0534 AE - 0.2496 AF + 1.3268 \times 10^4 BC + \\ & 222.2444 BD + 0.3696 BE + 0.3818 BF + \\ & 4696.7594 CD - 0.2732 CE - 0.6411 CF - 0.0614 DE - \\ & 0.3681 DF - 0.0014 EF \end{aligned}$$

The study's conclusions would be useful in the aluminium sector, for example, in the production of aluminium alloys. To produce alloys with modified properties designed for applications, it could utilise the capability

to predict and optimise mechanical properties based on changing alloying elements and or ageing treatment process conditions. The optimisation results found for alloying elements' weight percentages for Si, Fe, Mn, and Mg were found to be (0.5596, 0.100, 0.0122, 0.4531) respectively could be used to maximise the mechanical properties were a UTS of 303.339 MPa, YTS of 288.1529 MPa, %El of 16.3703% and Hardness of 118.096 by targeting the optimum ageing temperature and time that were found to be 175°C and 5.8129 hours.

The study outlines a model for enhancing the mechanical characteristics of aluminium alloy 6063. Combining the modelling methods and optimisation techniques used in the study was demonstrated to be a useful strategy to control material performance.

5.2 Recommendations and Future Work

Future studies could consider the following suggested recommendations:

1. A wider range of influencing variables could be considered in future studies. In the alloying elements variables, the addition of elements like Cu, Cr, and Titanium (Ti) could be considered in the future. The consideration of more alloying elements could provide a more detailed understanding of how the mechanical properties of aluminium alloys are affected.
2. Future studies could consider a wider range of for the ageing time and temperature. The ageing time range could start at lower values to understand how the mechanical properties are affected before the optimal ageing conditions. Also, the wider range could study the influence of over-ageing more carefully.

3. Other heat treatment variables could be considered as input variables, such as the solution treatment process variables as it is shown to influence certain properties of the aluminium alloy.
4. The approach of machine learning methods could be used to model the relationships between the variables and the mechanical properties. This approach could provide more accurate and reliable models.
5. To utilise the machine learning approach larger datasets are needed, therefore collaboration between researchers, aluminium producers and customers could be considered to facilitate the collection of larger datasets. The collaboration could provide information on the alloys' performance before and after ageing, also it could provide information about the alloys' performance under different conditions.
6. Microstructural analysis could be considered, as the results from it give information on the actual mechanisms that the different variables that influence the change in the alloy's mechanical properties.
7. Future studies could consider studying the impact of the different ageing elements and the ageing process on the environment. The sustainability and environment are rising concerns within the industries now.
8. Cost factors could be considered in the optimising process, especially in regard to the heat treatment variables. The treatment cost could be related to the time required.

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Appendices

Appendix 1: MATLAB code for stress-strain curve

Appendix 2: Normality plots of residuals

Appendix 3: Mechanical properties optimisation

MATLAB code

Appendix 4: Alloy 6063.32 properties optimisation

MATLAB code

Appendix 5: Alloy 6063.10 properties optimisation

MATLAB code

Appendix 1: MATLAB code for stress-strain curve

```
clc
clear all
close all

%filename
filename = 'S11.xlsx';

%Use reatable to import the data
data = readtable(filename);

% Display the matrix to verify that the data was imported correctly
T=data{:,3}; %Time
dell=data{:,1}; %delata L
F=data{:,2}; %Force

%calculation
D=9; %mm diameter
A=54; %mm guage lenght

stress=(4*F*1000)/( pi*D^2); %MPa
strain=dell/A; %dimensionless

% Plot the stress-strain curve
figure;
plot(strain, stress, 'b-');
xlabel('Strain');
ylabel('Stress');
title('Stress-Strain Curve');
grid on;

% Fit a linear model to the initial linear portion and find E
linear_region = 0.0548 < strain & strain < 0.0992; % Adjust this threshold
as needed
p = polyfit(strain(linear_region), stress(linear_region), 1);
E = p(1); %GPa

% Plot the linear fit
```

```

hold on;
plot(strain(linear_region), polyval(p, strain(linear_region)), 'r--');

% Calculate the 0.2% offset line
offset_strain = strain + 0.002;
offset_stress = polyval(p, offset_strain);

%Find UTS
UTS = max(stress);

% Plot the offset line and yield point
plot(offset_strain, offset_stress , 'g--');
legend('Stress-Strain Curve', 'Linear Fit', '0.2% Offset Line');

```

Appendix 2: Normality plots of residuals

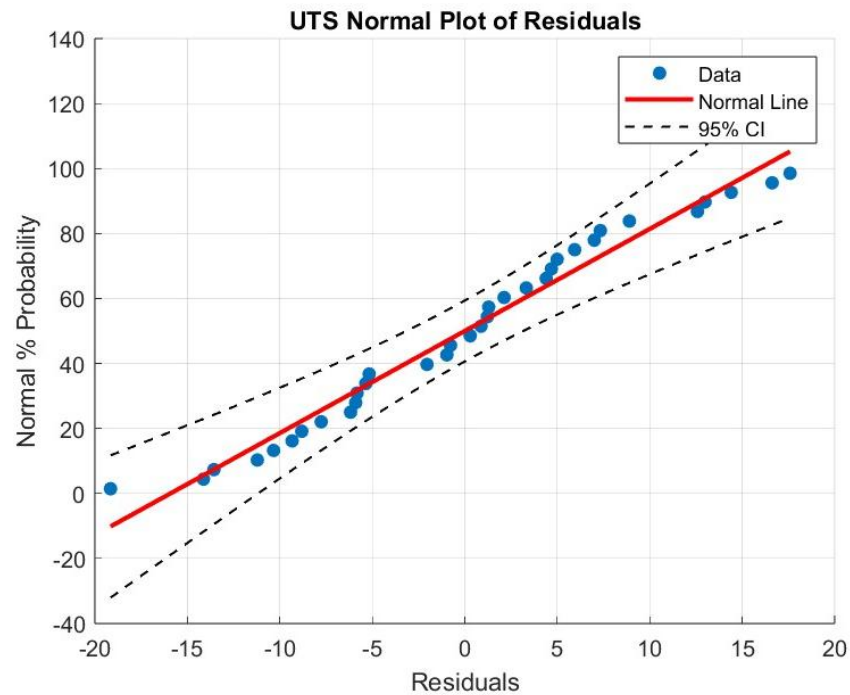


Figure A.1: Normality plot of residuals for UTS.

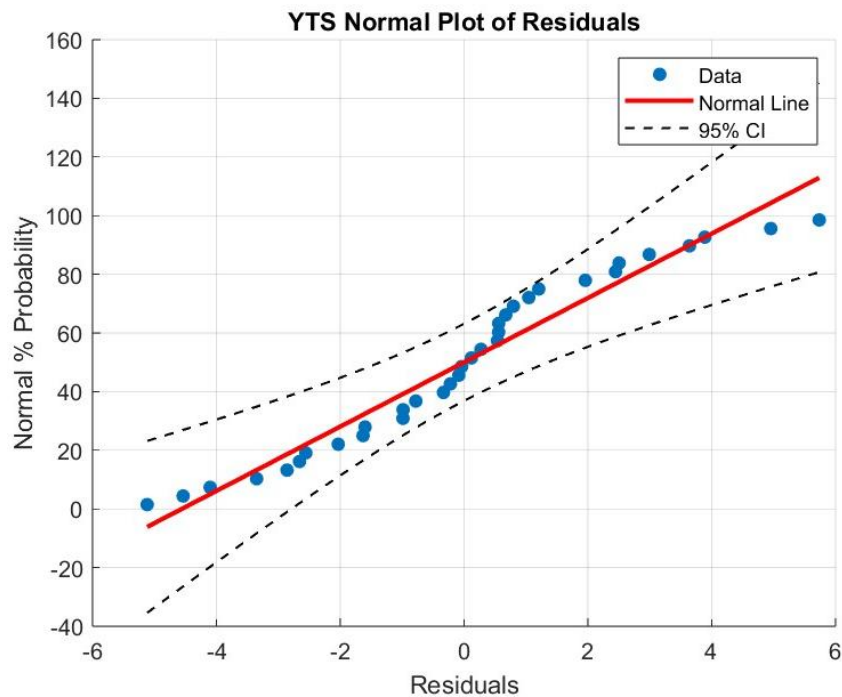


Figure A.2: Normality plot of residuals for YTS.

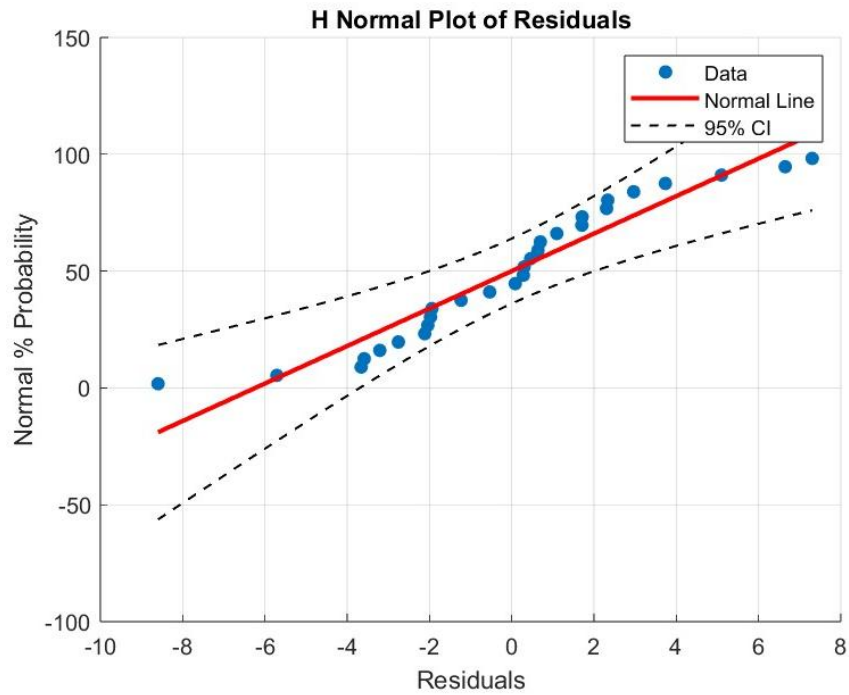


Figure A.3: Normality plot of residuals for H.

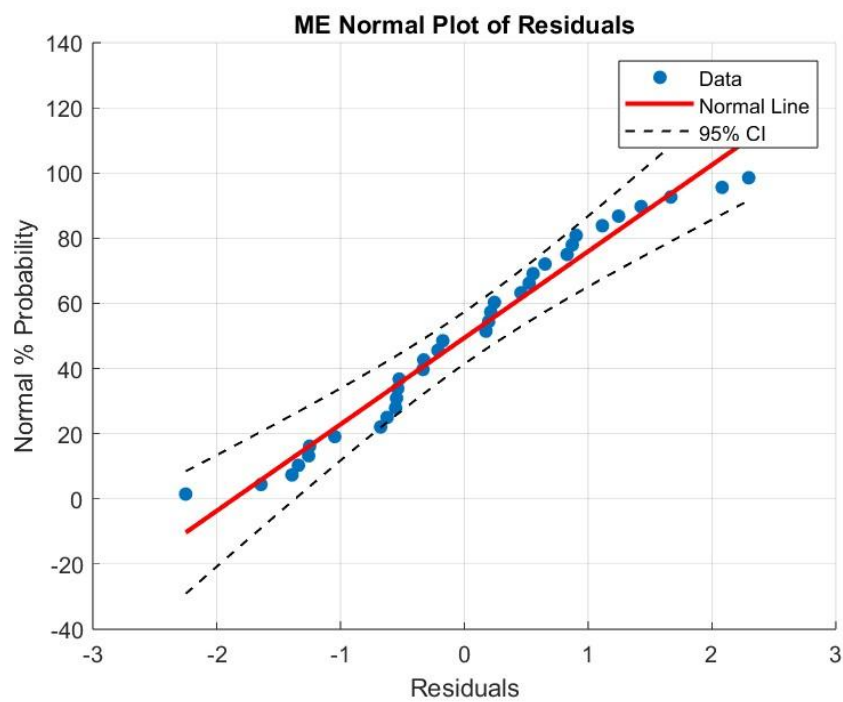


Figure A.4: Normality plot of residuals for ME.

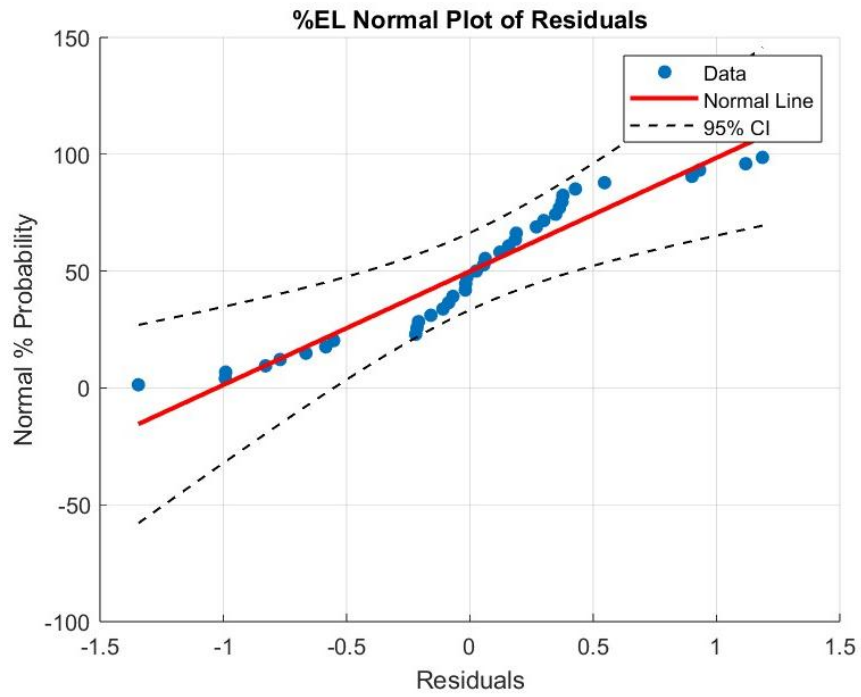


Figure A.5: Normality plot of residuals for %El.

Appendix 3: 6063 Mechanical properties optimisation MATLAB code

%Responses Numerical Model Functions in MATLAB

```
function ys = modelYieldStrength(x)
    A = x(1); B = x(2); C = x(3); D = x(4); E = x(5); F = x(6);
    ys = 62875.7 + -100181 * A + -172311 * B + -289544 * C + -70959.8 * D + ...
        -8.19513 * E + 14.9684 * F + 247300 * A * B + -168845 * A * C + ...
        116451 * A * D + 9.83191 * A * E + -20.0817 * A * F + ...
        1.16071e+06 * B * C + 25017.3 * B * D + 39.3856 * B * E + ...
        75.5598 * B * F + 344978 * C * D + -38.7628 * C * E + ...
        3.48828 * C * F + -4.69098 * D * E + 4.86 * D * F + -0.120623 * E * F;
end
```

```
function uts = modelUltimateTensileStrength(x)
    A = x(1); B = x(2); C = x(3); D = x(4); E = x(5); F = x(6);
    uts = 47872.4 + -75944.7 * A + -140714 * B + -216415 * C + -50159.3 * D + ...
        -7.12963 * E + -2.40764 * F + 206198 * A * B + -138810 * A * C + ...
        82939.3 * A * D + 6.93042 * A * E + -35.0634 * A * F + ...
        932732 * B * C + 14064.4 * B * D + 38.5927 * B * E + ...
        104.523 * B * F + 246953 * C * D + -32.5149 * C * E + ...
        53.6286 * C * F + -4.40973 * D * E + 34.6407 * D * F + -0.106343 * E *
    F;
end
```

```
function me = modelModulusOfElasticity(x)
    A = x(1); B = x(2); C = x(3); D = x(4); E = x(5); F = x(6);
    me = 785.416 + -1278.27 * A + -1960.07 * B + -3735.57 * C + -935.402 * D + ...
        -0.0581964 * E + 0.516292 * F + 2913.22 * A * B + -1881.34 * A * C + ...
        1581.7 * A * D + 0.0533891 * A * E + -0.249567 * A * F + 13267.9 * B *
    C + ...
        222.244 * B * D + 0.369585 * B * E + 0.381764 * B * F + 4696.76 * C * D
    + ...
        -0.273197 * C * E + -0.641096 * C * F + -0.0613819 * D * E + -0.368119
    * D * F + ...
        -0.00144707 * E * F;
end
```

```

function elong = modelElongation(x)
    A = x(1); B = x(2); C = x(3); D = x(4); E = x(5); F = x(6);
    elong = -3993.27 + 6970.09 * A + 11583.9 * B + 19884.1 * C + 3805.91 * D +
    ...
    0.0979653 * E + -0.0755585 * F + -19616.2 * A * B + 12933.1 * A * C +
    ...
    -7123.75 * A * D + -1.41115 * A * E + 6.53802 * A * F + -87314.4 * B *
    C + ...
    1359.13 * B * D + -0.970414 * B * E + -11.5474 * B * F + -22668.8 * C *
    D + ...
    3.9059 * C * E + -11.5028 * C * F + 1.13197 * D * E + -3.84525 * D * F
    + ...
    0.00637327 * E * F;
end

```

```

function hardness = modelHardness(x)
    A = x(1); B = x(2); C = x(3); D = x(4); E = x(5); F = x(6);
    hardness = -26453.2 + 42460.5 * A + 83914.8 * B + 126564 * C + 29728.6
    * D + ...
    -3.78773 * E + -14.6753 * F + -122552 * A * B + 91168.8 * A * C + ...
    -45332.1 * A * D + 0.87867 * A * E + -40.7572 * A * F + ...
    -570281 * B * C + -23636.4 * B * D + 10.7645 * B * E + ...
    37.1489 * B * F + -140299 * C * D + -1.07948 * C * E + ...
    143.385 * C * F + 1.73714 * D * E + 47.1628 * D * F + -0.00782207 * E *
    F;
end

```

% Desirability Function to Calculate di for Responses

```

function d = desirabilityFunction(y, goal, lower, upper, target)
    if strcmp(goal, 'max')
        if y < lower
            d = 0;
        elseif y > upper
            d = 1;
        else
            d = (y - lower) / (upper - lower);
        end
    elseif strcmp(goal, 'min')
        if y < lower
            d = 1;
        elseif y > upper

```

```

        d = 0;
    else
        d = (upper - y) / (upper - lower);
    end
elseif strcmp(goal, 'target')
    if y < lower || y > upper
        d = 0;
    elseif y <= target
        d = (y - lower) / (target - lower);
    else
        d = (upper - y) / (upper - target);
    end
elseif strcmp(goal, 'range')
    if y < lower || y > upper
        d = 0;
    else
        d = 1;
    end
else
    error('Invalid goal');
end
end

% Overall Desirability Function D , n does not include the goal "range"
function D = overallDesirability(d_values, goals)
    if any(strcmp(goals, 'range'))
        nonRangeIndices = ~strcmp(goals, 'range');
        nonRangeDesirabilities = d_values(nonRangeIndices);
    else
        nonRangeDesirabilities = d_values;
    end
    n = length(nonRangeDesirabilities);
    D = prod(d_values)^(1/n);
end

% Fitness Function based on the responses d values
function [fitness, ys, uts, me, elong, hardness] = fitnessFunction(x)
    ys = modelYieldStrength(x);
    uts = modelUltimateTensileStrength(x);

```

```

me = modelModulusOfElasticity(x);
elong = modelElongation(x);
hardness = modelHardness(x);

% Define desirability functions for each response
d_ys = desirabilityFunction(ys, 'max', 164.674, 284.961);
d_uts = desirabilityFunction(uts, 'max', 202.691, 311.724);
d_me = desirabilityFunction(me, 'range', 4.122, 5.851);
d_elong = desirabilityFunction(elong, 'max', 6.741, 19.66);
d_hardness = desirabilityFunction(hardness, 'max', 43.9237, 118.096);

% Array of individual desirability values and goals
d_values = [d_ys, d_uts, d_me, d_elong, d_hardness];
goals = {'max', 'max', 'range', 'max', 'max'};

% Calculate the overall desirability
% Fitness function to be ed
% Negative sign for ation
fitness = - overallDesirability(d_values, goals);
end

% Set GA options
options = optimoptions('ga', ...
    'PopulationSize', 300, ...
    'MaxGenerations', 600, ...
    'CrossoverFraction', 0.8, ...
    'MutationFcn', @mutationadaptfeasible, ... % Use mutationadaptfeasible
    for constrained optimisation
    'FunctionTolerance', 1e-9, ...
    'Display', 'iter', ...
    'PlotFcn', {@gaplotbestf});

% Run GA
nvars = 6; % Number of variables
lb = [0.35, 0.10, 0.01, 0.45, 175, 4]; % Lower bounds
ub = [0.64, 0.25, 0.06, 0.60, 210, 12]; % Upper bounds

[x_opt, fval, exitflag, output, population, scores] = ga(@fitnessFunction,
nvars, [], [], [], [], lb, ub, [], options);

```

```

% Evaluate the models with the optimised parameters
[~, ys_opt, uts_opt, me_opt, elong_opt, hardness_opt] =
fitnessFunction(x_opt);

% Display optimised parameters and model values
disp('Optimised Parameters:');
disp(x_opt);
disp('Optimised Yield Strength (YS):');
disp(ys_opt);
disp('Optimised Ultimate Tensile Strength (UTS):');
disp(uts_opt);
disp('Optimised Modulus of Elasticity (ME):');
disp(me_opt);
disp('Optimised Elongation:');
disp(elong_opt);
disp('Optimised Hardness:');
disp(hardness_opt);

```

Appendix 4: Alloy 6063.32 properties optimisation MATLAB code

%optimum ageing for alloy 6063.32

% Responses Numerical Model Functions in MATLAB

```
function ys = modelYieldStrength(x)
    A = x(1); B = x(2); C = x(3); D = x(4); E = x(5); F = x(6);
    ys = 62875.7 + -100181 * A + -172311 * B + -289544 * C + -70959.8 * D + ...
        -8.19513 * E + 14.9684 * F + 247300 * A * B + -168845 * A * C + ...
        116451 * A * D + 9.83191 * A * E + -20.0817 * A * F + ...
        1.16071e+06 * B * C + 25017.3 * B * D + 39.3856 * B * E + ...
        75.5598 * B * F + 344978 * C * D + -38.7628 * C * E + ...
        3.48828 * C * F + -4.69098 * D * E + 4.86 * D * F + -0.120623 * E * F;
end
```

```
function uts = modelUltimateTensileStrength(x)
    A = x(1); B = x(2); C = x(3); D = x(4); E = x(5); F = x(6);
    uts = 47872.4 + -75944.7 * A + -140714 * B + -216415 * C + -50159.3 * D + ...
        -7.12963 * E + -2.40764 * F + 206198 * A * B + -138810 * A * C + ...
        82939.3 * A * D + 6.93042 * A * E + -35.0634 * A * F + ...
        932732 * B * C + 14064.4 * B * D + 38.5927 * B * E + ...
        104.523 * B * F + 246953 * C * D + -32.5149 * C * E + ...
        53.6286 * C * F + -4.40973 * D * E + 34.6407 * D * F + -0.106343 * E *
    F;
end
```

```
function me = modelModulusOfElasticity(x)
    A = x(1); B = x(2); C = x(3); D = x(4); E = x(5); F = x(6);
    me = 785.416 + -1278.27 * A + -1960.07 * B + -3735.57 * C + -935.402 * D + ...
        -0.0581964 * E + 0.516292 * F + 2913.22 * A * B + -1881.34 * A * C + ...
        1581.7 * A * D + 0.0533891 * A * E + -0.249567 * A * F + 13267.9 * B *
    C + ...
        222.244 * B * D + 0.369585 * B * E + 0.381764 * B * F + 4696.76 * C * D
    + ...
        -0.273197 * C * E + -0.641096 * C * F + -0.0613819 * D * E + -0.368119
    * D * F + ...
        -0.00144707 * E * F;
end
```

```
function elong = modelElongation(x)
    A = x(1); B = x(2); C = x(3); D = x(4); E = x(5); F = x(6);
    elong = -3993.27 + 6970.09 * A + 11583.9 * B + 19884.1 * C + 3805.91 * D + ...
        0.0979653 * E + -0.0755585 * F + -19616.2 * A * B + 12933.1 * A * C + ...
        -7123.75 * A * D + -1.41115 * A * E + 6.53802 * A * F + -87314.4 * B *
    C + ...
        1359.13 * B * D + -0.970414 * B * E + -11.5474 * B * F + -22668.8 * C *
    D + ...
        3.9059 * C * E + -11.5028 * C * F + 1.13197 * D * E + -3.84525 * D * F
    + ...
        0.00637327 * E * F;
end
```

```

function hardness = modelHardness(x)
    A = x(1); B = x(2); C = x(3); D = x(4); E = x(5); F = x(6);
    hardness = -26453.2 + 42460.5 * A + 83914.8 * B + 126564 * C + 29728.6
    * D + ...
    -3.78773 * E + -14.6753 * F + -122552 * A * B + 91168.8 * A * C + ...
    -45332.1 * A * D + 0.87867 * A * E + -40.7572 * A * F + ...
    -570281 * B * C + -23636.4 * B * D + 10.7645 * B * E + ...
    37.1489 * B * F + -140299 * C * D + -1.07948 * C * E + ...
    143.385 * C * F + 1.73714 * D * E + 47.1628 * D * F + -0.00782207 * E *
    F;
end

% Desirability Function to Calculate di for Responses
function d = desirabilityFunction(y, goal, lower, upper, target)
    if strcmp(goal, 'max')
        if y < lower
            d = 0;
        elseif y > upper
            d = 1;
        else
            d = (y - lower) / (upper - lower);
        end
    elseif strcmp(goal, 'min')
        if y < lower
            d = 1;
        elseif y > upper
            d = 0;
        else
            d = (upper - y) / (upper - lower);
        end
    elseif strcmp(goal, 'target')
        if y < lower || y > upper
            d = 0;
        elseif y <= target
            d = (y - lower) / (target - lower);
        else
            d = (upper - y) / (upper - target);
        end
    elseif strcmp(goal, 'range')
        if y < lower || y > upper
            d = 0;
        else
            d = 1;
        end
    else
        error('Invalid goal');
    end
end

% Overall Desirability Function D , n does not include the goal "range"
function D = overallDesirability(d_values, goals)
    if any(strcmp(goals, 'range'))
        nonRangeIndices = ~strcmp(goals, 'range');
        nonRangeDesirabilities = d_values(nonRangeIndices);
    else
        nonRangeDesirabilities = d_values;
    end
    n = length(nonRangeDesirabilities);

```

```

    D = prod(d_values)^(1/n);
end

% Fitness Function based on the responses d values
function [fitness, ys, uts, me, elong, hardness] = fitnessFunction(x)
    ys = modelYieldStrength(x);
    uts = modelUltimateTensileStrength(x);
    me = modelModulusOfElasticity(x);
    elong = modelElongation(x);
    hardness = modelHardness(x);

% Define desirability functions for each response
    d_ys = desirabilityFunction(ys, 'max', 164.674, 284.961);
    d_uts = desirabilityFunction(uts, 'max', 202.691, 311.724);
    d_me = desirabilityFunction(me, 'range', 4.122, 5.851);
    d_elong = desirabilityFunction(elong, 'max', 6.741, 19.66);
    d_hardness = desirabilityFunction(hardness, 'max', 43.9237, 118.096);
    d_A = desirabilityFunction(x(1), 'range', 0.41, 0.47);
    d_B = desirabilityFunction(x(2), 'range', 0.14, 0.19);
    d_C = desirabilityFunction(x(3), 'range', 0.03, 0.05);
    d_D = desirabilityFunction(x(4), 'range', 0.53, 0.57);
    d_E = desirabilityFunction(x(5), 'range', 175, 210);
    d_F = desirabilityFunction(x(6), 'range', 4, 12);

% Array of individual desirability values and goals
    d_values = [d_ys, d_uts, d_me, d_elong, d_hardness, d_A, d_B, d_C, d_D,
d_E, d_F];
    goals = {'max', 'max', 'range', 'max', 'max', 'range', 'range',
'range', 'range', 'range', 'range'};

% Calculate the overall desirability
% Fitness function to be ed
% Negative sign for ation
    fitness = - overallDesirability(d_values, goals);
end

% Set GA options
options = optimoptions('ga', ...
    'PopulationSize', 300, ...
    'MaxGenerations', 600, ...
    'CrossoverFraction', 0.8, ...
    'MutationFcn', @mutationadaptfeasible, ... % Use mutationadaptfeasible
for constrained optimisation
    'FunctionTolerance', 1e-9, ...
    'Display', 'iter', ...
    'PlotFcn', {@gaplotbestf});

% Run GA
nvars = 6; % Number of variables
lb = [0.35, 0.10, 0.01, 0.45, 175, 4]; % Lower bounds
ub = [0.64, 0.25, 0.06, 0.60, 210, 12]; % Upper bounds

[x_opt, fval, exitflag, output, population, scores] = ga(@fitnessFunction,
nvars, [], [], [], [], lb, ub, [], options);

% Evaluate the models with the optimised parameters

```

```

[~, ys_opt, uts_opt, me_opt, elong_opt, hardness_opt] =
fitnessFunction(x_opt);

% Display optimised parameters and model values
disp('Optimised Parameters:');
disp(x_opt);
disp('Optimised Yield Strength (YS):');
disp(ys_opt);
disp('Optimised Ultimate Tensile Strength (UTS):');
disp(uts_opt);
disp('Optimised Modulus of Elasticity (ME):');
disp(me_opt);
disp('Optimised Elongation:');
disp(elong_opt);
disp('Optimised Hardness:');
disp(hardness_opt);

```

Appendix 5: Alloy 6063.10 properties optimisation MATLAB code

% Responses Numerical Model Functions in MATLAB

```
function ys = modelYieldStrength(x)
    A = x(1); B = x(2); C = x(3); D = x(4); E = x(5); F = x(6);
    ys = 62875.7 + -100181 * A + -172311 * B + -289544 * C + -70959.8 * D + ...
        -8.19513 * E + 14.9684 * F + 247300 * A * B + -168845 * A * C + ...
        116451 * A * D + 9.83191 * A * E + -20.0817 * A * F + ...
        1.16071e+06 * B * C + 25017.3 * B * D + 39.3856 * B * E + ...
        75.5598 * B * F + 344978 * C * D + -38.7628 * C * E + ...
        3.48828 * C * F + -4.69098 * D * E + 4.86 * D * F + -0.120623 * E * F;
end
```

```
function uts = modelUltimateTensileStrength(x)
    A = x(1); B = x(2); C = x(3); D = x(4); E = x(5); F = x(6);
    uts = 47872.4 + -75944.7 * A + -140714 * B + -216415 * C + -50159.3 * D + ...
        -7.12963 * E + -2.40764 * F + 206198 * A * B + -138810 * A * C + ...
        82939.3 * A * D + 6.93042 * A * E + -35.0634 * A * F + ...
        932732 * B * C + 14064.4 * B * D + 38.5927 * B * E + ...
        104.523 * B * F + 246953 * C * D + -32.5149 * C * E + ...
        53.6286 * C * F + -4.40973 * D * E + 34.6407 * D * F + -0.106343 * E *
    F;
end
```

```
function me = modelModulusOfElasticity(x)
    A = x(1); B = x(2); C = x(3); D = x(4); E = x(5); F = x(6);
    me = 785.416 + -1278.27 * A + -1960.07 * B + -3735.57 * C + -935.402 * D + ...
        -0.0581964 * E + 0.516292 * F + 2913.22 * A * B + -1881.34 * A * C + ...
        1581.7 * A * D + 0.0533891 * A * E + -0.249567 * A * F + 13267.9 * B *
    C + ...
        222.244 * B * D + 0.369585 * B * E + 0.381764 * B * F + 4696.76 * C * D
    + ...
        -0.273197 * C * E + -0.641096 * C * F + -0.0613819 * D * E + -0.368119
    * D * F + ...
        -0.00144707 * E * F;
end
```

```
function elong = modelElongation(x)
    A = x(1); B = x(2); C = x(3); D = x(4); E = x(5); F = x(6);
    elong = -3993.27 + 6970.09 * A + 11583.9 * B + 19884.1 * C + 3805.91 * D + ...
        0.0979653 * E + -0.0755585 * F + -19616.2 * A * B + 12933.1 * A * C + ...
        -7123.75 * A * D + -1.41115 * A * E + 6.53802 * A * F + -87314.4 * B *
    C + ...
        1359.13 * B * D + -0.970414 * B * E + -11.5474 * B * F + -22668.8 * C *
    D + ...
        3.9059 * C * E + -11.5028 * C * F + 1.13197 * D * E + -3.84525 * D * F
    + ...
        0.00637327 * E * F;
end
```

```
function hardness = modelHardness(x)
```

```

    A = x(1); B = x(2); C = x(3); D = x(4); E = x(5); F = x(6);
    hardness = -26453.2 + 42460.5 * A + 83914.8 * B + 126564 * C + 29728.6
* D + ...
    -3.78773 * E + -14.6753 * F + -122552 * A * B + 91168.8 * A * C + ...
    -45332.1 * A * D + 0.87867 * A * E + -40.7572 * A * F + ...
    -570281 * B * C + -23636.4 * B * D + 10.7645 * B * E + ...
    37.1489 * B * F + -140299 * C * D + -1.07948 * C * E + ...
    143.385 * C * F + 1.73714 * D * E + 47.1628 * D * F + -0.00782207 * E *
F;
end

```

% Desirability Function to Calculate di for Responses

```
function d = desirabilityFunction(y, goal, lower, upper, target)
```

```

    if strcmp(goal, 'max')
        if y < lower
            d = 0;
        elseif y > upper
            d = 1;
        else
            d = (y - lower) / (upper - lower);
        end
    elseif strcmp(goal, 'min')
        if y < lower
            d = 1;
        elseif y > upper
            d = 0;
        else
            d = (upper - y) / (upper - lower);
        end
    elseif strcmp(goal, 'target')
        if y < lower || y > upper
            d = 0;
        elseif y <= target
            d = (y - lower) / (target - lower);
        else
            d = (upper - y) / (upper - target);
        end
    elseif strcmp(goal, 'range')
        if y < lower || y > upper
            d = 0;
        else
            d = 1;
        end
    else
        error('Invalid goal');
    end
end

```

```
end
```

% Overall Desirability Function D , n does not include the goal "range"

```
function D = overallDesirability(d_values, goals)
    if any(strcmp(goals, 'range'))
        nonRangeIndices = ~strcmp(goals, 'range');
        nonRangeDesirabilities = d_values(nonRangeIndices);
    else
        nonRangeDesirabilities = d_values;
    end
    n = length(nonRangeDesirabilities);
    D = prod(d_values)^(1/n);
end

```

```

end

% Fitness Function based on the responses d values
function [fitness, ys, uts, me, elong, hardness] = fitnessFunction(x)
    ys = modelYieldStrength(x);
    uts = modelUltimateTensileStrength(x);
    me = modelModulusOfElasticity(x);
    elong = modelElongation(x);
    hardness = modelHardness(x);

    % Define desirability functions for each response
    d_ys = desirabilityFunction(ys, 'max', 164.674, 284.961);
    d_uts = desirabilityFunction(uts, 'max', 202.691, 311.724);
    d_me = desirabilityFunction(me, 'range', 4.122, 5.851);
    d_elong = desirabilityFunction(elong, 'max', 6.741, 19.66);
    d_hardness = desirabilityFunction(hardness, 'max', 43.9237, 118.096);
    d_A = desirabilityFunction(x(1), 'range', 0.42, 0.48);
    d_B = desirabilityFunction(x(2), 'range', 0.14, 0.19);
    d_C = desirabilityFunction(x(3), 'range', 0.03, 0.06);
    d_D = desirabilityFunction(x(4), 'range', 0.46, 0.51);
    d_E = desirabilityFunction(x(5), 'range', 175, 210);
    d_F = desirabilityFunction(x(6), 'range', 4, 12);

    % Array of individual desirability values and goals
    d_values = [d_ys, d_uts, d_me, d_elong, d_hardness, d_A, d_B, d_C, d_D,
d_E, d_F];
    goals = {'max', 'max', 'range', 'max', 'max', 'range', 'range',
'range', 'range', 'range', 'range'};

    % Calculate the overall desirability
    % Fitness function to be ed
    % Negative sign for ation
    fitness = - overallDesirability(d_values, goals);
end

% Set GA options
options = optimoptions('ga', ...
    'PopulationSize', 150, ...
    'MaxGenerations', 800, ...
    'CrossoverFraction', 0.1, ...
    'MutationFcn', @mutationadaptfeasible, ... % Use mutationadaptfeasible
for constrained optimisation.
    'FunctionTolerance', 1e-9, ...
    'Display', 'iter', ...
    'PlotFcn', {@gaplotbestf});

% Run GA
nvars = 6; % Number of variables
lb = [0.35, 0.10, 0.01, 0.45, 175, 4]; % Lower bounds
ub = [0.64, 0.25, 0.06, 0.60, 210, 12]; % Upper bounds

[x_opt, fval, exitflag, output, population, scores] = ga(@fitnessFunction,
nvars, [], [], [], [], lb, ub, [], options);

% Evaluate the models with the optimised parameters
[~, ys_opt, uts_opt, me_opt, elong_opt, hardness_opt] =
fitnessFunction(x_opt);

```

```
% Display optimised parameters and model values
disp('Optimised Parameters:');
disp(x_opt);
disp('Optimised Yield Strength (YS):');
disp(ys_opt);
disp('Optimised Ultimate Tensile Strength (UTS):');
disp(uts_opt);
disp('Optimised Modulus of Elasticity (ME):');
disp(me_opt);
disp('Optimised Elongation:');
disp(elong_opt);
disp('Optimised Hardness:');
disp(hardness_opt);
```

الخلاصة

تسعى هذه الدراسة إلى تحسين الخصائص الميكانيكية لسبائك الألومنيوم 6063 بناءً على مستويات العناصر المضافة وظروف المعالجة الحرارية للتقدم الاصطناعي. تُعرف سبائك الألومنيوم، وخاصةً تلك التابعة للسلسلة 6000، بخصائصها الميكانيكية الإيجابية الجيدة والتي تشمل الليونة، ونسبة القوة إلى الوزن، ومقاومة التآكل، وقابلية اللحام. هذا المزيج من الخصائص يجعلها مناسبة لمجموعة واسعة من التطبيقات الصناعية. تبحث هذه الدراسة كيف تتأثر الخصائص الميكانيكية لسبائك الألومنيوم 6063، التي يمكن قياسها عبر الصلابة، ونسبة الاستطالة، ومقاومة الشد بالتغير في النسب الوزنية للعناصر المضافة التالية: السيليكون، والحديد، والمنجنيز، والمغنيسيوم، كما تبحث الدراسة كيف يؤثر اختلاف درجة حرارة التقدم وزمنه على هذه الخصائص الميكانيكية.

اعتمدت هذه الدراسة على منهجية هجينة، عبر تطبيق منهجية تصميم التجارب ومنهجية سطح الاستجابة لدراسة تأثير مستويات العناصر المضافة وظروف معالجة التقدم الاصطناعي على الخصائص الميكانيكية. تم إنشاء نماذج عددية لحساب خصائص الميكانيكية وفقاً لمستويات هذه المتغيرات. حددت المستويات المثلى لكل من نسب العناصر وظروف معالجة التقدم لتحسين الخصائص الميكانيكية عبر الاستعانة بمزيج من تقنيات التحسين والخوارزميات الجينية. توضح نتائج الدراسة كيف تتأثر الخصائص الميكانيكية المختلفة، مثل قوة الشد القصوى، والصلابة، والليونة بالتغيرات والتفاعلات بين مستويات العناصر المضافة وظروف معالجة التقدم. تم التوصل إلى الظروف المثلى لتحسين الخصائص الميكانيكية لسبائك 6063، حيث تم تحديد النسب المثلى لكل من: السيليكون، والحديد، والمنجنيز، والمغنيسيوم بكونها: 0.559، 0.100، 0.012، 0.453 على التوالي. كما وُجد أن درجة حرارة التقدم المثلى هي 175 درجة مئوية والوقت الأمثل هو 5.8 ساعة.

تمثل هذه النتائج رؤية قيّمة لمختلف الصناعات حول كيفية تحسين الخصائص الميكانيكية المرغوبة لسبائك الألومنيوم من خلال التحكم في عملية معالجة التقدم الحرارية ومستويات العناصر المضافة. كما تشير استنتاجات الدراسة إلى وجود فرصة لإجراء دراسات أكثر شمولاً عبر بحوث أوسع نطاقاً في عمليات المعالجة الحرارية التي تخضع لها السبيكة قبل وبعد عملية التقدم الاصطناعي لتوفير فهم أكثر شمولاً للعوامل التي يمكن تحسينها للوصول إلى المزيج المرغوب من الخصائص الميكانيكية المختلفة.

جامعة البحرين

قسم الهندسة الميكانيكية



كلية الهندسة

نمذجة تأثير العناصر المضافة والتقادم على الخصائص الميكانيكية لسبائك الألومنيوم 6063

أطروحة مقدمة كجزء من متطلبات الحصول على درجة الماجستير في الإدارة الهندسية

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