

INVESTIGATION ON COATING GEOMETRY OF FRICTION SURFACED ALUMINIUM OVER CARBON STEEL BY MACHINE LEARNING APPROACH

Submitted in partial fulfilment of the requirements for the award of
Bachelor of Engineering degree in Automobile

by

Nassion Neupane (Reg No. 39860014)

Siddhartha Babu Chaudhary (Reg No. 39860021)



**DEPARTMENT OF AUTOMOBILE ENGINEERING
SCHOOL OF MECHANICAL ENGINEERING
SATHYABAMA**

**INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)**

**Accredited with Grade "A" by NAAC | 12B Status by UGC | Approved by AICTE
JEPPIAAR NAGAR, RAJIV GANDHI SALAI, CHENNAI - 600 119**

April - 2023



SATHYABAMA

INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)



Accredited with “A” grade by NAAC | 12B Status by UGC | Approved by AICTE

Jeppiaar Nagar, Rajiv Gandhi Salai, Chennai – 600 119

www.sathyabama.ac.in

DEPARTMENT OF AUTOMOBILE

BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **Nassion Neupane (Reg No. 39860014)**, and **Siddhartha Babu Chaudhary (Reg No. 39860021)**, who have done the project work entitled “**Investigation on coating geometry of friction surfaced aluminium over carbon steel by machine learning approach**” under my supervision from November 2022 to April 2023.

Internal Guide

Dr. DILLIP KUMAR SAHOO, M.E., Ph.D.

Head of the Department

Dr. V. K. BUPESH RAJA, M.E., Ph.D.

Submitted for Viva Voce examination held on 26-04-2023

Internal Examiner

External Examiner

DECLARATION

We, **Nassion Neupane (Reg No. 39860014)**, and **Siddhartha Babu Chaudhary (Reg No. 39860014)**, hereby declare that the Project Report entitled “**Investigation on coating geometry of friction surfaced aluminium over carbon steel by machine learning approach**” done by us under the guidance of **Dr. DILLIP KUMAR SAHOO, M.E., Ph.D.**, is submitted in partial fulfilment of the requirements for the award of Bachelor of Engineering degree in Automobile.

1.



2.



DATE:

PLACE: Chennai, Tamil Nadu

SIGNATURE OF THE CANDIDATE

ACKNOWLEDGEMENT

I am pleased to acknowledge my sincere thanks to the **Board of Management of SATHYABAMA** for their kind encouragement in doing this project and for completing it successfully. I am grateful to them.

I convey my thanks to **Dr. S. PRAKASH M.E., Ph.D.**, Dean, School of Mechanical Engineering, and **Dr. V.K. BUPESH RAJA, M.E., Ph.D.**, Head of the Department, Dept. of Automobile Engineering for providing me necessary support and details at the right time during the progressive reviews.

I would like to express my sincere and deep sense of gratitude to my Project Guide **Dr. DILLIP KUMAR SAHOO, M.E., Ph.D.**, Associate Professor, Department of Automobile, School of Mechanical Engineering for his valuable guidance, suggestions, and constant encouragement paved way for the successful completion of my project work.

I wish to express my thanks to all Teaching and Non-teaching staff members of the Department of Automobile who were helpful in many ways for the completion of the project.

ABSTRACT

This study focuses on analysing the effects of forced convection nitrogen shielding (FCNS) on the mechanical and corrosion performance of the deposited coatings when different metals are surfaced by friction. The study made the right process parameter selections and kept the substrate plate's preheating temperature constant at 200 °C throughout the deposition procedure. Throughout the procedure, three friction surfacing process parameters were taken into account along with four distinct nitrogen gas volumes. The study examined how these changes affected the output responses of the deposited aluminium, including coating width, coating thickness, tensile strength, and bending strength. Response surface methodology (RSM), artificial neural network (ANN), and particle swarm optimisation were the three optimisation strategies employed in the study to simulate the results of the deposition (PSO). In its whole, the study attempted to enhance the mechanical and corrosion characteristics of friction-surfaced aluminium coatings on carbon steel.

LIST OF CONTENTS

CHAPTER NO.	TITLE	PAGE NO.
	ABSTRACT	v
	LIST OF CONTENTS	vii
	LIST OF FIGURES	viii
	LIST OF TABLES	ix
1	INTRODUCTION	
	1.1 SURFACE ENGINEERING	1
	1.1.1 SCOPE OF SURFACE ENGINEERING	2
	1.1.2 WHY FRICTION SURFACING	4
	1.2 FRICTION SURFACING	5
	1.2.1 IMPORTANCE OF FRICTION SURFACING	7
	1.2.2 APPLICATION OF FRICTION SURFACING	8
2	LITERATURE SURVEY	9
3	AIM AND OBJECTIVE OF PRESENT INVESTIGATION	19
	3.1 AIM	19
	3.2 OBJECTIVE	19
	3.3 PROBLEM IDENTIFICATION	19
	3.4 PLAN AND SEQUENCE OF THE PROJECT	20
4	MATERIAL AND EXPERIMENTAL METHOD	21
	4.1 MATERIALS	21
	4.1.1 EN8 CARBON STEEL	21
	4.1.2 ALUMINIUM 6063	22
	4.2 EXPERIMENTAL PROCESS AND PARAMETER	24
	4.3 INDUCTION HEATING	25
	4.4 FORCED CONVECTION NITROGEN SHIELDING	25
	4.5 RESPONSE SURFACE METHODOLOGY	27
	4.6 ARTIFICIAL NEURAL NETWORKS	28
	4.6.1 FEEDFORWARD NEURAL NETWORK	29
	4.7 PARTICLE SWARM OPTIMIZATION	30

5	RESULT AND DISCUSSION	32
	5.1 APPERANCE OF COATING	32
	5.2 DEPOSITION CHARACTERSTICS	34
	5.3 TEMPERATURE PROFILE	35
	5.4 MECHINICAL CHARACTERSTICS	36
	5.4.1 MICRO HARDNESS TEST	37
	5.4.2 TENSILE STRENGTH	39
	5.4.3 BENDING	40
	5.5 MICROSTRUCTURAL STUDY	43
	5.5.1 SEM ANALYSIS	43
	5.6 CORRISION TEST	46
	5.7 SUMMARY	49
	5.8 OPTIMIZATIONS	49
	5.8.1 RESULTS FROM RSM	49
	5.8.2 RESULTS FROM ANN	55
	5.8.2.1 WEIGHT AND BIAS IN ANN	58
	5.8.3 RESULTS FROM PSO	63
	5.9 COMPARISION OF RSM, ANN AND PSO	68
6	CONCLUSIONS	73
	REFERENCES	75

LIST OF FIGURES

FIG NO.	TITLE	PAGE NO.
1.1	PRINCIPLE OF FRICTION SURFACE	6
4.1	EXPERIMENTAL SETUP OF FRICTION SURFACING (A)MODELING OF EXPERIMENTAL WORK (B)EXPERIMENTAL MACHINE (C) NITROGEN GAS SUPPLY SETUP	26
5.1	TEMPERATURE PROFILE DURING FORCED CONVECTION SHIELDING PROCESS	36
5.2	HARDNESS DEVELOPMENT	37
5.3	HARDNESS PROFILE, INDENTATION POINT IN LONGITUTIONAL DIRECTION AND INDENTATION POINT IN TRANSVERSE DIRECTION	38
5.4	HARDNESS PROFILE, HARDNESS VALUE AT INTERFACE IN LONGITUDINAL DIRECTION AT DIFFERENT OF FCS AND HARDNESS VALUE AT INTERFACE IN TRANSVERSE DIRECTION	39
5.5	(A)BEFORE TESTING AND (B) AFTER TESTING	40
5.6	TENSILE TEST RESULTS OF THE SAMPLE OBTAINED FROM FRICTION FORCED CONVECTION SHIELDING PROCESS	40
5.7	SPECIMEN AFTER (A)ROOT BEND TEST (B)FACE BEND TEST	41
5.8	BEND TEST RESULTS (A) ROOT BENDING (B) FACE BENDING	42
5.9	MICROSTRUCTURE VIEW AT THE INTERFACE	44
5.10	GRAIN SIZE DEVELOPMENT OF FORCED CONVECTION NITROGEN SHIELDING PROCESS	46
5.11	POLARIZATION TEST MACHINE	47

5.12	POLARIZATION RESPONSE OF ALUMINIUM 6063 AND EN8 CARBON STEEL	48
5.13	FLOWCHART OF RSM OPTIMIZATION	50
5.14	ARCHITECTURE OF 3-9-4 ARTIFICIAL NEURAL NETWORK	56
5.15	FLOW CHART USED FOR ANN OPTIMIZATION	56
5.16	PSO'S ALTERATION OF THE SEARCH POINT	63
5.17	FLOWCHART USED FOR PSO OPTIMIZATION	64

LISTS OF TABLES

TABLE NO	TITLE	PAGE NO
4.1	MECHTRODE AND SUBSTRATE MATERIALS	21
4.2	ELEMENTAL COMPOSITION OF EN8 MEDIUM CARBON STEEL	22
4.3	PROPERTIES OF EN8 CARON STEEL	22
4.4	ELEMENTAL COMPOSITION OF ALUMINIUM ALLOY AA6063	23
4.5	PROPERTIES OF ALUMINIUM AA6063	23
4.6	PARAMETRIC COMPOSITION USED FOR EXPERIMENTAL WORK	24
5.1	DEPOSITION SAMPLE OBTAINED THROUGH EXPERIMENTAL WORK	32
5.2	TENSILE AND BENDING TEST	42
5.3	CORRISION PARAMETERS IN POTENTIO-DYNAMIC POLORIZATION TEST	47
5.4	OBSERVED AND PREDICTED VALUES OF DEPOSITION WIDTH AND THICKNESS FROM RSM ALGORITHM	52
5.5	OBSERVED AND PREDICTED VALUES OF TENSILE STRENGTH AND BENDING STRENGTH FROM RSM ALGORITHM	53
5.6	WEIGHT AND BIAS BETWEEN INPUT AND HIDDEN LAYER	59
5.7	OBSERVED AND PREDICTED VALUES OF DEPOSITION WIDTH AND THICKNESS FROM ANN ALGORITHM	60

5.8	OBSERVED AND PREDICTED VALUES OF TENSILE STRENGTH AND BENDING STRENGTH FROM ANN ALGORITHM	61
5.9	OBSERVED AND PREDICTED VALUES OF DEPOSITION WIDTH AND THICKNESS FROM PSO ALGORITHM	65
5.10	OBSERVED AND PREDICTED VALUES OF TENSILE STRENGTH AND BENDING STRENGTH FROM PSO ALGORITHM	66
5.11	MAXIMUM AND MINIMUM PREDICTION ERRORS FOR DEPOSITION WIDTH	69
5.12	MAXIMUM AND MINIMUM PREDICTION ERRORS FOR DEPOSITION THICKNESS	69
5.13	MAXIMUM AND MINIMUM PREDICTION ERRORS FOR TENSILE STRENGTH	70
5.14	MAXIMUM AND MINIMUM PREDICTION ERRORS FOR BENDING STRENGTH	71

CHAPTER 1

INTRODUCTION

1.1 SURFACE ENGINEERING

The multidisciplinary area of surface engineering includes altering the surface characteristics of materials to raise its usefulness, performance, and durability. Changes to the material's surface texture, physical structure, or chemical makeup may be necessary. Surface engineering aims to provide materials with unique features that can be used for certain purposes, materials that can tolerate harsh conditions, resist wear and tear, and so on.

Surface engineering is significant in a variety of industries, including aerospace, automotive, electronics, and biomedical engineering. Surface engineering is employed in the aerospace sector to increase the efficiency of engine parts and the toughness of materials in harsh conditions. Surface engineering is used in the automobile industry to increase the wear resistance of engine components and to lower friction in the engine. The durability and performance of microelectronic devices are enhanced in the electronics sector via surface engineering. In the biomedical sector, surface engineering is utilised to produce friendly materials for implanted devices.

When it comes to surface engineering, there are a variety of approaches that may be applied, and the methodology that is employed depends on the application and goal. Among the most popular methods for surface engineering are:

- **Coatings:** Adding a thin layer of a substance to a material's surface to enhance its qualities. Enhancing corrosion resistance, wear resistance, or other qualities is one example of this.
- **Surface modification:** Altering the chemistry or physics of a material's surface. This may entail plasma therapy, laser processing, or ion implantation.
- **Surface texturing:** The process of giving a surface a particular pattern or texture to improve how well it performs in each application. Increasing a material's stickiness or lowering friction are two examples of this.

- Surface cleaning: Cleaning a material's surface to get rid of impurities and enhance its qualities.

Coating is one of the most often used methods in surface engineering. A material can have coatings applied to it in a few ways to enhance performance. For better corrosion resistance, wear resistance, or to create a particular surface texture, for instance, a coating may be applied. Chemical vapour deposition, physical vapour deposition, and electroplating are just a few of the methods that may be used to apply coatings.

Surface modification is yet another widely used method of surface engineering. A material's surface can be modified by changing its chemical or physical characteristics. Ion implantation, plasma therapy, or laser processing are a few examples of the methods that may be used to accomplish this. Ion implantation, for instance, can be used to introduce elements into a material's surface, whereas plasma treatment can be used to change the surface chemistry of a material.

For surface engineering, surface texturing is an additional method that may be applied. To improve the performance of a material in certain applications, surface texturing entails generating a specific surface texture or pattern. A material's adhesion may be improved, and friction may be decreased. Several methods, including laser processing, micro-machining, and electrochemical machining, can be used to texturize surfaces.

In a wide range of applications, surface engineering is essential for enhancing the performance and longevity of materials. The unique application and the intended result will influence the surface engineering approach that is chosen. Surface engineering is becoming a more significant discipline because of developments in materials science and engineering, and this trend is anticipated to continue in the future.

1.1.1 Scope of Surface Engineering

Surface engineering has a broad range of uses across a variety of sectors and businesses. Surface engineering is a multidisciplinary field that integrates ideas from engineering, physics, chemistry, and materials science. In order to increase a material's utility, performance, and durability, surface engineering aims to change the surface qualities of the material.

The following are included in the scope of surface engineering:

- **Aerospace Industry:** Materials used in the aircraft sector must survive harsh conditions, tolerate abrasion, and display special qualities. Surface engineering is therefore essential. Surface engineering is used to increase the longevity of materials in harsh conditions, the performance of engine components, and the resistance of materials to fatigue.
- **Automotive Industry:** In the automobile industry, surface engineering is used to increase the wear resistance of engine components and to lower engine friction. Surface engineering is also used to lighten materials, which can increase fuel efficiency, and to increase the corrosion resistance of automobile components.
- **Electronics Industry:** Surface engineering is utilised in the manufacturing of electronic devices to increase their performance and dependability. High electrical conductivity, thermal conductivity, and corrosion resistance are just a few of the unique features that may be found in thin films and coatings made via surface engineering.
- **Biomedical Industry:** Surface engineering is utilised in the biomedical sector of the economy to produce biocompatible materials for implanted gadgets. Surface engineering is a technique used to alter the surface characteristics of materials to improve their compatibility with the body and avoid immune system rejection.
- **Energy Industry:** In the energy sector, surface engineering is utilised to increase the durability and efficacy of materials used in energy generation and storage. The performance of materials used in solar cells, batteries, and fuel cells can be enhanced by surface engineering.

These industries are not the only ones where surface engineering may be used; it can also be used in a wide range of other industries, including manufacturing, construction, and military. Because materials science and engineering are developing, the area of surface engineering is expanding and is anticipated to become even more significant in the future. Surface engineering advancements make it possible to produce materials with special qualities that may be used for certain purposes, which can result in considerable enhancements in usefulness, performance, and durability.

1.1.2 Why Friction Surfacing

Friction surfacing is a solid-state coating procedure that has grown in popularity in recent years due to the multiple benefits it offers over traditional welding and coating processes. High pressure and speed are applied when rubbing two materials together, creating heat that helps the materials join. Friction surfacing is an adaptable method that may be used to join a variety of different dissimilar materials, including as metals, polymers, and ceramics.

Friction surfacing's reduced heat input is among its main features. The materials being bonded aren't exposed to high temperatures since the procedure generates little heat input. Because of this, the materials are less likely to be deformed or undergo metallurgical changes, which can happen when using conventional welding processes. Because filler material is not required because to the low heat input, the method can be more affordable and produce less waste overall.

Friction surfacing has the additional benefit of requiring little to no surface preparation. To establish a strong connection while using traditional welding procedures, the surface must frequently be extensively prepared. Nevertheless, friction surfacing only needs a limited amount of surface preparation, which can cut down on the time and expense of surface preparation.

A strong connection is formed between the materials being bonded by friction surfacing. When compared to other welding techniques, the bond strength is often stronger, and the connection is frequently metallurgically good. Because of this, friction surfacing is a popular option for applications where a reliable connection is needed.

Moreover, a variety of coating materials, including as metals, alloys, and metal matrix composites, may be applied via friction surfacing. Because of this, it is a common option for applications where requirements include corrosion resistance, wear resistance, or heat barrier qualities. The method is also eco-friendly because it doesn't generate any trash or dangerous emissions.

Several different sectors, such as aerospace, automotive, and energy, employ friction surfacing. Friction surfacing is a technique used in the aerospace industry to bind different types of materials, cover components, and fix broken parts. Applying coatings to engine parts, enhancing component wear resistance, and lowering friction in the

engine are all uses for it in the automotive sector. Friction surfacing is employed in the energy sector to increase the robustness and effectiveness of the materials used in energy production and storage.

Controlling the process parameters to guarantee a constant and dependable bonding is one of the difficulties of friction surfacing. The materials being bonded, the force and speed of the rubbing action, and the temperature produced by the process interact in a complicated way during the process. To guarantee a high-quality bond, the process parameters must be carefully managed.

In comparison to conventional welding and coating procedures, friction surfacing is a flexible and affordable approach that offers a few benefits. It is a popular option for a variety of applications due to the low heat input, little surface preparation, and high-quality bond. Future advancements in materials science and engineering are anticipated to lead to more and more uses for friction surfacing, which will increase its significance.

1.2 FRICTION SURFACING

To improve the performance of a metal surface, friction surfacing is a technique that may be used to apply a variety of materials, including tool steels, stainless steels, and hard facings. Using frictional heat and pressure, the desired substance is deposited into the surface using this method.

A solid consumable bar is rotated while having one of its ends firmly placed on a substrate material, such as a plate, disc, or cylinder. At the consumable's tip, heat is produced, creating a plasticized layer. This plasticized material is deposited on the substrate because of the substrate moving laterally with respect to the spinning consumable (see illustration).

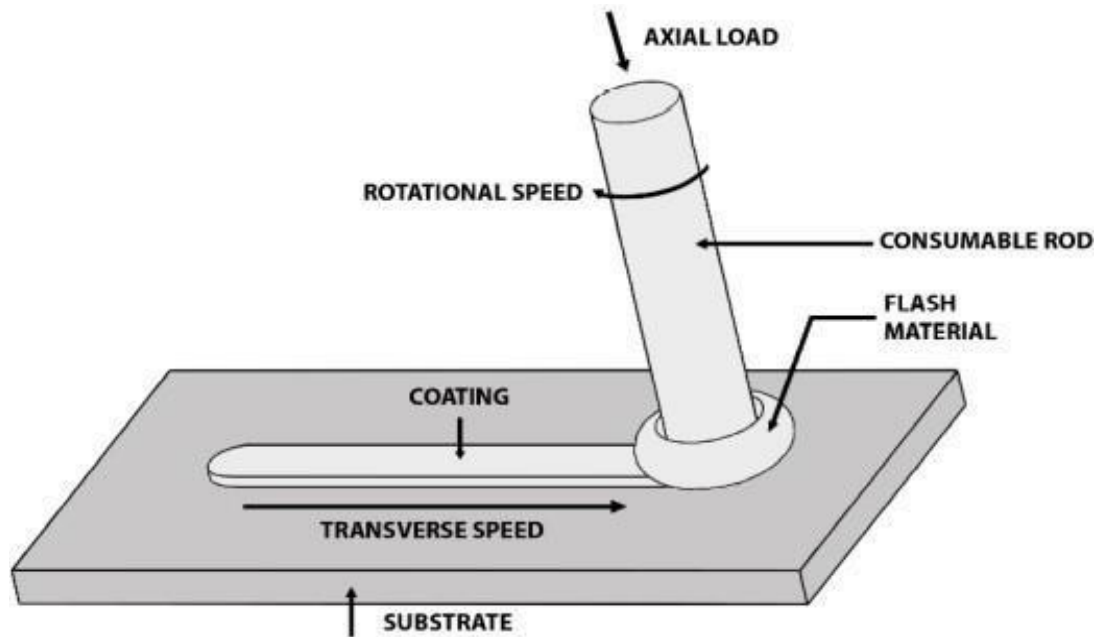


Fig.1.1: Principle of Friction surfacing.

There is no melting or mixing of the substrate material with the consumable material utilised in the deposition process, therefore the deposit has the same chemical make-up as the consumable material.

The deposit has high mechanical strength and adhesion and is naturally homogeneous. Even after withstanding loads equivalent to the ultimate tensile strength of the weaker material, the interface area typically survives unharmed. The bond quality near the deposit's margins, however, is often low, therefore this region might need to be removed. In general, the thickness of the deposit is minimal with high strength surface materials. The material that is deposited and the settings are what determine how the surface looks.

As friction surfacing is a solid phase technique, it is possible to utilise materials that are incompatible with metals. It is possible to produce unique material property combinations that are often impossible to realise in monolithic materials. As a result, less expensive or strategic materials are used.

By placing hard particles into one or more holes or slots drilled in the consumable bar, the procedure has been expanded to deposit metal matrix composites (MMCs). The matrix is made up of the substance of the bar and contains the hard particles.

1.2.1 Importance of friction surfacing

An essential solid-state coating method that provides several advantages and benefits is friction surfacing. The following are some of the main arguments in favour of friction surfacing:

Bonding dissimilar materials: Friction surfacing is especially helpful for joining different materials, such as composites, titanium, magnesium, and aluminium. It makes it possible to coat or bind materials that have previously proven challenging to coat or bond using conventional coating processes.

Reduced heat input: Friction surfacing is a solid-state coating process that produces less heat input. In situations where precise control of the heat input is necessary, this makes it perfect since it lowers the danger of distortion and material damage.

Improved coating quality: Friction surfacing creates coatings of excellent quality with a consistent structure and a solid bond. This occurs because of the materials not melting, which may otherwise result in porosity, cracking, and other flaws.

Lower environmental impact: Friction surfacing is a method that has a lower environmental impact than other methods since it requires less energy and creates less trash. Moreover, it is gas- and fume-free, making it safer for users and the environment.

Versatility: Friction surfacing is a flexible method that may be employed in a variety of industries, such as industrial manufacturing, automotive, aerospace, and marine. It may be used to generate new parts and structures as well as fix and restore broken ones.

Friction surfacing is a crucial coating method that has several benefits over other welding methods. It is a desirable solution for a variety of applications due to its capacity to connect disparate materials, generate high-quality coating with less heat input, and have a less environmental effect.

1.2.2 Application of Friction Surfacing

Friction surfacing is a solid-state coating technique that has a wide range of uses in several sectors. Friction surfacing is frequently used for the following purposes:

- Industry of aerospace: In the aircraft sector, damaged parts including engine parts, landing gear parts, and structural parts are often repaired and restored using friction surfacing. New parts for spacecraft and aeroplanes are also created with the help of it.
- Automotive sector: Damaged components including engine blocks, cylinder heads, and transmission parts may be repaired and restored using friction surfacing in the automobile industry. Moreover, it is employed in the construction of lightweight vehicles to link disparate materials.
- Maritime industry: Damaged parts like propellers, shafts, and rudders may be repaired and restored using friction surfacing in the marine business. Moreover, it is utilised to create brand-new boat and ship parts.
- Manufacturing in the industrial sector: Friction surfacing is used to repair and restore parts including pump housings, valves, and fittings. In the construction of specialist gear and equipment, it is also utilised to combine materials of different compositions.
- Medical industry: Orthopedic implants and prosthetic devices are repaired and restored using friction surfacing in the medical sector.

Friction surfacing is a flexible coating technique that is applied to a variety of products and industries. It is a preferred option for many production processes due to its capacity to bind incompatible materials, generate high-quality coat with less heat input, and have a smaller environmental effect.

CHAPTER 2

LITERATURE SURVEY

1. B. Arora, A. Kumar, S. Kumar, S. S. Mahapatra, and R. Sharm, Formation of Composite Surface during Friction Surfacing of Steel with Aluminium, Materials Today: Proceedings, Volume 18, Part 1, 2019, Pages 262-269.

Aluminium may be deposited on a steel substrate and then surfaced using friction to create a composite surface. The technology has a few benefits over conventional coating techniques, including low heat input, little deformation, and decreased porosity. By modifying the process parameters, the microstructure and characteristics of the composite surface may be improved. Potential uses for the composite surface created by friction surfacing include the maritime engineering, automotive, and aerospace sectors.

2. N. Ramkumar, P. Sathiya, Mechanical evaluation and thermal modelling of friction welding of mild steel and aluminium, Journal of Manufacturing Processes, Volume 16, Issue 3, July 2014, Pages 346-354.

The study looked at the friction-welded junctions between aluminium and mild steel's mechanical characteristics and thermal behaviour. The friction welding procedure, according to the authors, produced a strong metallurgical link with base materials' inferior tensile strength and hardness. To mimic the temperature distribution throughout the operation, they also created a numerical model and compared the output with experimental data. The temperature profile and weld quality under various welding circumstances could be predicted using the model, which demonstrated good agreement with the experimental data.

3. R. George Sahaya Nixon, Dr. B.S. Mohanty, Friction surfacing of metal coatings on steel and aluminium substrate, Advanced Materials Research Vols. 816-817 (2013), pp 254-259.

The study examined the influence of manufacturing factors on the mechanical and microstructural characteristics of friction-surfaced coatings on steel and aluminium substrates. It was discovered that by adjusting process variables including the

pressure used to apply the coating and the tool's rotating speed, the coating quality and characteristics could be maximised. The study also shed light on the potential of friction surfacing as an economical and effective coating method for a variety of industrial applications.

4. S. Kumar, S. Kumar, S. Maheshwari, S. Singh, and S. Dixit, Friction surfacing process of aluminium alloys, Transactions of Nonferrous Metals Society of China, Volume 29, Issue 11, November 2019, Pages 2325-2336.

A study of the literature on friction surfacing of aluminium alloys provides the most recent scientific findings. The authors analyse the influence of process variables on the microstructure and characteristics of the deposited coatings, such as tool material, tool shape, rotational speed, feed rate, and axial force. The article discusses the different friction surfacing methods in detail and emphasises the process's potential uses in the aerospace and automotive sectors.

5. Arvind Kumar Gupta, Partha Sarathi De, Sankha Santra, Sudip Kumar Pal, Inductive heating effects on friction surfacing of stainless steel onto an aluminium substrate, Surface Engineering, 2021

Inductive heating's impact on the friction surfacing of stainless steel onto an aluminium substrate is examined in this research. The scientists discovered that inductive heating increased the interfacial bonding strength, decreased surface roughness, and enhanced coating quality. The outcomes demonstrated the potential of inductive heating as a technology to improve friction surfaces.

6. D. Taneja, A. Mondal, N. N. Das, and S. Kumar, Transferring mechanism of the coating rod in friction surfacing, The International Journal of Advanced Manufacturing Technology, Volume 91, Issues 1–4, 2017, Pages 377-386.

The study looked at the coating rod's transferring process in friction surfacing. To comprehend the procedure, the authors used numerical models and experimental data. They discovered that several factors, including the coated rod's material qualities, the process parameters, and the tool geometry, had an impact on the creation of a homogeneous coating on the substrate surface. The study can assist to improve the friction surfacing process by illuminating the elements that influence coating quality.

7. Alhashemi, A., Ahmed, M., Alqahtani, S., Alhajri, N., & Alshahrani, A., Effects of surface coating on reducing friction and wear of orthopaedic implants, *International Journal of Medical Engineering and Informatics*, 2020, 12(3), 226-237.

The study assesses how surface coatings might lessen wear and friction on orthopaedic implants. The authors conduct a comparative investigation of several coatings, including diamond-like carbon, titanium nitride, and hydroxyapatite coatings. The findings demonstrate that the coatings greatly decrease the wear rate and coefficient of friction of the implants, potentially extending their lifespan and improving their performance.

8. Ibrahim M. Deiab, Ahmed A. D. Sarhan, and Stephen Newman, A review of cryogenic cooling in machining processes, *International Journal of Machine Tools and Manufacture*, Volume 51, Issue 8, July 2011, Pages 557-580.

The report offers a thorough analysis of the cryogenic cooling method used in machining operations. It describes the workings of cryogenic cooling, its advantages, as well as its drawbacks and restrictions. The current advancements in research and potential prospects for cryogenic cooling in machining are also highlighted in the article.

9. P. Schindele, C. Czettl, R. Kopp, and K. Bobzin, Optimization and characterization of friction surfaced coatings of ferrous alloys, *Surface and Coatings Technology*, Volume 369, 25 October 2019, Pages 166-178.

An analysis of friction surfacing process parameters for coating ferrous alloys onto steel substrates is presented in the paper. Investigation was done into how several process variables, such as rotating speed, axial force, and feed rate, affected the coatings' quality and features. According to the study, increasing the axial force caused the coatings' thickness to drop while increasing the rotational speed and feed rate caused the coatings' thickness to grow. To assess the coatings' characteristics, the authors also performed microstructural analysis and hardness tests on them.

10. Shashank Mishra, Anil Kumar Dahiya, and Pankaj Kumar, Influence of friction surfacing process parameters to deposit AA6351-T6 over AA5052-H32 using

conventional milling machine, *Journal of Manufacturing Processes*, Volume 51, August 2020, Pages 219-232.

The friction surfacing method was used in the study to examine how several process variables, including rotating speed, traverse speed, and axial force, affected the coating quality and microstructure of AA6351-T6 on AA5052-H32 substrate. While traverse speed had a little impact on coating quality, the scientists discovered that increasing rotational speed and axial force increased the bonding strength between the coatings and the substrate. According to the study, the coating thickness grew as the axial force and rotational speed increased while dropping as the traverse speed increased.

11. G. Casalino, E. Serra, L. Cultrone, F. Ravasio, and A. Gatto, Wear characterization of functionally graded Al-SiC composite coatings produced by Friction Surfacing, *Surface and Coatings Technology*, volume 358, part B, pages 490-498, 2019.

The wear behaviour of functionally graded Al-SiC composite coatings made via friction surfacing was examined by the authors. The findings demonstrated that the coatings had outstanding wear resistance and that adding SiC particles enhanced the coatings' wear behaviour. The study also discovered that creating functionally graded composite coatings with desirable qualities may be done affordably using the friction surfacing approach.

12. J. Martinez-Martinez, J. A. Rodríguez-Martínez, G. Rodríguez-Rodríguez, A. E. Coy-Arechavaleta, L. E. Murr, and S. M. Wiederhorn, Influence of external cooling configuration on friction surfacing of AA6082 T6 over AA2024 T351, *Journal of Manufacturing Processes*, Volume 36, November 2018, Pages 295-305.

In the study, the effect of external cooling configuration on the friction surfacing process of attaching AA6082 T6 to AA2024 T351 is examined. The scientists discovered that in order to stop heat damage and oxidation of the materials throughout the process, external cooling is crucial. In addition, they noted that when adjusting the process settings, external cooling might result in considerable changes in the microstructure and mechanical characteristics of the coatings.

13. Anuj Sharma, Ravi Kant, S.K. Singh, and J. Ramkumar, Feasibility Study of Friction Surfaced Coatings over Non-Ferrous Substrates, *Materials Today: Proceedings*, Volume 5, Issue 2, Part 1, 2018, Pages 6726-6735.

The study investigates the viability of covering non-ferrous substrates using friction surfacing. The authors look at how process variables like tool rotational speed and traverse speed affect the coatings' microstructure and microhardness. Also, they examine how well the coatings adhere to various substrates. The study's findings support the possibility of better wear resistance and surface qualities with friction surfacing as a coating method for non-ferrous substrates.

14. S. Nazir, Z. Shahid, N. Iqbal, M. Arslan, Basic friction angle of granite fracture after heating and rapid cooling treatments, *Bulletin of Engineering Geology and the Environment*, 2020.

In the study, the fundamental friction angle of granite fracture surfaces was examined in relation to heating and quick cooling treatments. Findings revealed that following heating and quick cooling treatments, the fundamental friction angle dramatically decreased, indicating the possible risk of rockfall in places with such geological circumstances. The work offers crucial information for geotechnical engineering and rock mechanics, particularly for assessing the stability of rock slopes in hot settings.

15. Ali Hosseini, Asghar Rezaei, Farzad Jafari, and Hamidreza Paydar, Influence of external cooling configuration on friction surfacing of AA6082 T6 over AA2024 T351, *The International Journal of Advanced Manufacturing Technology*, volume 99, issues 5-8, February 2019, pages 1451-1464.

The study looked at how cooling from the outside affected the friction surfaces of the aluminium alloys AA6082 T6 and AA2024 T351. The authors discovered that by lowering the thickness of the intermetallic layer and strengthening the link between the coating and the substrate, employing an external water spray as a cooling mechanism during the friction surfacing process may considerably enhance the quality of the coatings. The study also showed that the microstructure of the coating is influenced by the cooling rate used throughout the process, and that employing a greater cooling rate can result in the creation of smaller grains and a more homogenous microstructure.

16. M. Rahman, S. Mitra, K. Manna, P. Saha, Process modeling and parameter optimization of surface coatings using artificial neural networks (ANNs), *Journal of Intelligent Manufacturing*, 2015.

The authors suggested a method for modelling and improving surface coating process parameters using artificial neural networks (ANNs). The study demonstrated that the ANNs-based method is a useful tool for anticipating the ideal operating conditions for surface coating applications.

17. M. Emre Demirel, Ahmet Yakut, İrfan Kılınç, Ali Kaplan, Artificial neural network-based prediction technique for coating thickness in Fe-Al coatings fabricated by mechanical milling, *Journal of Alloys and Compounds*, Volume 729, 2017, Pages 1098-1105.

The paper suggests a coating thickness prediction method for Fe-Al coatings produced by mechanical milling based on artificial neural networks (ANN). The milling duration, ball-to-powder ratio, and rotating speed were used as input parameters by the authors, while coating thickness was used as an output parameter. The outcomes shown that the suggested approach can forecast the coating thickness effectively and with little error. This method may be used to optimise the coating process and obtain the required coating thickness in the manufacturing sector.

18. N. Janarthanan, V. Balasubramanian, and V. Selladurai, Optimization of friction surfacing process parameters for aa1100 aluminum alloy coating with mild steel substrate using response surface methodology (RSM), *Journal of Materials Engineering and Performance*, 2021.

RSM is a useful tool for maximising the friction surfacing process parameters for AA1100 aluminium alloy on mild steel substrate. To achieve the required coating qualities, the process parameters can be optimised using RSM to create a mathematical model that specifies the link between the process parameters and the coating properties. To guarantee the correctness and generalizability of the RSM models, the calibre and volume of the input data should be carefully taken into account.

19. Muhammad Azhar Khan, Xiaoqiang Li, Rana Muhammad Shakeel, Muhammad Azhar Khan, Muhammad Abbas Choudhary, Tariq Mahmood, and Wei Gao, Response surface methodology study on the influence of nitrogen flow rate and

deposition temperature on the tribological properties of nitrogen-doped diamond-like carbon coating, *Applied Surface Science*, Volume 416, 30 October 2017, Pages 905-913.

For nitrogen doped DLC coatings, RSM can be a valuable technique for maximising the deposition parameters to attain the necessary tribological characteristics. To achieve the required tribological qualities, the deposition parameters can be optimised using RSM to create a mathematical model that depicts the link between the deposition parameters and the coating's tribological properties.

20.M. Abuquteishat, M. Y. H. Bangash, and R. A. Mahamood, Application of response surface methodology for the optimisation of micro friction surfacing process, *The International Journal of Advanced Manufacturing Technology*, 2016.

To improve the micro friction surfacing process parameters for surface roughness and microhardness of coatings on AA6061-T6 aluminium alloy, the study used response surface approach. The outcomes demonstrated that the feed rate and rotating speed were the most important variables impacting the coatings' microhardness and surface roughness. The ideal process parameters, which resulted in a surface roughness of 0.89 μm and a microhardness of 378 HV, were found to be a feed rate of 0.12 mm/rev and a rotating speed of 1900 rpm.

21.Md. Rafiul Islam, Mohammad Shorif Uddin, Mohammad Imrul Jubair, and Hossam Faris, A Micro-GA Embedded PSO Feature Selection Approach to Intelligent Facial Emotion Recognition, *IEEE Access*, Volume 8, 2020.

Particle swarm optimisation (PSO) and a micro-genetic algorithm (Micro-GA) are used in the work to present a unique method for intelligent face emotion identification. Using four publicly accessible datasets, the suggested method was tested, and the findings demonstrated that it performed better in terms of accuracy and computing efficiency than current approaches.

22.S. Karakaya and Y. Öztürk, Prediction of clad characteristics using ANN and combined PSO-ANN algorithms in laser metal deposition process, *The International Journal of Advanced Manufacturing Technology*, 2021.

To forecast the features of the clad produced by the laser metal deposition (LMD) method, the research suggests using artificial neural networks (ANN) and a combination of particle swarm optimisation (PSO) and ANN algorithms. The study demonstrates that, in comparison to utilising ANN alone, the combined PSO-ANN method enhances the accuracy of predictions for clad height, breadth, and dilution. The suggested method may help with LMD process parameter optimisation and clad layer quality enhancement.

23. S. K. Saha, S. N. Maiti, and B. K. Routroy, Machining Parameters Optimization of Titanium Alloy using Response Surface Methodology and Particle Swarm Optimization under Minimum-Quantity Lubrication Environment, *Materials Today: Proceedings*, Volume 5, Issue 2, 2018, Pages 6289-6299.

The machining settings for a titanium alloy in a minimum-quantity lubrication (MQL) environment were optimised by the authors using a combination of response surface methodology (RSM) and particle swarm optimisation (PSO). They discovered that, among the three variables, cutting speed, feed rate, and depth of cut all significantly affected machining performance. Surface roughness, cutting force, and tool wear were all decreased because of the adjusted settings.

24. Gourhari Ghosh, Prosun Mandal & Subhas Chandra Mondal Modeling and optimization of surface roughness in keyway milling using ANN, genetic algorithm, and particle swarm optimization, *The International Journal of Advanced Manufacturing Technology* volume 100, pages 1223–1242 (2019).

Artificial neural network (ANN), genetic algorithm (GA), and particle swarm optimisation were used by the authors of this research to present a model for predicting the surface roughness in keyway milling (PSO). They trained the ANN using experimental data and then utilised GA and PSO to optimise the input parameters to reduce surface roughness. The outcomes demonstrated that the suggested model could predict the surface roughness accurately, and that the optimisation strategies were successful in bringing the surface roughness down to a desirable level.

25. Rashmi Laxmikant Malghan, Karthik M. C. Rao, Arun Kumar Shettigar, Shrikantha S. Rao & R. J. D'Souza, Application of particle swarm optimization and response surface methodology for machining parameters optimization of aluminium matrix composites in milling operation, *Journal of the Brazilian*

The goal of the study was to utilise particle swarm optimisation and response surface methods to optimise the machining parameters of aluminium matrix composites during milling operations. The authors used response surface methods to construct a prediction model for surface roughness and cutting force after conducting tests to determine the values of the machining parameters. The machining settings were then optimised using particle swarm optimisation, and the outcomes were contrasted with those of the tests. The study discovered that the suggested method was successful in maximising the machining parameters for milling operations on aluminium matrix composites.

26. Pradeep V. Badiger, Vijay Desai, M. R. Ramesh, B. K. Prajwala & K. Raveendra, Cutting Forces, Surface Roughness and Tool Wear Quality Assessment Using ANN and PSO Approach During Machining of MDN431 with TiN/AlN-Coated Cutting Tool, Arabian Journal for Science and Engineering volume 44, pages 7465–7477 (2019).

The authors of this study looked at the machining of MDN431 steel using a cutting tool that was TiN/AlN coated. The cutting forces, surface roughness, and tool wear were predicted and optimised using particle swarm optimisation (PSO) and artificial neural network (ANN) techniques. The PSO technique was utilised to optimise the cutting parameters for better machining performance after the experimental data were used to train the ANN models. To enhance the machining performance of MDN431 steel, the study found that the ANN and PSO technique can accurately anticipate and optimise the machining parameters.

27. Md. Jahangir Alam, Mohammad Yeakub Ali, and Hossein Mokhtari, Prediction of clad characteristics using ANN and combined PSO-ANN algorithms in laser metal deposition process, The International Journal of Advanced Manufacturing Technology, Volume 115, Issue 5-6, pp 1203–1215, 2021.

To forecast the clad properties in the laser metal deposition (LMD) process, the study presented a combination technique employing artificial neural networks (ANN) and particle swarm optimisation (PSO). The authors employed ANN to create a prediction model after conducting experiments to gather the input data. Next, by modifying the

process settings, they used PSO to optimise the clad properties. The outcomes demonstrated that the combined PSO-ANN technique is successful in clad characteristic optimisation and prediction in the LMD process.

28. Pramod Kumar, Sumeet Sharma, and S. K. Jha, Measurement of WEDM performance characteristics of aero-engine alloy using RSM-based TLBO algorithm, *Journal of Manufacturing Systems*, Volume 57, Issue C, Pages 184-198, 2020.

By using the wire electrical discharge machining (WEDM) method to machine a high-temperature nickel-based alloy used in aero-engine components, the authors hoped to maximise its performance. They modelled the link between the machining parameters (pulse-on time, pulse-off time, servo voltage, and wire tension) and performance attributes using response surface methodology (RSM) (material removal rate and surface roughness). They next applied the teaching-learning-based optimisation (TLBO) method to identify the ideal machining parameter configuration that would provide the highest rate of material removal and the lowest level of surface roughness. According to the study, the RSM-based TLBO algorithm is a useful method for streamlining the WEDM process while milling aero-engine alloy.

29. Zahra Rahmati, Hamed Jamshidi Aval, Salman Nourouzi and Roohollah Jamaat: Modeling and experimental study of friction surfacing of AA2024 alloy over AA1050 plates, *Mater. Res. Express* 6, 2019, 0865g2.

Research on the friction surfacing of AA2024 alloy over AA1050 plates using both experimental and modelling methodologies is described in the literature. The process variables, such as rotating speed and pressure, were discovered by the authors to have a considerable impact on the quality of the deposited layer. The findings demonstrated that increasing the rotating speed and pressure resulted in a drop in the interface shear strength and an increase in the thickness of the deposited layer. To replicate the process, the scientists also created a finite element model, and they used experimental data to confirm the model's predictions. Overall, the study sheds light on the friction surfacing procedure and might be helpful in adjusting the process variables to get the deposited layer to have the desired qualities.

CHAPTER 3

AIM AND OBJECTIVE OF PRESENT INVESTIGATION

3.1 AIM

This study aims to investigate the impact of forced convection nitrogen shielding (FCNS) on the coating geometry of friction surfaced aluminium over carbon steel using a mix of experimental and machine learning methods.

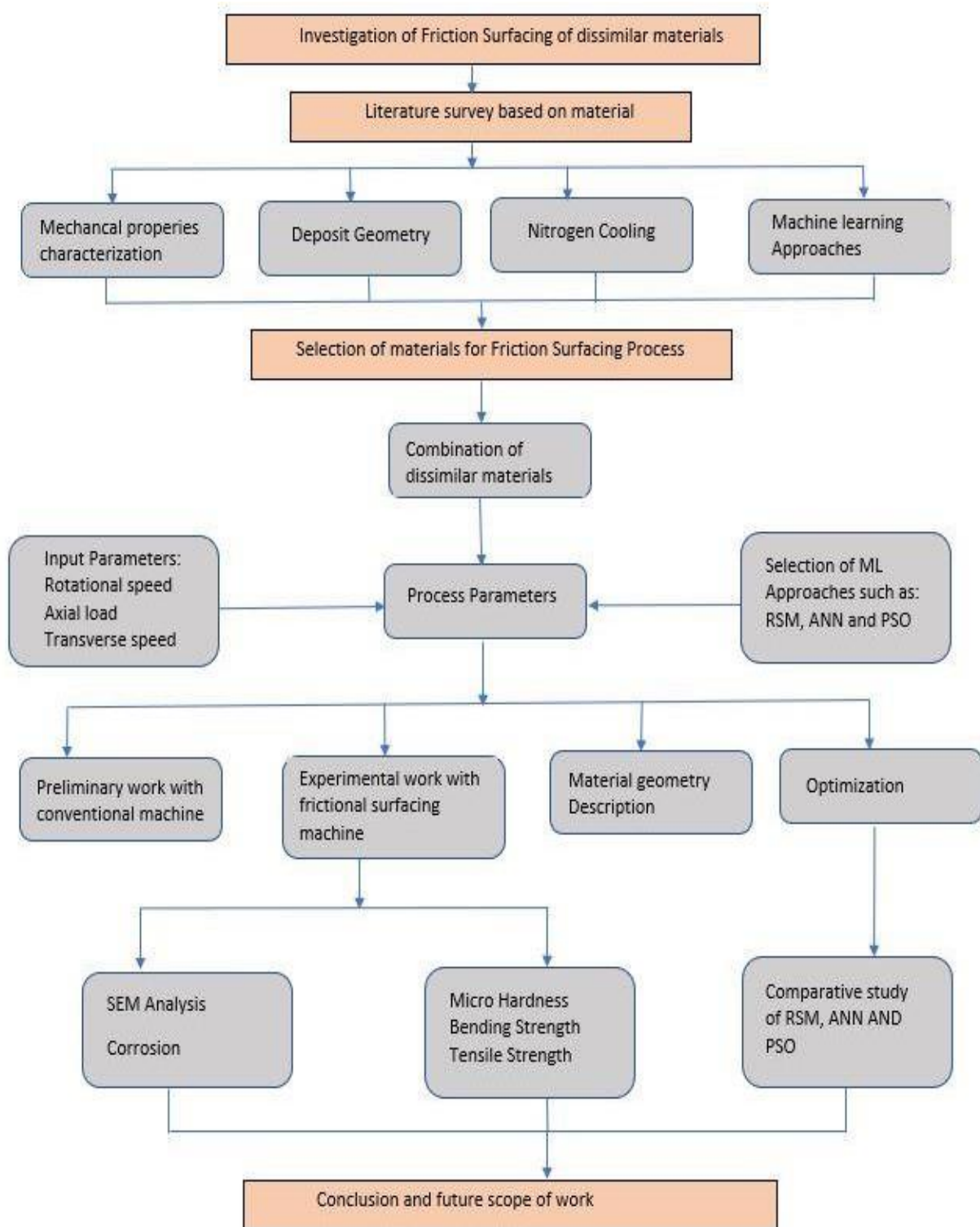
3.2 OBJECTIVE

By conducting experiments to ascertain the hardness, bending, and tensile strength of the coating and the microstructure using SEM analysis, as well as by developing and comparing the performance of three machine learning models, including an artificial neural network (ANN), a particle swarm optimisation (PSO), and a friction surfaced aluminium over carbon steel, the aim of this investigation is to evaluate the effect of forced convection nitrogen shielding (FCNS) on the coating geometry of friction surfaced aluminium. To gain understanding of the relationship between the FCNS conditions and the coating geometry of friction surfaced aluminium over carbonsteel, the results from the machine learning models will be analysed. Recommendations for improving the FCNS conditions to achieve the desired coatinggeometry will also be given.

3.3 PROBLEM IDENTIFICATION

This study seeks to close various knowledge gaps regarding the friction-surfaced aluminium coating geometry on carbon steel. The objective of the project is to create and compare machine learning models for predicting coating geometry, comprehend the link between forced convection nitrogen shielding (FCNS) circumstances and coating geometry, and pinpoint the crucial aspects affecting coating quality. The development of coating quality and the optimisation of process parameters have been hampered by the lack of information in these fields. By resolving these issues, this inquiry will be able to greatly enhance the coating quality of friction-surfaced aluminium over carbon steel and establish optimum process parameters for friction surfacing.

3.4 PLAN AND SEQUENCE OF THE PROJECT WORK



CHAPTER 4

MATERIAL AND EXPERIMENTAL METHOD

4.1 MATERIALS

Due to its low weight and excellent corrosion resistance, aluminium is frequently used in a wide range of industries. Carbon steel and its alloys are also popular due to their strength and durability. With a diameter of 18 mm and a length of 100 mm, aluminium was utilised in this investigation as a mechtrode, or consumable rod. The base metal, or substrate, was made of low carbon, medium carbon, and stainless steel, all of which had the identical measurements of 6 mm thick, 60 mm wide, and 100 mm long. Based on the literature assessment and their extensive use in the sector, these materials were chosen.

Table 4.1: Mechtrode and Substrate materials

Mechtrode	Substrate
Aluminium AA6063	EN8 carbon steel

4.1.1 EN8 Carbon Steel

The mechanical qualities of EN8 Carbon Steel are good even at temperatures as high as 930 degrees Fahrenheit (500 degrees Celsius), and it is simple to process using standard industrial techniques. Its chemical composition provides strong defence against a variety of forms of corrosion, including stress-corrosion cracking, intergranular corrosion, pitting, and corrosion in crevices and pits. The majority of EN8 CS Plates also include chromium, iron, and nickel-based components.

Metal firms may provide a variety of forms and patterns thanks to the extra components that make EN8 CS Coils adaptable for usage in many sectors. EN8 CS Slating Coils may be hot worked at temperatures between 1600 and 2150 degrees Fahrenheit and maintain their mechanical integrity even at high temperatures. Moreover, these EN8 CS Perforated Coils are simple to weld using traditional methods.

Table 4.2. Elemental composition of EN8 medium carbon steel

Material	C	Mn	P	S	Si	Ni	Fe
% Of composition	0.35	0.60	0.05	0.05	0.11	0.01	Balance

Table 4.3: Properties of EN8 carbon steel

Density	2.68 g/cm ³
Tensile Strength, Ultimate	310 MPa
Tensile Strength, Yield	280 MPa
Specific heat	800 J/Kg °C
Thermal conductivity	150 W/m °C
Modulus of Elasticity	68.3 GPa
Melting Point	620°C

Applications of EN8 carbon steel:

- Manufacturing of gears, shafts, gearboxes, nuts, studs, and other mechanical parts.
- Buildings, bridges, and other infrastructure are being constructed.
- Fabrication of tools and dies for many sectors, including the manufacturing, aerospace, and automotive.
- The production of machine parts and components for the paper and textile industries.
- Manufacturing of agricultural machinery like ploughs and cultivators.

4.1.2 Aluminium 6063

The most common alloy for extrusion is 6063 aluminium, thus it makes sense to take it into account. The usage of this alloy in architectural applications is widespread. It is frequently referred to as architectural aluminium as a result.

Position number two has 6063 in first place. Both belong to the 6000 family and are mostly alloyed with silicon and magnesium. They have many of the same

characteristics as a result. They both offer comparable levels of workability, weldability, and corrosion resistance. Each of them has a wide range of uses.

One significant distinction is that 6061 is stronger than 6061, and at the T6 temper, its strength is comparable to that of structural steel. It is frequently employed in structural applications as a result. On the other hand, 6063 has the benefit of being simpler to mould into intricate patterns due to its smooth surfaces. Moreover, it offers higher corrosion resistance and is well suited for anodizing.

It is used in a variety of products including Railings, balustrades, construction supplies, electrical parts, irrigation tubes, maritime equipment, pipelines, shop fixtures, sign frames, storage tanks, truck frames and trailers, and window and door frames. This alloy has a moderate strength.

Table 4.4. Elemental composition of Aluminium alloy AA 6063

Material	Mg	Si	Cr	Mn	Ti	Zn	Fe	Al
% Of composition	0.56	0.47	0.1	0.1	0.1	0.1	0.35	Balance

Table 4.5: Properties of Aluminium AA6063

Density	7.87 g/cm ³
Tensile Strength, Ultimate	565 MPa
Tensile Strength, Yield	310 MPa
Specific heat	485 J/Kg °C
Thermal conductivity	46 W/mK
Modulus of Elasticity	200 GPa
Melting Point	1,500 °C

Applications of Aluminium 6063:

- Because to its light weight and good corrosion resistance, aluminium 6063 is frequently used in the construction of doors, windows, and curtain walls.

- The alloy is utilised to make automobile components including body panels, frames, and heat sinks.
- Due to its excellent electrical conductivity, aluminium 6063 is employed in the production of bus bars and electrical conductors.
- Because to its strength and endurance, the alloy is utilised in the production of furniture, fittings, and displays.
- Because to its corrosion resistance and endurance, it is utilised in the manufacture of pipe systems for the transfer of fluids and gases.

4.2 EXPERIMENTAL PROCESS AND PARAMETERS

The experimental samples are prepared by using a custom-made friction surfacing machine with a single line deposition for a length of about 100 mm. Before preparing the experimental samples, the substrate plate was neatly cleaned and removed the presence of any oxidised layer by milling machining process. The substrate plate must be flat and even surface to ensure a smooth and vibration less contact with mechtrode face during operation. To eliminate the formation of any contaminant compounds during FS process, both mechtrode and substrate materials are thoroughly cleaned by acetone solution. By considering present literature reviews and machine feasibility, the range of process parameters were selected and shown in table 4.6.

Table 4.6. Parametric Combinations used for experimental work.

Experiment No.	Axial force (kN)	Rotational speed (rpm)	Transverse speed(mm/min)
E1	4	1500	75
E2	4	2000	150
E3	4	2500	225
E4	5	1500	75
E5	5	2000	150
E6	5	2500	225
E7	6	1500	75
E8	6	2000	150
E9	6	2500	225

4.3 INDUCTION HEATING

An induction unit (5 kW output power) was used to supply the inductive heat to the substrate plate and after reaching the required temperature, the deposition process started. Three different range of temperature as 200 C was selected for substrate heating which was based on the recrystallization temperature of the consumable rod material. The main aim of substrate inductive heating was to ensure uniform temperature formation at a substrate coating interface and also to reduce the dwell period time.

4.4 FORCED CONVECTION NITROGEN SHIELDING

A forced convection nitrogen process was used to shield the deposition area speed up the heat dissipation from the deposition area to avoid the formation of any intermetallic compounds. During deposition process, two distributors of nitrogen gas were positioned on either side of the substrate plate at a distance of 40mm from the substrate end. Each distributor has maintained with eight nozzles with an internal diameter of 3mm. Four different volume flow rate of nitrogen as 0 L/min, 5L/min, 10L/min, and 15L/min were used to prepare the deposition samples and the corresponding experimental processes are named as FCNS-0, FCNS-5, FCNS-10 and FCNS-15 respectively. The experimental setup is displayed in fig 4.1. The nitrogen shielding was applied at the end of the dwell period and just before the deposition process and continued to after deposition process till the surface temperature of the deposition to reach nearly 150°C.

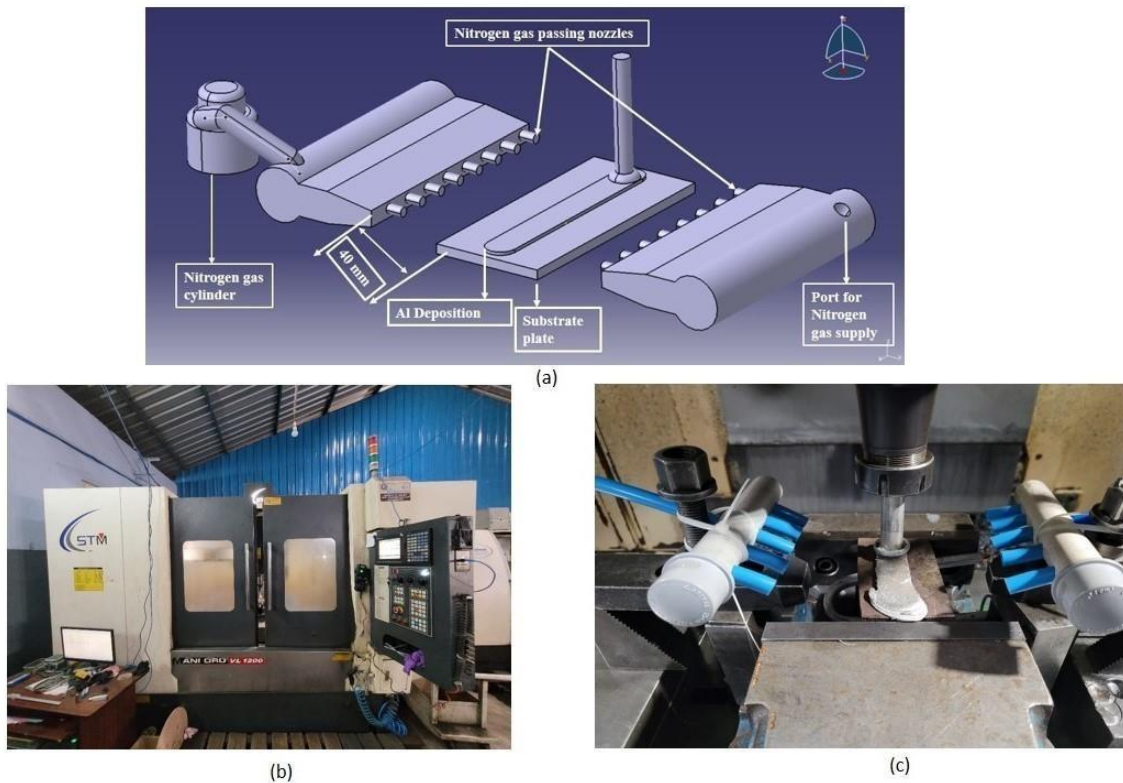


Fig.4.1 Experimental Setup of friction surfacing (a) modeling of experimental work (b) experimental machine (c) nitrogen gas supply set up.

Four set of experimental samples were prepared. One set of samples are prepared without forced convection nitrogen shielding process and other set of samples are prepared with forced convection nitrogen shielding process. During Friction surfacing, the dwell period was kept constant and maintained at a time period of 15 sec. When the mechtrode face is enough plasticized, the deposition process initiated. During forced convection nitrogen shielding, the nitrogen gas supply started just after the completion of dwell phase. The forced convection nitrogen shielding process was continued during and after the deposition phase and till to reach a pre-set temperature. To study the mechanical behaviour of aluminium deposition, a total 18 samples were prepared with and without forced convection nitrogen shielding process with suitable process parameter combinations.

4.5 RESPONSE SURFACE METHODOLOGY

Response Surface Methodology (RSM) is a statistical technique used to model and optimize the relationship between input variables and output responses of a system or process. It is widely used in engineering, science, and business to improve the quality and efficiency of products and processes.

RSM involves the construction of a mathematical model that relates the input variables to the output responses using regression analysis. The model is used to identify optimal input settings that produce the desired output response. The process of constructing the model and finding the optimal input settings is called "response surface optimization."

The steps involved in response surface optimization are as follows:

1. **Design of Experiments:** A set of experiments is designed using a statistical design of experiments (DOE) technique. The DOE should be carefully designed to ensure that all the relevant input variables are included and that the experiment points are chosen in a way that allows the model to be accurately estimated.
2. **Data Collection:** The designed experiments are conducted, and the output responses are recorded for each set of input variables.
3. **Regression Analysis:** The data collected from the experiments is used to construct a mathematical model that relates the input variables to the output responses using regression analysis. The model can be linear, quadratic, or higher order, depending on the complexity of the relationship between the input variables and the output responses.
4. **Model Validation:** The constructed model is validated using a set of independent data. The validation data should be different from the data used to construct the model, to ensure that the model is accurate and can be used for prediction.
5. **Optimization:** The constructed model is used to identify the optimal input settings that produce the desired output response. The optimal input settings

can be determined using either numerical optimization or graphical optimization techniques.

RSM has several advantages over other optimization techniques, such as trial-and-error and one-variable-at-a-time approaches. It is a more efficient and systematic approach to optimization that can identify the optimal input settings in a shorter time and with less experimentation. It also provides insights into the relationships between the input variables and the output responses, which can be used to improve the design of the system or process.

4.6 ARTIFICIAL NEURAL NETWORKS

Artificial Neural Networks (ANNs) are a type of machine learning model that are inspired by the structure and function of biological neurons in the human brain. ANNs have proven to be an effective tool for a wide range of applications, including image and speech recognition, natural language processing, and predictive analytics.

The basic building block of an ANN is the artificial neuron or perceptron, which takes input from other neurons or directly from the data, performs a calculation, and produces an output. Neurons are organized into layers, with each layer processing information before passing it on to the next layer. The first layer is the input layer, which receives the raw data. The output layer produces the result, while the intermediate layers are known as hidden layers.

Training an ANN involves adjusting the weights of the connections between neurons, so that the network can learn to make accurate predictions or classifications. This is done using an optimization algorithm, such as backpropagation, which adjusts the weights to minimize the error between the predicted output and the true output. The process of training an ANN is known as supervised learning, because the network is provided with labeled examples of input and output pairs.

There are several different types of ANNs, each with their own unique structure and function. Feedforward neural networks are the most common type, and they process information in a single direction, from the input layer to the output layer. Recurrent neural networks (RNNs), on the other hand, are designed to handle sequences of data, and they are capable of retaining information from previous inputs. Convolutional

neural networks (CNNs) are specialized for image and video processing, and they use a hierarchical structure to detect patterns and features in the data.

One of the strengths of ANNs is their ability to learn and adapt to new data, making them well-suited for tasks such as image recognition and natural language processing, which involve complex patterns and relationships between different data points. For example, a CNN can be trained to recognize objects in an image by learning to identify patterns such as edges, corners, and textures.

However, ANNs are not without their limitations. One of the biggest challenges in designing ANNs is determining the optimal structure and parameters for a given task. Too few neurons or layers may result in underfitting, where the network is unable to capture the complexity of the data, while too many can lead to overfitting, where the network becomes too specialized to the training data and performs poorly on new data. Additionally, ANNs can be computationally expensive to train, especially for large datasets.

Despite these challenges, ANNs have proven to be a powerful tool for solving complex problems in a wide range of fields, from medicine to finance to entertainment. As research continues to advance, it is likely that ANNs will continue to play a significant role in shaping the future of machine learning and artificial intelligence.

4.6.1 Feedforward Neural Networks

Feedforward neural networks (FFNNs) are a type of artificial neural network in which information flows in one direction, from the input layer through one or more hidden layers to the output layer. They are widely used in machine learning and deep learning for tasks such as classification, regression, and prediction.

The basic building block of an FFNN is a neuron, which receives inputs from other neurons or the input layer, applies a mathematical transformation to the inputs, and produces an output that is passed on to the next layer. The output of each neuron is determined by a combination of the inputs, a set of weights that determine the strength of the connections between neurons, and an activation function that introduces non-linearity into the network.

The structure of an FFNN can vary depending on the problem being solved, but typically consists of an input layer, one or more hidden layers, and an output layer. The number of neurons in each layer, as well as the choice of activation function, are hyperparameters that can be tuned to optimize performance.

FFNNs are trained using backpropagation, a gradient descent optimization algorithm that adjusts the weights of the network to minimize the difference between the predicted output and the actual output. This process is repeated for a large number of iterations, or epochs, until the network converges to a set of weights that produce satisfactory performance on the training data.

4.7 PARTICLE SWARM OPTIMIZATION

Particle Swarm Optimization (PSO) is a stochastic optimization algorithm that is inspired by the collective behavior of swarms or flocks in nature, such as bird flocks or fish schools. The algorithm is commonly used in engineering, science, and business for solving optimization problems.

In PSO, a swarm of particles moves through a search space, where each particle represents a potential solution to the optimization problem. The position of each particle in the search space represents a candidate solution, and the velocity of the particle represents the direction and speed of movement through the search space.

The particles move through the search space by updating their velocity and position based on their own best-known position (the position with the best fitness value that the particle has encountered so far) and the best-known position of the swarm (the position with the best fitness value that any particle in the swarm has encountered so far).

The velocity of each particle is updated at each iteration by combining its current velocity with two components: the cognitive component, which is a measure of the particle's past experience, and the social component, which is a measure of the swarm's past experience. The cognitive component drives the particle towards its own best-known position, while the social component drives the particle towards the best-known position of the swarm.

PSO has several advantages over other optimization algorithms. It is a population-based algorithm that can search multiple areas of the search space simultaneously, which can lead to better exploration of the solution space. It is also a simple and computationally efficient algorithm that can handle high-dimensional search spaces.

CHAPTER 5

RESULT AND DISCUSSION

5.1 APPEARANCE OF COATING

The particular materials and circumstances involved in the friction process can have an impact on the appearance of friction surfaces. In general, when two surfaces come into contact and rub against one another, the surfaces can get worn and deformed, and heat and frictional forces can also be produced.

For instance, in metal-to-metal contact, the friction surfaces may deteriorate and form microscopic ridges or scratches as a result of wear brought on by the sliding action. Over time, this may cause greater friction and decreased performance. Due to the high temperatures produced by the friction process, the surfaces may also change colour or get oxidised.

The process parameter selection largely determined the coating's look and tensile strength. For all possible combinations of the process parameters, the coating size and surface roughness were not the same. When the pace of the forced convection nitrogen shielding process is increased, it has been seen that nice flat and uniform coatings are produced.

Table 5.1: Deposition samples obtained through Experimental work.

S. No	Deposition method	Parameter	Photograph of the deposition top surface
1	FCNS-0	A: 5, B: 2000, C=150	

2		A:5, B:2500, C=225	
3		A:6, B=1500, C=150	
4	FCNS-5	A: 4, B:2000, C=150	
5		A:5, B:2500, C=150	
6		A:6,B=2000, C=75	

7	FCNS-10	A: 5, B:2500,C=75	
8		A:5, B:2500, C=225	

9		A:6,B=2000,C=150	
10	FCNS-15	A: 4, B: 2500,C=75	
11		A:5, B:2500, C=150	
12		A:6,B=2000,C=150	

5.2 DEPOSITION CHARACTERISTICS

The deposition properties were investigated by visually evaluating the coatings formed after treating the mechtrode materials with friction surfacing. Surface roughness, coating length, breadth, and thickness were recognised as essential aspects in connection to the process parameters of axial force, rotating speed, and transverse speed. Employing five various geometries of mechtrode, the deposition properties of AA6063 Aluminium alloy over Low Carbon Steel. Deposits on both the advancing and retreating sides of the consumable rod's transverse and rotational speed.

The transverse speed was shown to have a significant impact on the surface roughness of the coatings. The coating's features, such as length, breadth, and thickness, were discovered to be continuous and homogenous, and to be reliant on friction surfacing process parameters. The deposit formed by the MF5 mechtrode was discovered to be continuous and homogenous over its whole length. This was ascribed

to the mechtrode's optimal region of contact with the substrate during the dwell phase, which resulted in the creation of a restricted flash and continuous dynamic recrystallization during the deposition phase.

The width and thickness measurements of the valves for FCNS-0, FCNS-5, FCNS-10, and FCNS-15 demonstrate that the microstructure, morphology, and composition of the deposited layer are influenced by the cooling rate during friction surfacing. Intermetallic compound production is more likely to occur at lower cooling rates of 0 L/min when exposed to high temperatures for an extended period of time. Higher cooling rates of 15 L/min, however, resulted in less intermetallic compound production in the stronger layer. A balance between intermetallic compound production and cracking may be reached at intermediate cooling rates of 5 L/min and 10 L/min, resulting in a desired mix of strength and ductility in the deposited layer. All things considered, the cooling rate should be determined by the particular application requirements and the desired qualities of the deposited layer.

5.3 TEMPERATURE PROFILE

For the deposition of different materials to occur successfully during friction surfacing, the temperature profile of the friction surface is essential. The quality of the deposited material is crucially dependent on the interfacial temperature at the electrode-substrate contact in this process. With a non-contact IR thermometer positioned almost one metre away from the region of the deposition process, the temperature profile of the whole deposition process may be captured.

The temperature rises adiabatically throughout the dwell time and becomes steadier during the deposition phase. The viscoplastic deformation of the electrode caused by the application of transverse speed causes a modest decrease in temperature to be observed at the start of the deposition phase, indicating the start of the coating process. The interfacial temperature develops steadily in all four nitrogen shielding techniques, and no significant variations are seen during the deposition process as a result of nitrogen shielding.

The post-deposition procedure, however, has undergone substantial adjustments. In all four procedures, the temperature profile reveals a drop in temperature following

deposition, which is most likely caused by the heat lost during the friction process. Knowing the temperature profile during friction surfacing might offer crucial information for enhancing the process variables and guaranteeing the calibre of the deposition material.

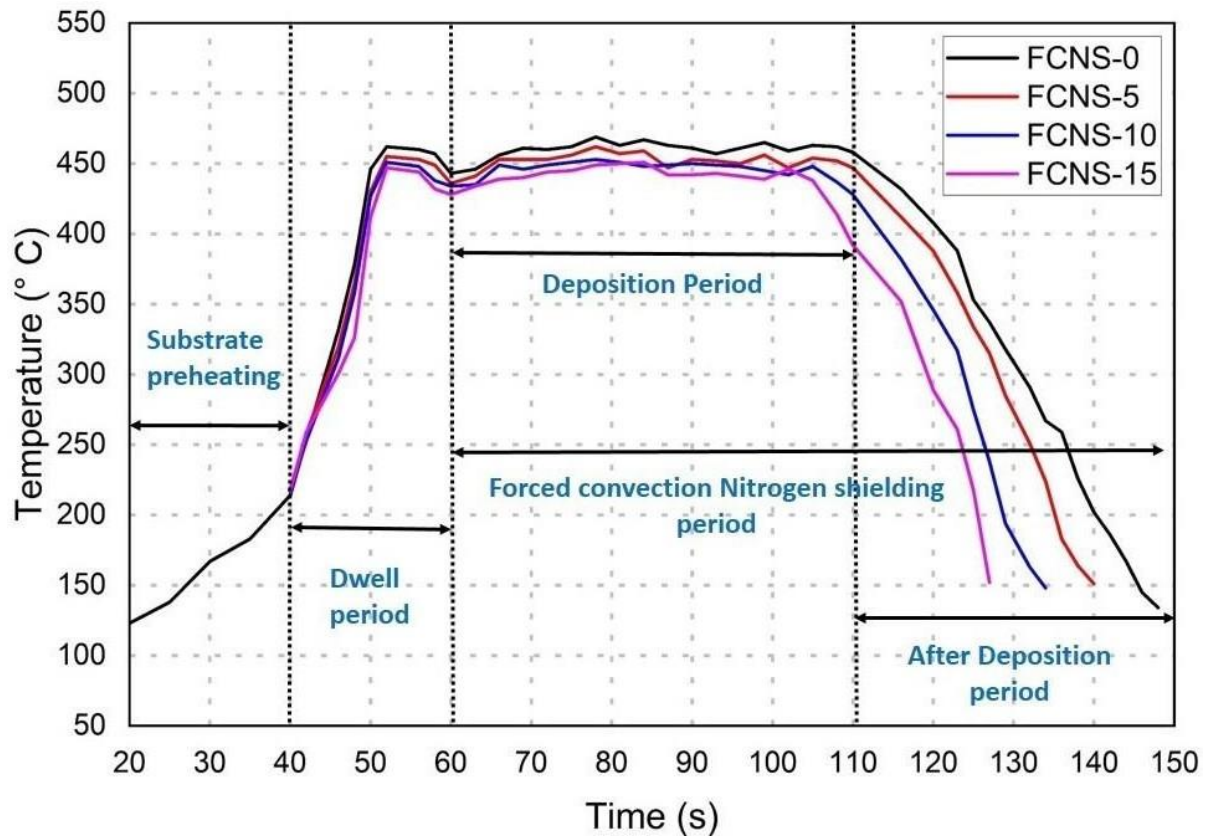


Fig.5.1 Temperature Profile during forced convection shielding process.

5.4 MECHANICAL CHARACTERISTICS

The word "mechanical characteristics" refers to a material's physical attributes that relate to its capacity to endure mechanical forces, such as strength, stiffness, toughness, and ductility. Mechanical tests like as tensile, compression, and impact testing are frequently used to evaluate these properties. Material mechanical properties are essential factors in engineering and design because they can impact the performance and dependability of a product or structure. A material with high strength and stiffness, for example, may be suitable for use in load-bearing applications, whereas a material with high toughness and ductility may be more suited for use in applications requiring impact and deformation resistance.

5.4.1 Micro Hardness Test

An instrument called a Vickers micro-hardness test set is frequently used to assess micro-hardness. The procedure entails applying a few grammes of pressure to a diamond indenter as it presses into the material's surface. The micro-hardness value is determined based on the stress applied and the size of the resultant indentation, which is examined under a microscope.

The test specimen must be well prepared, with a smooth and level surface finish, in order to produce accurate and trustworthy micro-hardness data. The indentations ought to be positioned with a constant distance between each one and at regular intervals. To guarantee precise and consistent findings, attention should also be taken to manage the test load and the load duration.

To measure the micro-hardness the test sample are underwent ten indentations with 10 mm spacing, while maintaining a gap of 6 mm between the advancing side, centre, and retreating side. Initially, the hardness value decreased during friction surfacing due to high heat and rapid transfer of grains. However, as the process continued, the material's hardness increased due to heat dissipation and the application of nitrogen to improve grain size. The graph in figure 5.2 shows the development of hardness over time.

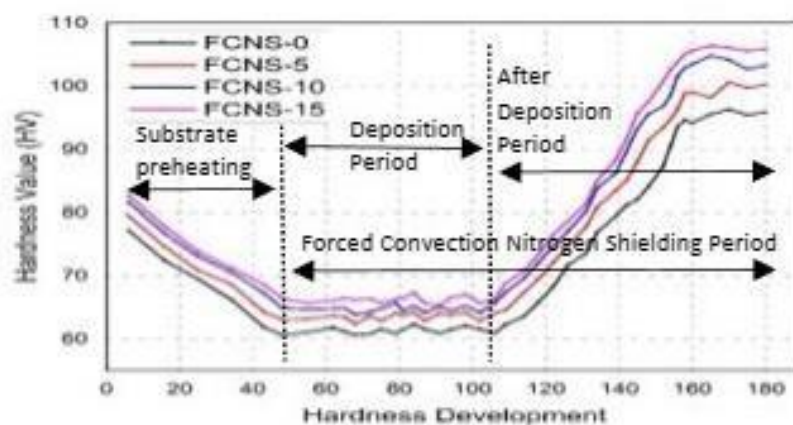


Fig.5.2 Hardness development

Micro-hardness studies on both longitudinal and traverse surfaces were carried out in order to comprehend how substrate heating and FCNS impacted the friction surface's

micro-hardness. On the material's surface, indentations were produced for the traverse section, and every 10 mm along the longitudinal region, they were made. The findings demonstrated that FCNS increased micro-hardness values. The maximum hardness values were attained when nitrogen was supplied at a rate of 15L/min, as shown in Figure 5.4's surface micro-hardness plot of the FS sample from the longitudinal segment. At a high of 107.5 Hv in the middle of the samples, the hardness values climbed steadily from both the advancing and retreating sides.

The research found that when nitrogen gas supply rose, the material's micro-hardness increased as well. Higher micro-hardness values were obtained with nitrogen gas supply at a rate of 15L/min compared to substrate heating and nitrogen gas supply rates of 5L/min and 10L/min. The increase in the material's hardness characteristic results from the refining of grain size brought on by the process of strengthening grain boundaries. Because to the larger concentration of reinforcing particles in the longitudinal samples, the longitudinal area had a higher micro-hardness value than the transverse section.

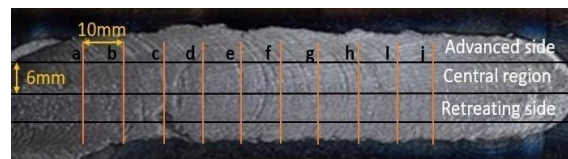
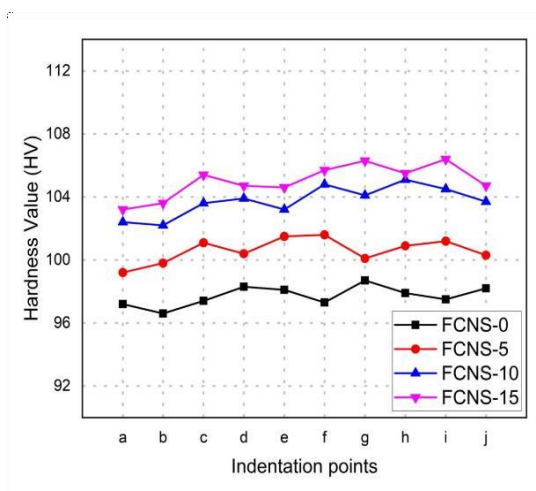
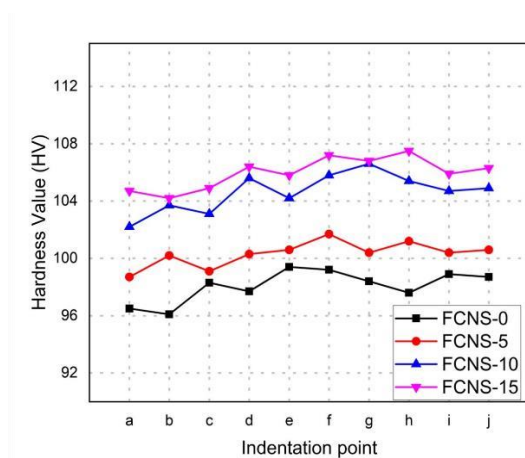


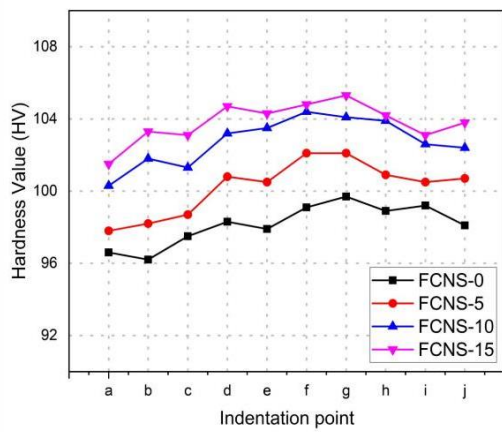
Fig.5.3: Hardness profile: Indentation point in longitudinal direction and Indentation points in traverse direction.



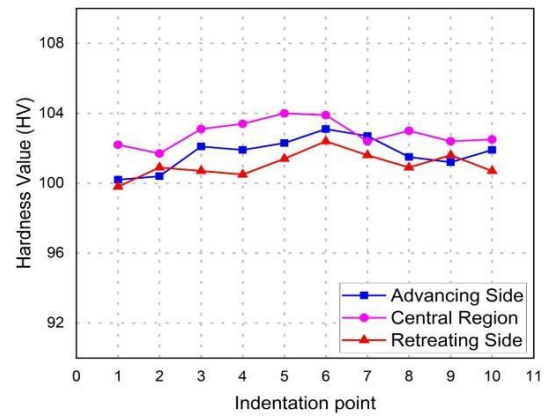
(a)



(b)



(c)



(d)

Fig.5.4: Hardness profile, hardness value at interface in longitudinal direction at different of FCNS and hardness value at interface in traverse direction

5.4.2 Tensile Strength

The tensile test on a friction-surfaced aluminium was performed using an INSTRON universal testing equipment with a 50KN capability. Wire-cut EDM was used to cut through the ASTM E -2448 standard with a typical tensile test specimen that was 44 mm long and 6 mm wide. Both the test specimen used for the tensile testing before to and the test specimen following the test are shown in Figure 5.5. The test specimen was then dragged while undergoing continual deformation until it broke. The test's load and deformation data were logged, and the material's tensile strength was determined using those numbers. A plot of the acquired tensile test results is shown in Figure 5.6. The results demonstrate that a forced convection nitrogen shielding at a rate of 15L/min generated the largest tensile force, which is 690 Mpa, when compared to other rates of forced convection nitrogen shielding and substrate heating. This is mostly caused by the relatively quick cooling rate that results from the quick removal of heat. As a result, at the location of interfacial deposition, a fine-grained microstructure is produced, which also aids in raising the coatings' tensile strength. In this case, the maximum tensile strength achieved was 690 MPa, which represents the maximum force that the material can withstand before breaking under tension.

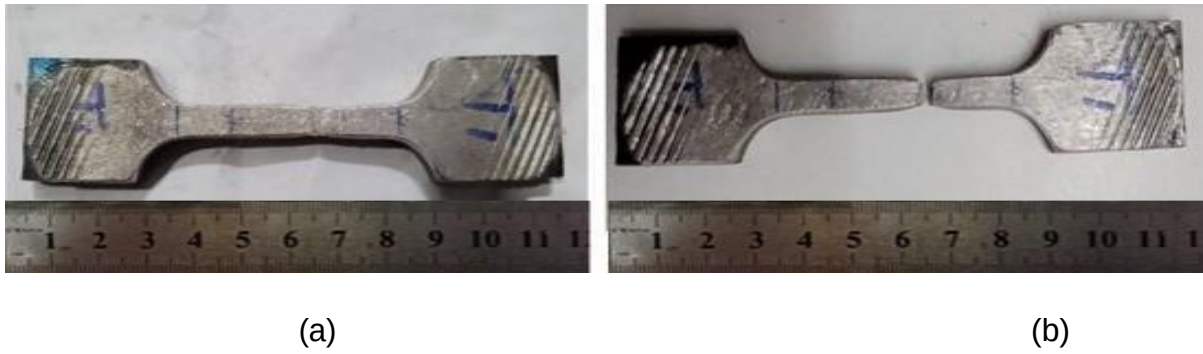


Fig.5.5 (a) before testing and (b) after testing.

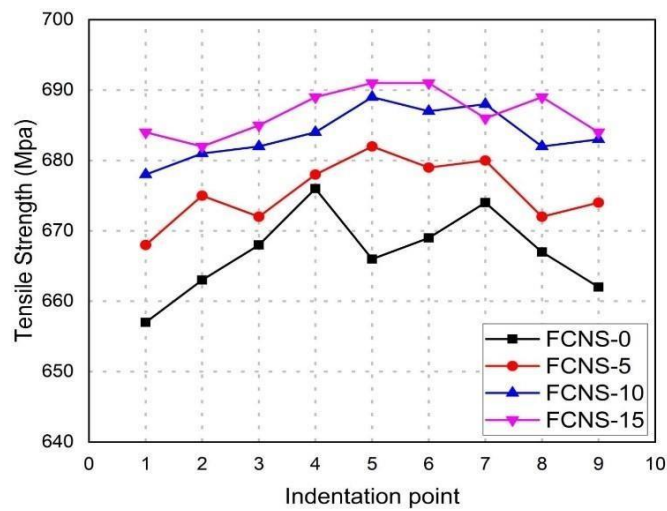


Fig.5.6: Tensile test results of the sample obtained from friction forced convection shielding process.

5.4.3 Bending

A three- or four-point bending test can be used to gauge the bending strength of a material with friction surfaces. A test specimen is created by cutting or milling a piece of the friction-surfaced material, and it is then put into the bending fixture of a universal testing machine to conduct the test. Using the apparatus, a load is delivered to the test specimen. Both the load and displacement data are recorded as the test is being run. The computed bending strength, which is often expressed in megapascals, is subsequently derived from the collected data (MPa).

The bending test for friction-surfaced materials revealed that, with the exception of one specimen (shown in fig. 5.7), the specimens could bend more than 150 degrees without the coating layer detaching from the substrate. When the bending was examined, it was found that several of the coating layers had side cracks, with the retreated side having more severe cracks than the advanced side. The retreated side, which was uneven compared to the advanced side, was where the crack was found to begin. Whereas specimens made with forced convection nitrogen shielding at rates of volume 5L/min and 10L/min had just a few minor fractures at both sides, specimens made with substrate heating had all fissures at the retreated and advanced sides. Only one specimen made at a cooling rate of 15L/min had no fractures on either side, proving that better bonding is achieved with an adequate coolant flow during friction surfacing. Figure 5.8 illustrates the maximum bending strength, which was determined to be 496 MPa for the root bend and 489 MPa for the face bend at an angle of 140° and 15 L/min of cooling, respectively. The outcomes show how crucial it is to regulate the coolant supply and cooling rate during friction surfacing in order to improve the material's mechanical properties and bonding.

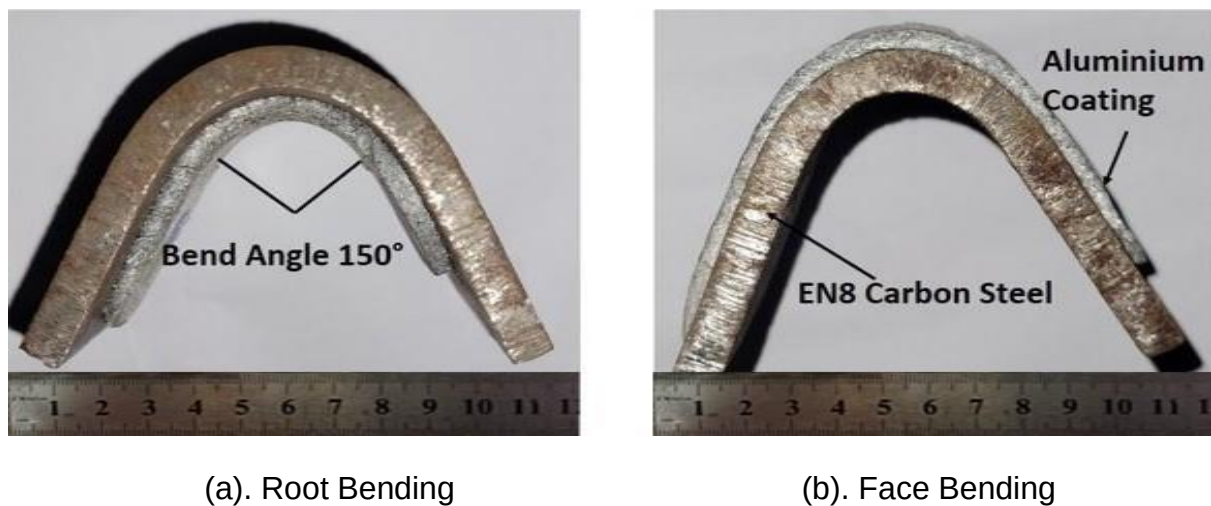


Fig. 5.7: Specimen after (a) root bend test (b) face bend test

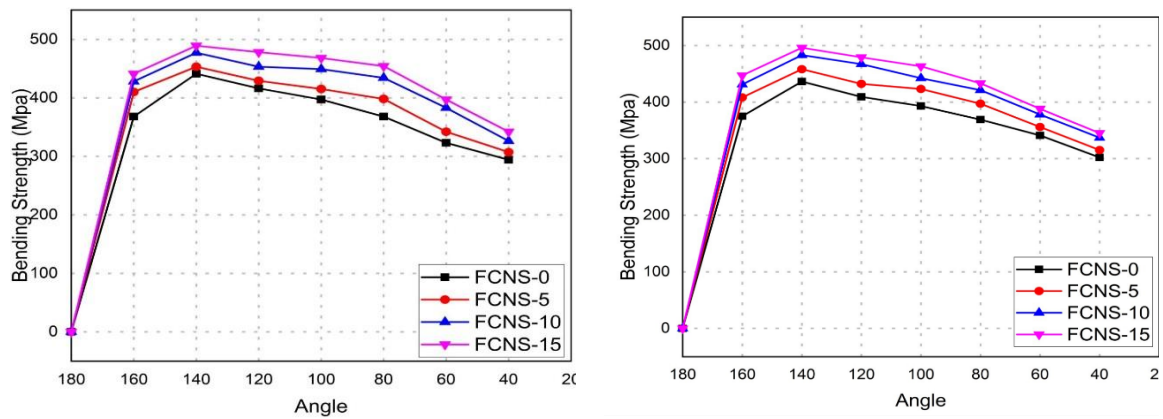


Fig.5.8: Bend test results (a) root bending (b) Face bending.

Table 5.2: Tensile and bending test.

Parametri c Combinati ons	Tensile strength				Bending strength			
	FCNS- 0	FCNS -5	FCNS -10	FCNS- 15	FCNS -0	FCNS- 5	FCNS- 10	FCNS- 15
1	657	668	678	684	375	408	431	447
2	663	675	681	682	436	458	483	496
3	668	672	682	685	409	432	467	479
4	676	678	684	689	393	423	442	463
5	666	682	689	691	369	397	421	433
6	669	679	687	691	341	356	378	388
7	674	680	688	686	322	315	337	345
8	667	672	682	689	375	398	422	435
9	662	674	683	684	387	407	428	431
Average Value	667	676	684	687	375	398	423	435

5.5 MICROSTRUCTURAL STUDY

To comprehend the physical and mechanical characteristics of materials, such as metals, ceramics, polymers, and composites, microstructural analysis is a procedure that looks at the microscopic structure of such materials. It entails the observation and examination of a material's atomic and subatomic microstructure using a variety of analytical instruments, including optical and electron microscopy, X-ray diffraction, and spectroscopy.

A material's internal structure, which includes the configuration of its atoms and crystals, the size of its grains, flaws, and the makeup of its phases, is referred to as its microstructure. The mechanical characteristics of the material, such as strength, toughness, ductility, and fatigue resistance, can be significantly influenced by the microstructure. The processes governing a material's behaviour under various loading situations by examining its microstructure, and they can devise plans to improve the material's characteristics for certain uses. For instance, in the study of metallurgy, microstructural analysis is employed to comprehend the links between the structure and properties of alloys and to create new materials with enhanced performance traits. Microstructural analysis is important in materials science and engineering because it enables the design and development of innovative materials with specialised features for a variety of commercial and technical applications.

5.5.1 SEM Analysis

The microstructure of an aluminium coating layer with small carbide particles is shown in Figure 5.9. The sample with the highest bond strength was obtained by placing aluminium on carbon steel, and the SEM image was taken at a distance of 50 μm . Dynamic recrystallization is the most common process for grain refinement in friction surfacing (FS). Due to the high temperature and severe plastic deformation brought on by dynamic recrystallization, FCNS-15 has equiaxed and very small grains. The surface temperature of the aluminium is raised to slightly below its melting point during the FS process, causing it to become plasticized. The aluminium deforms and plows into the asperities of the EN8 medium carbon steel, resulting in the interlocking of the substrate and the coated surface. The dynamic recrystallization process is influenced by the FS parameters and cooling rate. Depending on the friction surfacing settings

and cooling technique, multiple dynamic recrystallization processes may occur in aluminium alloys exposed to FCNS. As a result, the matrix is refined and recrystallized, and the tiny carbide particles in the coating layer are evenly distributed. Forced convection nitrogen shielding was used during the friction surfacing process to reduce the grain size and improve the mechanical properties of FS carbon steel and aluminium.

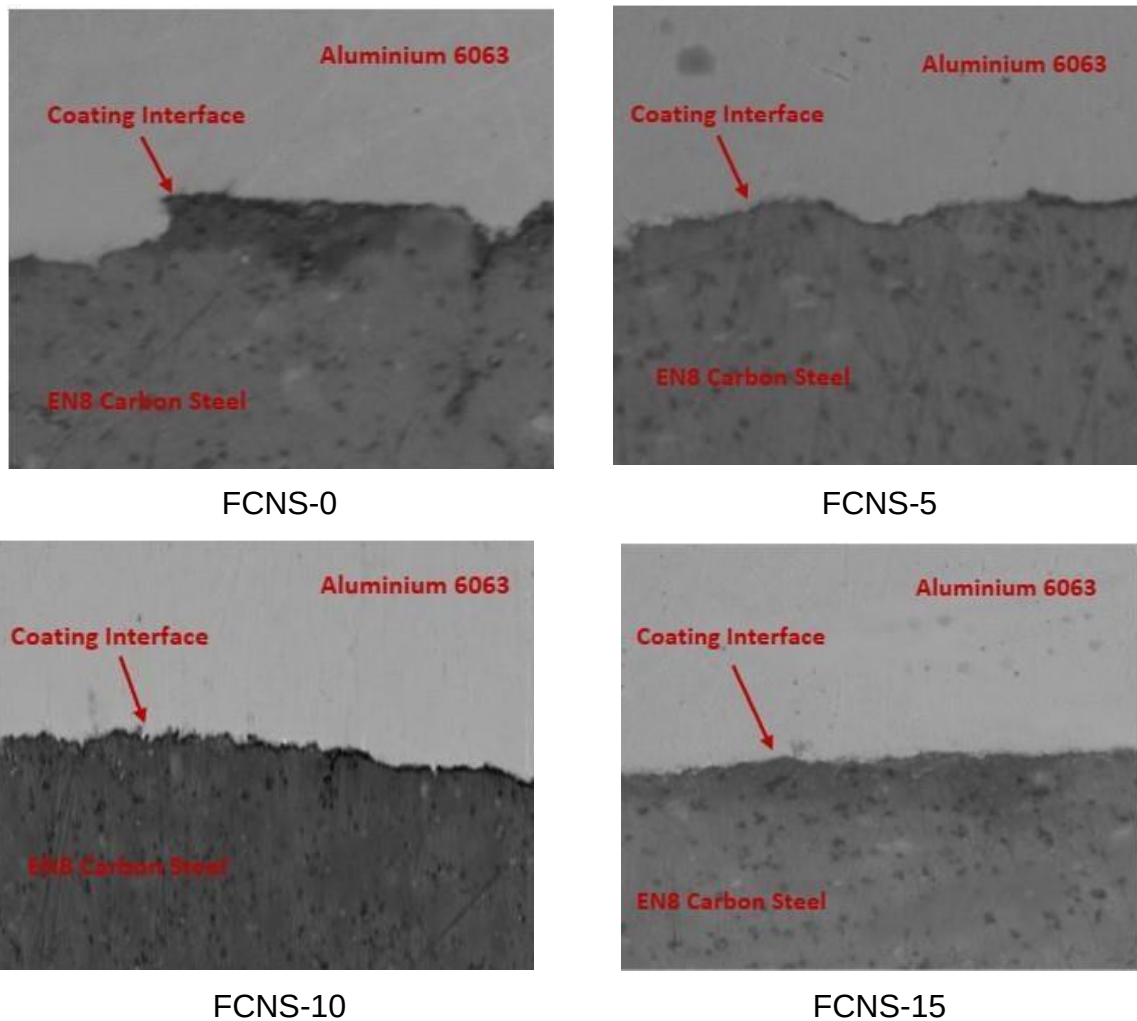
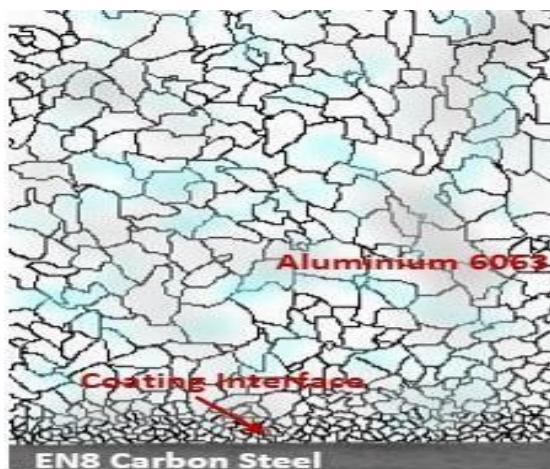


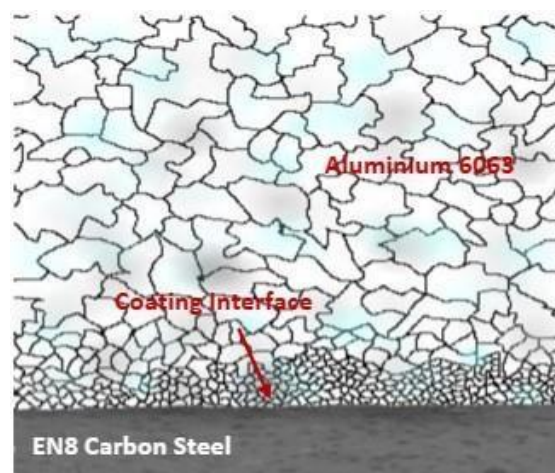
Fig. 5.9: Microstructural view at the interface

The grain size of friction surface aluminium is greatly affected by the substrate heating and cooling rates as well as the use of forced convection nitrogen shielding during the friction surfacing process. The extremely fine grain characteristics observed in the

coated aluminium metal materials were comparable to those of the coated metal carbon steel. Both substrate heating and forced convection nitrogen shielding produced very fine grain characteristics, but the forced convection rate of 15L/min produced the best grain size, as depicted in Fig. 5.10. However, there were some microstructural differences observed between the substrate heating and forced convection nitrogen shielding surfaces compared to the substrate heating and forced convection nitrogen shielding at 5L/min and 10L/min. These variations were anticipated due to the migration of material from one end to the other, which ultimately resulted in a stronger bond between the substrate and mechtrode. The use of forced convection nitrogen shielding during friction surfacing reduced the number of pores in the material, resulting in a high-quality, uniform surface made when the nitrogen was added at an increasing rate. Overall, the grain size of friction surface aluminium is an essential factor that can be optimized through the use of suitable friction surfacing parameters and cooling techniques to achieve the desired mechanical properties.



FCNS-0



FCNS-5

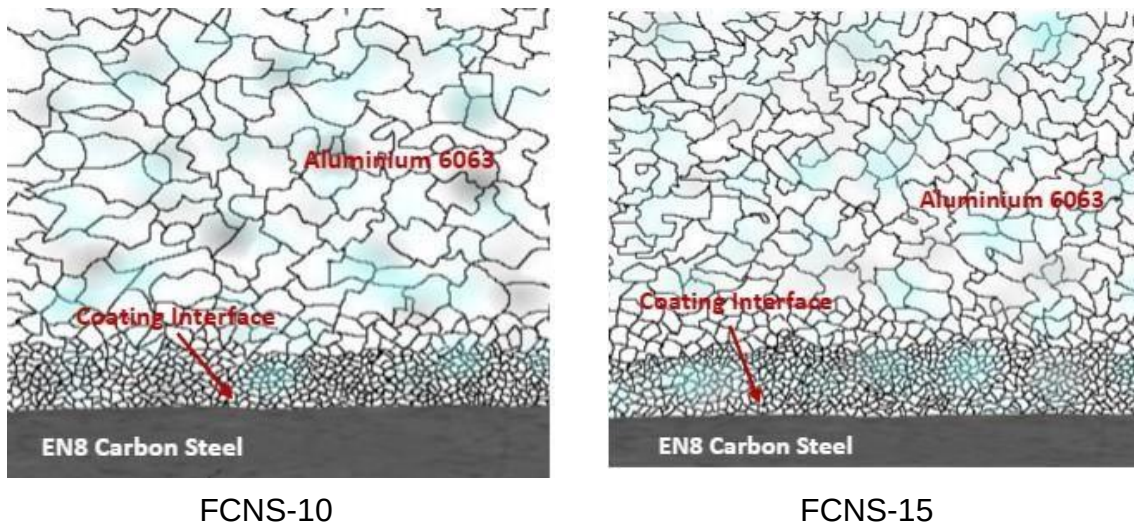


Fig. 5.10: Grain size development of forced convection nitrogen shielding process.

5.6. CORROSION TEST

The Tafel polarisation potential method is a method for figuring out a metal sample's corrosion potential and current. In this experiment, the Tafel polarisation potential was tested using an open circuit potential with a scan level of 0.5 mV/Sec. To find the Tafel area and determine the corrosion potential and corrosion current values in mm per year for both the substrate and the coating material, the anodic and cathodic polarisation curves were produced. ZSimpWin software was used to analyse the data while the ambient temperature was 25°C.

The potentiodynamic polarisation curves of the electrode and substrate material in a 5.1% NaCl solution were shown in Figure 5.11. The potentiodynamic polarisation test produced the corrosion potential and corrosion current data. The findings demonstrated that aluminium 6063 had a low corrosion current and high corrosion potential values, which suggested a high level of corrosion resistance. While EN8 carbon steel had a poorer corrosion resistance than aluminium, it did have a greater corrosion current and a lower corrosion potential. The EN8 steel substrate's Tafel graph showed a steeper slope, which denoted poor corrosion resistance. A smaller slope was seen in the coating material, which suggests improved corrosion resistance.

In conclusion, the Tafel polarisation potential technique is a helpful approach for figuring out the corrosion potential and current values of metal samples. The experiment's findings demonstrated that aluminium 6063 has greater corrosion resistance than EN8 carbon steel, and that the substrate material's corrosion resistance is superior to that of the coating material.

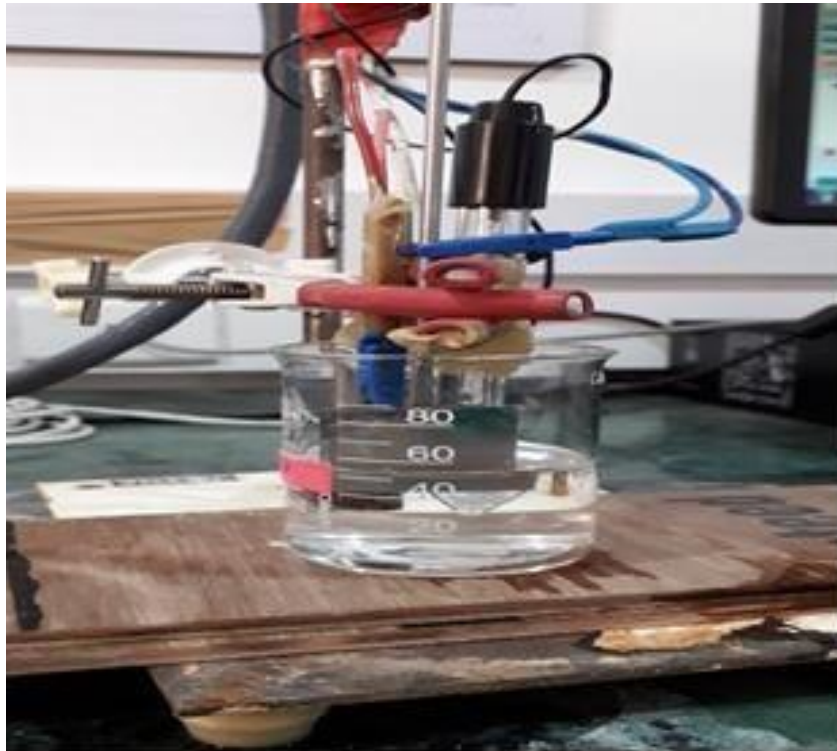


Fig 5.11: polarization test machine

Table 5.3: Corrosion parameters in potentiodynamic polarization test

Sample	I _{corr} Corrosion current in amps/cm ²	Error Corrosion Potential in V	Area of sample In cm ²	log (I _{corr} /A)	Tafel Slope
EN8 Carbon steel	1.82×10 ⁻²	-0.7085	1	-3.1841	-8.92×10 ⁻³

AA6063- EN8- FCNS-0	5.84×10^{-4}	-0.5678	1	-4.1286	-2.81×10^{-3}
AA6063- EN8- FCNS-5	4.64×10^{-4}	-0.5193	1	-4.2891	-1.73×10^{-3}
AA6063- EN8- FCNS-10	3.71×10^{-5}	-0.4862	1	-4.4528	-1.48×10^{-3}
AA6063- EN8- FCNS-15	3.84×10^{-5}	-0.4891	1	-4.5874	-1.31×10^{-3}
AA6063	6.16×10^{-6}	-0.3045	1	-4.8426	-2.48×10^{-4}

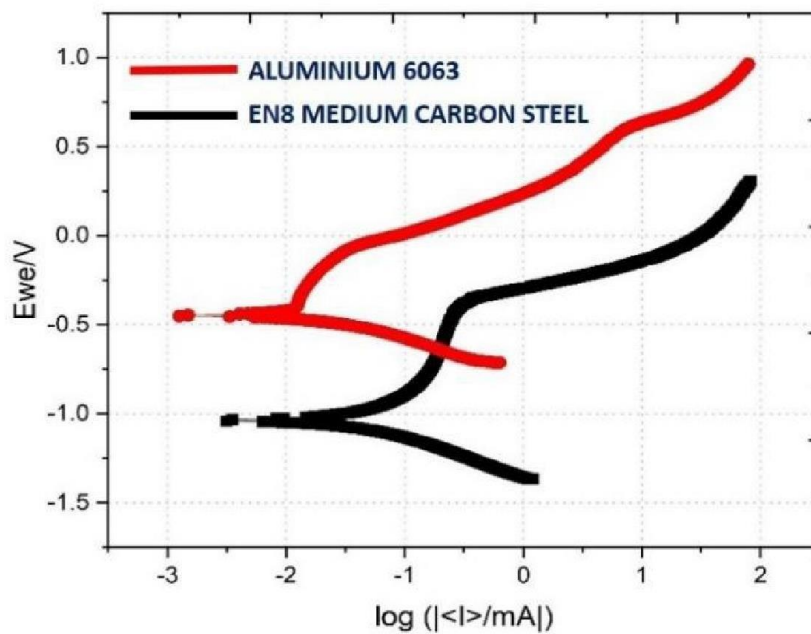


Fig 5.12: Polarization response of Aluminium 6063 and EN8 carbon steel

5.7 Summary

The quality of coatings generated by the friction surfacing process is heavily impacted by process factors such as interfacial temperature, temperature profile, and coolant supply. The study found that by shrinking grain size and fortifying grain boundaries, forced convection nitrogen shielding can improve the material's micro-hardness and tensile strength. Controlling the supply of coolant and the pace of cooling can also enhance the mechanical properties and bonding of the deposited material. A sufficient coolant flow throughout the operation can also boost the bending strength of materials with friction surfaces. Dynamic recrystallization using forced convection nitrogen shielding can be used to improve the grain size and microstructure of aluminium coating layers. The corrosion potential and current of various materials were also measured using the Tafel polarisation potential technique, which demonstrated that the substrate material had stronger corrosion resistance than the coated material. Overall, this study offers insightful knowledge about the friction surfacing process and its influence on the calibre of the coating and material characteristics.

5.8 OPTIMIZATION

Optimization in friction surfacing is done to achieve the desired properties of the coating such as better bonding strength, uniformity, and smoothness of the surface. By optimizing the process parameters such as the rotational speed, axial force, and traverse speed, we can achieve the desired microstructure and mechanical properties of the coating, such as increased hardness, wear resistance, and corrosion resistance. Optimization also helps in reducing the production time and cost by finding the optimal set of parameters that can provide the desired results with minimum resources. Therefore, optimization in friction surfacing is crucial to ensure that the process is efficient, cost-effective, and produces high-quality coatings.

5.8.1 Results From RSM

Response Surface Methodology is a powerful statistical technique used to optimize the relationship between input variables and output responses of a system or process. It involves the construction of a mathematical model that relates the input variables to

the output responses using regression analysis, and the use of the model to identify the optimal input settings that produce the desired output response. RSM is widely used in engineering, science, and business to improve the quality and efficiency of products and processes.

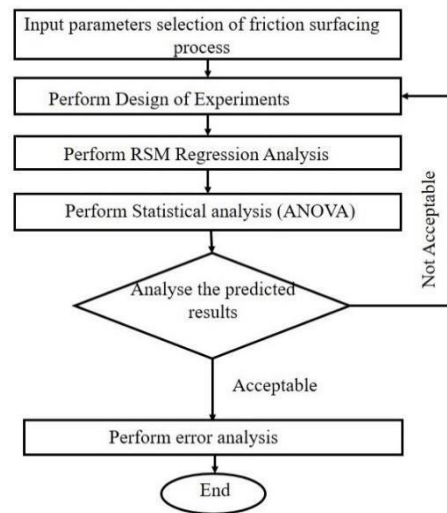


Fig. 5.13: Flow chart of RSM optimization.

It is feasible to describe independent elements in quantitative form as stated in equation (5.1) under numerous experimental circumstances.

The following functional link or reaction may therefore be thought of between these factors:

$$Z = \Phi(x_1, x_2, x_3, \dots, x_p) \pm e_r \dots\dots\dots (5.1)$$

Where, P is the quantitative variables, $x_1, x_2, \dots, x_p$ and the response variable is Z . Response function or response surface is the name of the function. Errors in the experiment are measured by the residual e_r . In this study, RSM was used to create a mathematical model for the FS aluminium alloy quality feature in the form of multiple regression equations. While using the RSM, the independent variable was seen as a surface which could be fitted using a mathematical model.

The response surface 'Z' is represented by the second-order polynomial (regression) equation, which is given by

$$Z = b_0 + \sum b_i x_i + \sum b_{ii} x_i^2 + \sum b_{ij} x_i x_j + e_r \dots\dots\dots (5.2)$$

The regression coefficients can be estimated using a variety of experimental design techniques. It was carried out with the aid of a CCF design matrix, which featured star points in the centre of each factorial space face. Three levels of each factor are required for this variety. CCF designs offer reasonably accurate predictions throughout the entire design space without requiring the use of points outside the initial factor range. The CCF design was used to obtain each and every coefficient using the statistical software programme Design-Expert. The final model was created using these coefficients after identifying the significant coefficients (at 95% confidence level). Using these coefficient, the final mathematical model was developed. The mathematical model for estimating the deposition width, deposition thickness, tensile strength and bending strength are shown in eqⁿ 5.3 to 5.6.

$$\begin{aligned} \text{Deposition width (DW):} \quad & -3.146 + (2.3824 Z_1) + (0.007313 Z_2) - (0.03275 Z_3) + (0.002344 Z_1 Z_2) - (0.007915 Z_2 Z_3) - (0.000788 Z_1 Z_3) + (0.016872 Z_1^2) + (0.0047495 Z_2^2) - (0.4091 Z_3^2) \\ & \dots\dots\dots(5.3) \end{aligned}$$

$$\begin{aligned} \text{Deposition Thickness (DT):} \quad & 1.3148 + (0.39367 Z_1) - (2.8784 Z_2) + (0.43657 Z_3) - (0.009463 Z_1 Z_2) + (0.021364 Z_2 Z_3) - (0.003156 Z_1 Z_3) + (0.11570 Z_1^2) + (0.002647 Z_2^2) + (0.4514 Z_3^2) \dots\dots\dots(5.4) \end{aligned}$$

$$\begin{aligned} \text{Tensile Strength (TS):} \quad & +188.46 - (0.1962 Z_1) - (0.4687 Z_2) - (0.9411 Z_3) - (1.3965 Z_1 Z_2) + (0.0385 Z_2 Z_3) + (1.70145 Z_1 Z_3) + (6.36 Z_1^2) - (0.00379 Z_2^2) - (11.62 Z_3^2) \dots\dots\dots(5.5) \end{aligned}$$

$$\begin{aligned} \text{Bending Strength (BS):} \quad & +214.31 - (1.5974 Z_1) - (0.8758 Z_2) - (3.7845 Z_3) - (0.1867 Z_1 Z_2) + (0.8574 Z_2 Z_3) + (3.00237 Z_1 Z_3) + (3.7014 Z_1^2) - (0.02879 Z_2^2) - (8.743 Z_3^2) \dots\dots\dots(5.6) \end{aligned}$$

Table 5.4: Observed and predicted values of Deposition width and Thickness from RSM algorithm.

Exp . Mat rix	DEPOSITION WIDTH, DW (mm)						DEPOSITION THICKNESS, DT (mm)					
	Obs erve d valu e	Predicted Value			Max . Err (%)	Min . Err (%)	Ob ser ved val ue	Predicted value			Max . Err (%)	Min . Err (%)
		1	2	3				1	2	3		
1	22.74	23.027	22.885	22.557	1.2617	0.6439	1.85	1.8841	1.8656	1.8784	1.8439	0.8468
2	23.17	23.368	23.442	23.298	1.1732	0.5782	1.54	1.8201	1.8355	1.8748	1.9473	0.9423
3	23.17	22.944	22.983	23.062	0.9748	0.4672	1.54	1.5658	1.5662	1.5662	1.7031	0.8143
4	22.61	22.871	22.749	22.417	1.1522	0.6134	2.33	2.351	2.3762	2.3648	1.9831	0.9023
5	20.34	20.189	20.533	20.11	1.1322	0.7415	2.55	2.5046	2.5151	2.535	1.7832	0.5917
6	20.34	20.165	20.156	20.471	0.9031	0.6419	2.55	2.5728	2.5028	2.5878	1.8535	0.8972
7	22.47	22.627	22.634	22.73	1.1575	0.5801	1.86	1.8812	1.8354	1.8956	1.9658	1.0722
8	21.22	21.488	21.356	21.433	1.2619	0.6432	1.66	1.632	1.6295	1.6444	1.8401	0.9438
9	21.22	21.393	21.013	21.105	0.9737	0.5425	1.66	1.6932	1.6434	1.6896	2.0012	1.0023
10	20.9	21.051	21.099	21.15	1.1976	0.7514	1.66	1.6753	1.6277	1.6915	1.9483	0.9274

11	22.1 1	22.32 6	22.2 53	22.2 96	0.97 48	0.64 82	1.7 7	1.80 58	1.788 3	1.80 65	2.06 42	1.03 62
12	22.1 1	21.91 3	21.8 54	21.9 93	1.14 26	0.52 78	1.7 7	1.73 51	1.791 5	1.74 41	1.97 39	1.21 84
13	24.2 5	24.44 2	24.4 07	24.4 84	0.96 42	0.64 92	2.3 3	2.35 15	2.364 8	2.37 62	1.98 33	0.92 38
14	23.2 2	23.41 6	23.5 17	23.0 98	1.27 9	0.52 77	1.6 9	1.67 02	1.661 5	1.65 88	1.84 72	1.17 42
15	23.2 2	23.43 7	23.4 19	23.3 21	0.93 61	0.43 41	1.6 9	1.65 64	1.676 3	1.39 21	1.99 36	0.81 12
16	21.0 9	21.29 1	21.1 98	21.2 69	0.95 25	0.51 34	2.3 3	2.29 02	2.308 5	2.37 45	1.91 13	0.92 44
17	20.4 4	20.55 1	20.5 34	20.6 11	0.83 57	0.46 11	1.4 4	1.46 84	1.411	1.45 62	2.01 5	1.13 09
18	20.4 4	20.75 4	20.5 4	20.6 95	1.53 81	0.48 7	1.4 4	1.45 89	1.414 9	1.45 21	1.74 39	0.84 3
Mean error % (Experimental wise)		0.931	0.80 16	0.81 24				1.50 78	1.282 4	1.49 64		

Table 5.5: Observed and predicted values of Tensile strength and bending strength from RSM algorithm.

	TENSILE STRENGTH TS (MPa)				BENDING STRENGTH, BS (MPa)			
		predicted value				Predicted Value		

Ex p. Ma tri x	Obs erv ed valu e	1	2	3	Max . Err (%)	Min. Err (%)	Obs erv ed valu e	1	2	3	Max . Err (%)	Min. Err (%)
1	660. 00	658.7 61	654.8 91	657.4 41	0.74 1	0.18 77	325. 00	321.1 05	326.7 35	3,22, 341	1.19 82	0.53 41
2	680. 00	684.2 29	681.5 89	676.4 11	0.62 2	0.23 38	345. 00	347.6 46	346.4 92	348.3 92	0.98 34	0.43 27
3	680. 00	679.2 97	682.0 35	675.4 64	0.66 7	0.10 77	345. 00	343.3 88	348.5 59	349.4 03	1.27 64	0.46 72
4	685. 00	688.6 16	683.6 62	684.4 32	0.52 8	0.19 53	445. 00	442.6 49	446.6 58	450.4 78	1.23 12	0.52 83
5	665. 00	669.6 41	663.1 48	665.6 35	0.69 8	0.09 55	415. 00	4,11, 287	412.3 55	413.0 14	0.89 45	0.47 85
6	665. 00	665.7 2	663.1 2	660.0 98	0.73 7	0.10 83	415. 00	419.4 65	416.4 4	412.3 42	1.07 61	0.34 72
7	690. 00	688.3 08	693.5 39	689.3 08	0.51 3	0.10 02	460. 00	463.5 45	457.5 03	464.3 47	0.94 52	0.54 28
8	670. 00	669.3 74	664.1 71	667.3 74	0.87 1	0.09 34	445. 00	439.4 67	441.3 57	447.5 52	1.24 32	0.57 36
9	670. 00	668.5 05	666.4 59	663.9 63	0.90 1	0.22 3	445. 00	438.8 07	440.5 92	447.0 56	1.39 15	0.46 22
10	705. 00	699.8 64	701.2 41	704.2 45	0.73 1	0.10 77	480. 00	481.7 38	484.2 19	483.2 55	0.87 9	0.36 21
11	675. 00	679.6 31	675.6 31	681.0 27	0.89 3	0.09 35	450. 00	451.6 43	454.2 1	452.2 15	0.93 56	0.49 23

12	675. 00	676.1 51	677.5 78	678.9 69	0.58 8	0.17 06	450. 00	445.4 57	447.8 35	444.8 84	1.13 68	0.48 11
13	695. 00	698.9 26	692.4 51	695.5 46	0.56 5	0.07 86	410. 00	408.5 63	414.5 07	407.8 37	1.09 93	0.52 76
14	690. 00	686.3 41	689.3 82	685.7 56	0.61 5	0.08 98	440. 00	445.2 47	443.5 56	441.8 32	1.19 26	0.41 64
15	690. 00	694.5 74	690.9 27	693.5 77	0.66 3	0.13 44	440. 00	442.6 48	443.7 51	441.4 15	0.85 26	0.32 16
16	725. 00	721.1 23	723.1 14	719.6 64	0.73 6	0.26 01	455. 00	453.2 38	451.6 36	452.3 58	0.73 93	0.38 71
17	725. 00	729.9 51	725.6 95	727.6 69	0.68 3	0.09 59	440. 00	445.6 65	438.7 16	442.4 16	1.28 76	0.29 18
18	695. 00	689.4 05	695.0 829	696.0 09	0.80 5	0.14 52	440. 00	436.5 14	441.4 26	435.7 62	0.96 31	0.32 41
Mean error % (experim ental wise)		0.454 1	0.400 1	0.441 1				0.825	0.673 2	0.726 3		

The RSM algorithm's predicted values for the tensile strength are shown in Table 5.5. The measured highest and minimum error ranges were 0.901% and 0.079%, respectively. In case of bending strength calculation, the overall measured maximum and minimum error ranges were 1.2876% to 0.2918% respectively.

5.8.2 Results From ANN

In this analysis, three parameters are taken for input layer and each input response is connected to 9 neurons of hidden layer and all neurons are connected to four output

responses. So, the 3-9-4 structural architecture network has been prepared and used for developing the ANN model. The prepared ANN architecture and flow chart followed during simulation are shown in figure 5.14 and figure 5.15 respectively.

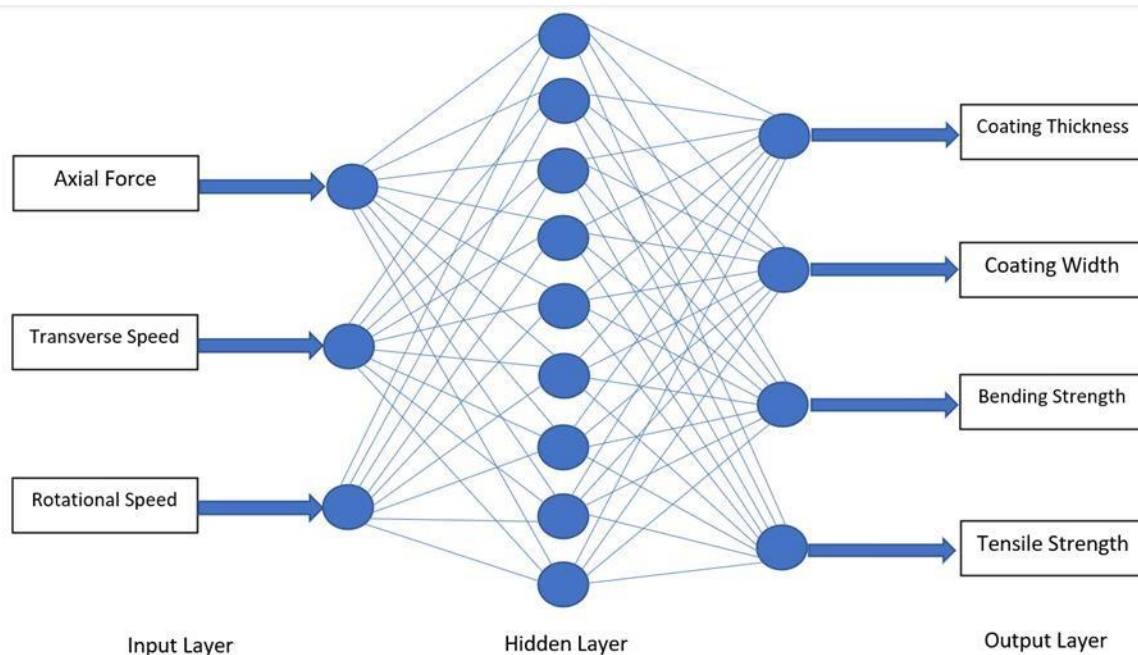


Fig.5.14: Architecture of 3–9–4 artificial neural network

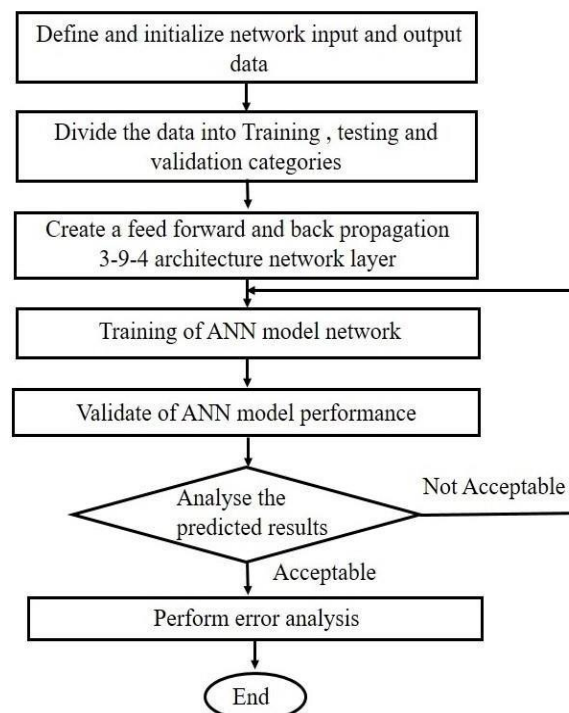


Figure 5.15: Flow chart used for ANN optimization.

MATLAB software is used for developing the model for both training and testing data of the network. A 12 patterns experimental results were used for training and a 6 patterns data were used for testing the ANN model. Without simulating the Hessian matrix, the model was trained using the Levenberg-Marquardt optimization technique, which approaches second order training speeds.

Log-sigmoid' transfer function were applied between hidden and output layers to predict the output responses. The log-sigmoid transfer function is expressed as

$$F(X) = \frac{1}{1+e^{-x}} \dots\dots\dots (5.7)$$

Where X is the weighted sum of the input.

The deposition width, deposition thickness, tensile strength and bending strength were been calculated by using the equation 5.8 to 5.11.

Deposition width

$$= \frac{1}{1+e^{-(-0.238xC1+0.055xC2-0.137xC3+0.019xC4+0.13xC5-0.198xC6-2.8733xC7+0.178xC8-4.718xC9+1.7416)}} \dots\dots\dots (5.8)$$

Deposition Thickness

$$= \frac{1}{1+e^{-(-2.368xC1+0.145xC2-0.874xC3+0.354xC4+3.13xC5-0.246xC6-0.743xC7+0.471xC8-8.476xC9+0.842)}} \dots\dots\dots (5.9)$$

Tensile Strength

$$= \frac{1}{1+e^{-(-1.931xC1-0.784xC2+1.128xC3+0.081xC4-2.137xC5-0.874xC6+2.043xC7-0.778xC8-2.718xC9+7.848)}} \dots\dots\dots (5.10)$$

Bending Strength

$$= \frac{1}{1+e^{-(0.031 \times C_1 + 0.784 \times C_2 - 0.094 \times C_3 + 1.254 \times C_4 + 0.023 \times C_5 - 0.798 \times C_6 - 4.741 \times C_7 + 0.574 \times C_8 - 1.318 \times C_9 + 2.712)}} \dots\dots (5.11)$$

Where C (i=1, 2, 3,...9) can be calculated by sing the following formula

$$C_i = \frac{1}{1+e^{-W_i}} \dots\dots\dots (5.12)$$

Where W_1 to W_9 can be calculated as follows

$$C_i = U_{1i} \times Z_1 + U_{2i} \times Z_2 + U_{3i} \times Z_3 + U_{4i} \dots\dots\dots (5.13)$$

5.8.2.1 Weight and Bias In ANN

In an Artificial Neural Network (ANN), weight and bias are the two most important parameters that determine the behaviour and output of the network.

Weight:

A weight is a parameter that represents the strength of the connection between two neurons in the network. It determines how much influence the input from one neuron has on the output of another neuron. The weights are initially set to random values and are adjusted during the training process to optimize the performance of the network.

Bias:

A bias is a parameter that is added to the weighted sum of the inputs of a neuron before applying the activation function. It is used to shift the activation function left or right, which allows the network to model complex relationships between the inputs and

outputs. Like weights, biases are also initially set to random values and are adjusted during the training process.

Together, weights and biases determine the output of each neuron in the network, which in turn determines the overall output of the network. During the training process, the weights and biases are adjusted through backpropagation, a technique that calculates the error between the actual output of the network and the desired output and updates the weights and biases accordingly.

In summary, weights and biases are the two most important parameters in an Artificial Neural Network that determine the behaviour and output of the network. The weights represent the strength of the connections between the neurons, while the biases are used to shift the activation function. They are adjusted during the training process to optimize the performance of the network.

Table 5.6: Weight and bias between input and hidden layer.

i	U_{1i}	U_{2i}	U_{3i}	U_{4i}
1	44.12	-31.48	61.74	21.42
2	13.46	9.86	-54.63	-63.75
3	-41.24	7.52	-26.58	28.74
4	-56.72	-41.57	18.74	-21.74
5	7.84	2.56	31.41	58.74
6	18.71	7.43	-89.51	27.49
7	6.53	-19.86	21.48	44.36
8	19.46	21.41	6.75	-11.45
9	11.23	1.19	-98.46	59.87

Table 5.7: Observed and predicted values of Deposition width and Thickness from ANN algorithm.

Ex p. Ma tri x	DEPOSITION WIDTH, DW , (mm)						DEPOSITION THICKNESS DT, (mm)					
	Obs erv ed valu e	Predicted Value			Max. Err (%)	Min. Err (%)	Obs erve d valu e	Predicted Value			Max . Err (%)	Min. Err (%)
		1	2	3				1	2	3		
1	22.74	22.545	22.965	22.631	0.9874	0.4782	1.85	1.8727	1.828	1.8362	1.2301	0.7492
2	23.17	23.455	21.991	23.073	1.2315	0.4173	1.54	1.5311	1.517	1.5211	1.4952	0.5828
3	23.17	23.051	23.362	23.323	0.8272	0.5145	1.54	1.5612	1.5474	1.5548	1.3826	0.4821
4	22.61	22.411	22.54	22.778	0.8837	0.3103	2.33	2.3174	2.3625	2.3062	1.3954	0.5432
5	20.34	20.415	20.16	20.538	0.9736	0.3711	2.55	2.5663	2.5292	2.5102	1.5639	0.6421
6	20.34	20.479	20.577	20.274	1.1653	0.3265	2.55	2.5754	2.5097	2.5605	1.5829	0.4128
7	22.47	22.586	22.669	22.709	1.063	0.5182	1.86	1.8862	1.8851	1.871	1.4122	0.5932
8	21.22	20.978	21.118	21.416	1.1432	0.4825	1.66	1.6492	1.6831	1.645	1.3926	0.6532
9	21.22	21.332	21.4	21.057	0.8522	0.5292	1.66	1.645	1.6346	1.6525	1.5354	0.4534
10	20.9	20.999	21.01	20.693	0.9748	0.7895	1.66	1.6886	1.6689	1.685	1.7282	0.5391
11	22.11	21.959	22.318	22.296	0.9425	0.6829	1.77	1.742	1.775	1.785	1.5822	0.4827

12	22.1 1	22.2 98	22.2 6	22.2 36	0.85 22	0.57 17	1.77	1.79 22	1.78 27	1.79 44	1.38 37	0.71 99
13	24.2 5	24.1 23	23.9 71	24.0 62	1.15 33	0.52 54	2.33	2.29 15	2.31 73	2.30 5	1.65 39	0.54 82
14	23.2 2	23.4 93	23.4 2	23.3 01	1.16 87	0.34 71	1.69	1.66 14	1.65 98	1.67 83	1.79 03	0.69 41
15	23.2 2	23.1 46	23.4 03	23.4	0.78 64	0.32 12	1.69	1.69 92	1.71 69	1.71 45	1.59 35	0.54 63
16	21.0 9	21.1 91	21.2 85	21.2 49	0.92 3	0.48 05	2.33	2.28 7	2.32 24	2.29 5	1.84 93	0.32 84
17	20.4 4	20.2 37	20.5 86	20.3 23	0.99 21	0.57 28	1.44	1.41 5	1.42 42	1.42 96	1.73 89	0.72 67
18	20.4 4	20.3 54	20.6 71	20.2 42	1.13 22	0.42 15	1.44	1.45 87	1.44 9	1.46 19	1.52 1	0.62 8
Mean error % (Experim ental wise)		0.70 28	0.85 2	0.71 9				1.20 27	1.19 83	1.03 15		

Table 5.8: Observed and predicted values of Tensile strength and bending strength from ANN algorithm.

Ex p. Ma tri x	TENSILE STRENGTH ,TS (MPa)						BENDING STRENGTH, BS (MPa)					
	Obs erv ed valu e	Predicted Value			Max Err (%)	Min. Err (%)	Obs erv ed valu e	Predicted Value			Max Err (%)	Min. Err (%)
		1	2	3				1	2	3		
1	660. 00	660.5 43	662.4 22	661.1 27	0.36 7	0.08 24	325. 00	327.2 39	324.0 51	325.5 98	0.68 91	0.29 17
2	680. 00	686.1 06	682.7 6	679.7 24	0.89 8	0.04 06	345. 00	343.4 14	342.4 35	344.4 14	0.74 32	0.16 96

3	680. 00	680.9 22	677.1 92	681.6 41	0.30 6	0.13 56	345. 00	346.3 07	344.2 19	341.1 14	1.01 27	0.37 89
4	685. 00	683.8 53	685.3 58	690.4 32	0.79 3	0.05 15	445. 00	447.4 85	446.2 66	448.8 85	0.87 32	0.28 46
5	665. 00	668.1 17	664.2 8	666.6 49	0.49 8	0.10 83	415. 00	413.2 66	408.6 37	413.5 87	0.81 02	0.12 57
6	665. 00	664.9 77	665.0 55	661.8 81	0.46 9	0.00 35	415. 00	411.9 97	413.4 98	412.1 51	0.72 34	0.36 18
7	690. 00	690.8 91	698.1 78	691.9 64	0.26 4	0.12 92	460. 00	463.2 64	462.1 55	465.1 43	1.11 81	0.46 86
8	670. 00	671.9 06	665.7 05	670.6 62	0.64 1	0.09 88	445. 00	443.4 03	444.4 02	449.2 95	0.96 53	0.35 91
9	670. 00	669.3 83	672.4 66	670.5 37	0.36 8	0.08 01	445. 00	443.7 12	441.8 61	442.6 83	0.70 53	0.28 94
10	705. 00	705.2 53	705.5 87	702.0 32	0.42 1	0.03 59	480. 00	480.8 48	482.4 88	483.1 38	0.65 38	0.17 68
11	675. 00	675.0 91	676.2 54	672.0 53	0.43 7	0.01 35	450. 00	448.2 91	454.0 06	446.7 35	0.89 03	0.37 97
12	675. 00	675.5 78	677.0 38	674.1 06	0.30 2	0.08 56	450. 00	454.2 66	448.7 14	453.4 58	0.94 81	0.28 56
13	695. 00	691.0 73	697.4 11	695.7 34	0.56 5	0.03 83	410. 00	410.5 95	411.5 18	406.2 94	0.90 37	0.37 03
14	690. 00	691.9 41	687.7 71	690.5 84	0.32 3	0.08 46	440. 00	436.8 06	441.2 5	437.5 41	0.72 59	0.28 41
15	690. 00	688.8 19	690.7 09	691.0 38	0.26 3	0.10 28	440. 00	444.2 28	442.6 45	440.6 44	0.91 87	0.14 64
16	725. 00	723.3 92	721.4 04	727.9 24	0.49 6	0.16 01	455. 00	451.9 9	445.1 96	453.9 72	1.14 21	0.43 75
17	725. 00	724.6 67	727.4 95	729.8 72	0.67 2	0.04 59	440. 00	439.7 85	437.9 02	436.2 52	0.85 18	0.47 67
18	695. 00	693.9 85	697.8 84	695.8 29	0.41 5	0.11 93	440. 00	442.4 54	438.5 62	443.9 71	0.70 39	0.32 66

Mean error % (Experim ental wise)	0.204 959	0.339 851	0.267 831				0.510 539	0.474 766	0.651 466		
---	--------------	--------------	--------------	--	--	--	--------------	--------------	--------------	--	--

5.8.3 Results From PSO

Particle Swarm Optimization is a stochastic optimization algorithm inspired by the collective behaviour of swarms or flocks in nature. It is commonly used in engineering, science, and business for solving optimization problems. PSO is a population-based algorithm that uses the experience of the swarm to guide particles through the search space towards the optimal solution. It is a simple and efficient algorithm that can handle high-dimensional search spaces.

The search point of PSO alteration is shown in figure 5.16 and the flow chart used for PSO simulation is displayed in figure 5.17.

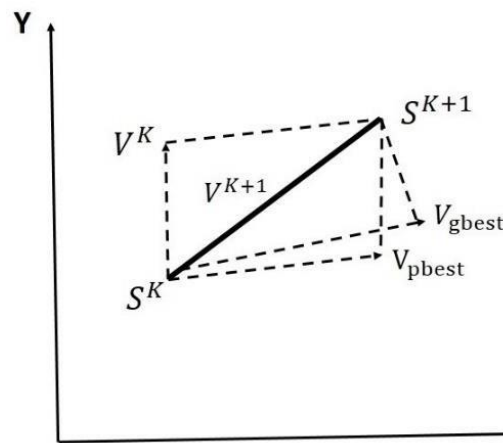


Figure 5.16: PSO's alteration of the search point

Where S^k and S^{k+1} represents the Present search location and new search location respectively. V^k and V^{k+1} stands for current velocity and improved velocity. V_{pbest} and V_{gbest} are the calculated velocity using P_{best} and g_{best} values respectively.

w is determined by the following formula

$$w = w_{\max} - t * \frac{(w_{\max} - w_{\min})}{T_{\max}}$$

Where, $w_{\max}$ and $w_{\min}$ are the highest and lowest inertia weight values and these values are set to be 0.85 and 0.45. The t denotes the current iterations and $T_{\max}$ indicates the iteration number.

The fundamental formula of the PSO is represented by

$$x_{i,t+1}^j = x_{i,t}^j + v_{i,t+1}^j \quad (3.40)$$

$$v_{i,t+1}^j = c * v_{i,t}^j + c_1 \text{rand} * (p_{\text{best}} - x_{i,t}^j) + c_2 \text{rand} * (g_{\text{best}} - x_{i,t}^j) \quad (3.41)$$

Where $x_{i,t+1}^j$ is the position of particle i at (t+1)th iteration, whereas $x_{i,t}^j$ is the position of particle i at tth iteration. $v_{i,t+1}^j$ is the velocity of the particle at (t+1)th iteration. c_1 and c_2 are the inertia weights. p_{best} is the best solution achieved to date by that particle and g_{best} is also the finest particle obtained to date by any particle in the area of the particle.

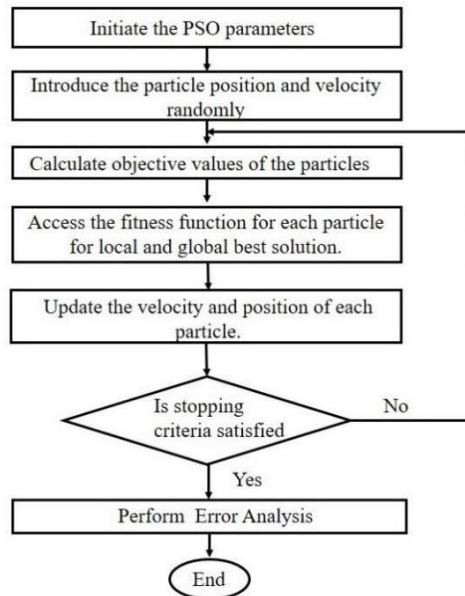


Figure 5.17. Flowchart used for PSO optimization.

Table 5.9: Observed and predicted values of Deposition width and Thickness from PSO algorithm.

Ex p. Ma tri x	DEPOSITION WIDTH, DW (mm)						DEPOSITION THICKNESS, DT (mm)					
	Obs erv ed valu e	Predicted Value			Max . Err (%)	Min. Err (%)	Obs erve d valu e	Predicted Value			Max. Err (%)	Min. Err (%)
		1	2	3				1	2	3		
1	22.7	22.9	22.4	22.7	1.23	0.17	1.85	1.83	1.84	1.85	0.90	0.11
	4	21	62	83	13	59		32	12	21	81	35
2	23.1	23.2	23.2	23.2	0.34	0.25	1.54	1.52	1.53	1.55	1.05	0.17
	7	36	5	36	52	89		75	73	62	19	53
3	23.1	23.0	23.2	23.2	0.58	0.28	1.54	1.55	1.53	1.55	0.97	0.31
	7	34	35	85	72	22		5	51	12	4	82
4	22.6	22.5	22.7	22.7	0.82	0.47	2.33	2.35	2.31	2.33	0.86	0.27
	1	03	45	96	17	11		02	65	65	7	9
5	20.3	20.4	20.4	20.4	0.63	0.44	2.55	2.55	2.57	2.54	0.90	0.10
	4	71	33	41	91	25		26	32	24	98	2
6	20.3	20.4	20.4	20.4	0.57	0.32	2.55	2.58	2.54	2.57	1.25	0.31
	4	37	06	56	18	61		19	19	54	37	46
7	22.4	22.5	22.3	22.3	0.51	0.13	1.86	1.85	1.85	1.84	0.88	0.26
	7	11	53	92	96	22		5	41	35	26	81
8	21.2	21.0	21.2	21.3	0.96	0.36	1.66	1.65	1.65	1.67	0.93	0.26
	2	15	97	37	46	15		64	55	55	82	64
9	21.2	21.2	21.3	21.3	0.60	0.16	1.66	1.64	1.66	1.63	1.16	0.28
	2	55	48	33	54	42		06	47	94	36	53
10	20.9	20.9	20.8	20.8	0.46	0.23	1.66	1.76	1.66	1.66	1.37	0.15
		98	51	26	84	41		88	25	75	25	53
11	22.1	22.1	22.2	21.9	0.78	0.20	1.77	1.76	1.78	1.79	1.17	0.21
	1	55	34	29	33	44		61	86	07	33	87
12	22.1	21.9	22.1	22.3	0.92	0.38	1.77	1.76	1.75	1.75	0.94	0.18
	1	53	96	15	73	91		67	33	93	2	54

13	24.2 5	24.4 46	24.1 35	23.9 98	1.03 82	0.47 28	2.33	2.35 88	2.35 05	2.33 64	1.23 75	0.27 49
14	23.2 2	23.1 57	23.3 34	23.0 62	0.64 91	0.27 29	1.69	1.70 58	1.68 26	1.70 68	0.99 62	0.43 27
15	23.2 2	23.1 75	23.0 63	23.3 11	0.69 04	0.19 46	1.69	1.70 44	1.70 06	1.69 39	0.85 26	0.23 41
16	21.0 9	21.1 72	21.2 99	20.9 35	0.99 43	0.38 16	2.33	2.30 94	2.30 87	2.32 7	0.91 31	0.12 56
17	20.4 4	20.3 85	20.5 89	20.5 38	0.72 69	0.27 13	1.44	1.44 45	1.45 58	1.45 79	1.24 52	0.31 85
18	20.4 4	20.5 68	20.3 62	20.5 46	0.62 81	0.38 33	1.44	1.42 62	1.44 56	1.44 65	0.95 69	0.39 4
Mean error % (Experim ental wise)		0.46 84	0.53 53	0.56 78				0.75 1891	0.51 5812	0.63 2089		

Table 5.10: Observed and predicted values of Tensile strength and bending strength from PSO algorithm.

Ex p. Ma tri x	TENSILE STRENGTH TS (MPa)						BENDING STRENGTH, BS (MPa)					
	Obs erv ed valu e	Predicted Value			Max . Err (%)	Min. Err (%)	Obs erv ed valu e	Predicted Value			Max . Err (%)	Min. Err (%)
		1	2	3				1	2	3		
1	660. 0	661. 49	660. 82	660. 21	0.22 6	0.03 18	325. 00	325. 48	324.2 1	326.4 3	0.44	0.14 77
2	680. 00	680. 27	681. 21	679. 87	0.17 8	0.03 97	345. 00	346. 63	347.9 3	345.8 7	0.84 91	0.25 2

3	680. 00	679. 32	680. 23	681. 91	0.28 1	0.03 38	345. 00	345. 92	343.6 4	346.4 3	0.41 45	0.26 67
4	685. 00	684. 64	687. 82	685. 56	0.41 2	0.05 26	445. 00	444. 55	447.4 9	445.9 1	0.55 96	0.10 11
5	665. 00	664. 27	663. 87	665. 82	0.17 1	0.10 97	415. 00	414. 37	417.2 9	413.8 4	0.55 18	0.15 18
6	665. 00	664. 97	665. 11	668. 32	0.49 9	0.00 45	415. 00	416. 53	415.3 2	414.4 3	0.36 87	0.07 71
7	690. 00	689. 12	688. 98	691. 61	0.23 3	0.12 75	460. 00	459. 69	462.5 4	460.2 1	0.55 22	0.04 57
8	670. 00	671. 45	670. 64	670. 78	0.21 6	0.09 56	445. 00	446. 2	445.6 5	446.8 7	0.42 02	0.14 61
9	670. 00	670. 44	672. 54	670. 21	0.37 9	0.03 13	445. 00	444. 36	445.8 9	447.1 8	0.48 99	0.14 38
10	705. 00	704. 66	705. 23	708. 09	0.43 8	0.03 26	480. 00	479. 64	480.3 2	481.7 4	0.36 25	0.06 67
11	675. 00	672. 23	674. 98	675. 47	0.41 1	0.00 03	450. 00	449. 71	451.4 3	452.8 3	0.62 89	0.06 44
12	675. 00	674. 75	676. 9	675. 16	0.28 1	0.02 37	450. 00	449. 32	451.5 1	450.4 3	0.33 56	0.09 56
13	695. 00	694. 75	694. 12	695. 98	0.14 1	0.03 7	410. 00	411. 87	412.8 3	409.3 9	0.69 02	0.14 88
14	690. 00	691. 44	689. 91	688. 94	0.20 9	0.01 3	440. 00	442. 79	439.5 4	440.4 2	0.63 4	0.09 56
15	690. 00	691. 77	691. 44	690. 72	0.25 6	0.10 43	440. 00	440. 93	443.3 4	438.6 3	0.75 91	0.21 14
16	725. 00	725. 63	726. 32	724. 57	0.18 2	0.05 93	455. 00	456. 35	457.8 6	454.1 4	0.62 86	0.18 9
17	725. 00	726. 27	725. 32	724. 65	0.17 5	0.04 41	440. 00	442. 24	440.3 8	438.9 2	0.50 91	0.08 64
18	695. 00	696. 58	695. 57	694. 87	0.22 7	0.01 87	440. 00	438. 68	441.9 4	440.7 3	0.44 09	0.16 6

Mean error % (experim ental wise)	0.13 838 5	0.22 753 3	0.15 036 7				0.26 060 5	0.355 769	0.312 044		
---	------------------	------------------	------------------	--	--	--	------------------	--------------	--------------	--	--

Tables 5.9 shows predicted results of deposition width and thickness by PSO algorithm which confirms that all the deposition width values are correctly anticipated and the maximum and minimum error was estimated as 1.2313% and 0.1322% respectively and also observed that the inaccuracy level was just below 2% for most of the sample combinations. The deposition thickness showing the maximum and minimum error of 1.2537% and 0.1020% respectively which indicate a very close anticipation values with experimental results. The predicted values of tensile and bending strength are showcased in table 5.10. In case of tensile strength, the maximum and minimum error range has been observed as 0.499% and 0.0003% respectively with a very minimum divergence level of 0.002%. Similarly, 0.8491% and 0.0457% was estimated for maximum and minimum error range for bending strength. A strong anticipation between predicted and experimental values were seen in PSO simulation.

5.9. COMPARISON OF RSM, ANN AND PSO

The predicted percentage of error for the four output responses obtained using the RSM, ANN, and PSO optimization algorithms is compared in Tables 5.11 to 5.14.

The three runs of the RSM, ANN, and PSO simulations are shown in Table 5.11 along with the highest, lowest, and mean values for the maximum and minimum prediction errors for the deposition width. Table 5.9 shows that the PSO-based simulation predicted the data the most accurately, with average maximum and minimum errors of 0.733% and 0.301%, respectively. For this simulation, the average global prediction error was only 0.301%. With an average error rate of 0.4684%, experiment 1 provided the PSO algorithm's best mean error values (refer Table 5.10). Average errors for the top performing RSM and ANN experiments were 0.841% and 0.733%, respectively

(refer Table 5.4 and Table 5.7). For the three mentioned experiments, the PSO-based simulation yielded a low average error value of 0.1322%.

Table 5.11: Maximum and minimum prediction errors for the deposition width.

	RSM algorithm			ANN algorithm			PSO algorithm		
	Maximum error	Minimum error	Average error	Maximum error	Minimum error	Average error	Maximum error	Minimum error	Average error
Highest value	1.538	0.742	1.140	1.232	0.683	0.958	1.231	0.473	0.872
Lowest value	0.836	0.434	0.635	0.786	0.310	0.548	0.3452	0.1322	0.239
Mean value	1.100	0.581	0.841	1.003	0.464	0.733	0.733	0.301	0.517

Table 5.12: Maximum and minimum prediction errors for the deposition thickness.

	RSM algorithm			ANN algorithm			PSO algorithm		
	Maximum error	Minimum error	Average error	Maximum error	Minimum error	Average error	Maximum error	Minimum error	Average error
Highest value	2.015	1.7031	1.859	1.8493	1.2301	1.5397	1.3725	0.8526	1.113
Lowest value	1.2184	0.5917	0.905	0.7492	0.3284	0.5388	0.4327	0.1020	0.2673

Mean value	1.911	0.944	1.427	1.546	0.573	1.059	1.0354	0.2478	0.6412
------------	-------	-------	-------	-------	-------	-------	--------	--------	--------

For studies carried out utilizing RSM, ANN, and PSO-based simulations, The highest, lowest, and mean values for the maximum and minimum deposition thickness prediction errors are displayed in Table 5.12. In this instance, the PSO-based model outperformed other models and yielded the lowest mean average prediction error of 0.6412%. The PSO approach was used in experiment 2, which had the best mean error values for deposition thickness, with an average error rate of 0.5158%. The average thickness error for the top performing RSM and ANN trials was 1.2824% and 1.2824%, respectively (see Tables 5.4 and 5.7). Over the course of the three tests, the PSO-based prediction model obtained an error value as low as 0.1020%.

Table 5.13: Maximum and minimum prediction errors for the tensile strength.

	RSM algorithm			ANN algorithm			PSO algorithm		
	Maximum error	Minimum error	Average error	Maximum error	Minimum error	Average error	Maximum error	Minimum error	Average error
Highest value	0.901	0.260	0.581	0.898	0.160	0.529	0.499	0.126	0.313
Lowest value	0.513	0.079	0.296	0.263	0.0083	0.136	0.141	0.0003	0.071
Mean value	0.697	0.140	0.418	0.472	0.0789	0.275	0.272	0.047	0.159

The maximum and minimum errors of tensile strength prediction for tests conducted using RSM, ANN, and PSO algorithms are shown in Table 5.13 along with their

highest, lowest, and mean values. The PSO-based simulation likewise worked well in this case, with the lowest mean average prediction error of 0.159% and a prediction error percentage ranging from 0.313% to 0.071%. The mean error values for experiment 1 utilizing technique had an average error percentage of 0.138%. (Refer Table 5.12). The three trials are displayed in Table 20 and the PSO-based prediction model attained an error value of as little as 0.0003% in each. RSM was used to calculate the tensile strength with a minimal error value of 0.0786%. (Refer to Table 5.5). Using ANN, the tensile strength's minimal error value of 0.0083% was attained (refer to Table 5.7).

Table 5.14: Maximum and minimum prediction errors for the bending strength

	RSM algorithm			ANN algorithm			PSO algorithm		
	Maximum error	Minimum error	Average error	Maximum error	Minimum error	Average error	Maximum error	Minimum error	Average error
Highest value	1.2876	0.7393	1.013	1.142	0.6538	0.8979	0.8491	0.3356	0.5923
Lowest value	0.5736	0.2918	0.433	0.4767	0.1257	0.3012	0.2667	0.0457	0.1562
Mean value	1.073	0.442	0.757	0.854	0.311	0.582	0.535	0.136	0.335

Table 5.14 displays the highest, lowest, and mean values as well as the maximum and minimum prediction errors of the bending strength for tests conducted using RSM, ANN, and PSO based simulations. The PSO-based simulation likewise worked well in this case, with the lowest mean average prediction error of 0.335% and a prediction error percentage ranging from 0.5923% to 0.1562%. The mean error values for experiment 1 utilizing technique had an average error percentage of 0.2606%. (Refer Table 5.7). The three tests are reported in Table 5.7 and the PSO-based prediction model attained an error value as low as 0.0457% in each one. Using RSM, the minimal error value for the bending strength was found to be 0.2918 percent (refer to Table 5.5) and by using ANN algorithm, the minimal error value for the bending strength was 0.1257%. (Refer to Table 5.7)

CHAPTER 6

CONCLUSION

Correlations between the friction surfacing of aluminium alloy AA6063 over carbon steel alloy EN8 were examined in the study detailed in this paper at various concentrations of the three FS process parameters, and experimental measurements of the four mechanical properties—resulting deposition width, deposition thickness, tensile strength, and bending strength—were made. Also, the FS process was simulated using RSM, ANN, and PSO, three evolutionary optimisation approaches. Based on the observed values of the mean square error (MSE) between the anticipated and experimental values, the simulation skills of various algorithms were also assessed and contrasted. Primary conclusions from the current study

1. Aluminum AA6063 is successfully deposited over EN8 carbon steel by appropriate process parametric combinations.
2. The mechanical characteristics of friction surfaced aluminium deposition, including as hardness, bending and tensile strength, were successfully enhanced by thenitrogen forced convection shielding method.
3. The microstructure image received from electronic backscattered (EBDS shows that the restoration activities and dynamically recrystallized grain growth are higher volume of nitrogen supplied during FCNS process, as a result an improved mechanical strength of the coating.
4. The corrosion behaviour was analysed by electrochemical impedance and potentio dynamic polarization test. The impedance test shows a less corrosion current of the aluminium coating at FCNS-15 process. The potential dynamic polarization test confirms a lesser (I_{corr}) and higher (E_{corr}) value of aluminium coating in FCNS-15 process which provide a better corrosion resistance deposition compared to other processes.

5. These findings show that the nitrogen forced convection shielding technology has the potential to improve the efficiency of FS aluminium deposition in a variety of applications, especially with regard to its mechanical and corrosion characteristics.

6. The PSO-based simulation of this procedure performed best and was most accurate in predicting the deposition width, deposition thickness, tensile strength, and bending strength values.

7. The MSE for the PSO-based simulation had the lowest values for the deposition width, thickness, tensile strength, and bending strength, which were 0.1322%, 0.1020%, 0.0035%, and 0.0457%, respectively

8. Using PSO-based simulation, the highest mean values of the MSE for the deposition width, deposition thickness, tensile strength, and bending strength were around 0.872%, 1.113%, 0.313%, and 0.5923% respectively.

9. The three optimization methods that were employed all performed better than RSM-based simulation, which was shown to have the lowest performance.

10. For percentage deposition thickness forecasts, the maximum MSE was found to have a value as high as 2.015%. Whereas the mean error stayed at 1.859% for the RSM-based simulation.

11. It was found that the performance of ANN-based simulations was intermediate between RSM and of PSO based simulations.

Additionally, a very effective model for forecasting deposition width, deposition thickness, tensile strength, and the bending strength response parameters of the FS process may be effectively simulated using the PSO approach. The absence of a bigger collection of sample points, which unquestionably may have aided in the development of a better model, is a discernible shortcoming of this work. Therefore, if a large data set for this topic becomes accessible in the future, other prediction model generation approaches can be used to produce models for this problem.

REFERENCES

- [1]. Alexopoulos, N.D.; Velonaki, Z.; Stergiou, C.I.; Kourkoulis, S.K. Effect of ageing on precipitation kinetics, tensile and work hardening behavior of Al-Cu-Mg (2024) alloy. *Mater. Sci. Eng.* 2017, 700, 457–467.
- [2] .A P Povendhan, Balakumharen a P, Padmanaban Ramasamy, Vaira Vignesh Ramalingam, Optimizing the tensile strength of friction stir welded dissimilar aluminium alloy joints using particle swarm optimization, December 2018, Materials Today: Proceedings 5(11):24820-24826 DOI:[10.1016/j.matpr.2018.10.280](https://doi.org/10.1016/j.matpr.2018.10.280).
- [3]. Ashok Kumar, U., & Laxminarayana, P. (2014). Friction surfacing process of aluminum alloys. In 5th international & 26th all india manufacturing technology, design and research conference (AIMTDR 2014) December.
- [4] B. Vijaya Kumar, G. Madhusudhan Reddy, and T. Mohandas, *Def. Technol.* 11, 275 (2015).
- [5]. Chen, R.; Xu, Q.; Guo, H.; Xia, Z.; Wu, Q.; Liu, B. Modeling the precipitation kinetics and tensile properties in Al-7Si-Mg cast aluminum alloys. *Mater. Sci. Eng.* 2017, 685, 403–416.
- [6]. Chen Y, Jiang Y, Ding H, Zhao J and Li J 2018 Effects of friction-stir processing with water cooling on the properties of an Al–Zn–Mg–Cu alloy *Mater. Sci. Technol.* (United Kingdom) **34** 153–60
- [7]. Cho, J.H.; Han, S.H.; Lee, C.G. Cooling effect on microstructure and mechanical properties during friction stir welding of Al-Mg-Si aluminum alloys. *Mater. Lett.* 2016, 180, 157–161.
- [8] G. Elatharasan, V.S. Senthil Kumar, *Procedia Eng.* 64, 1227 (2013)
- [9]. Hanke, Stefanie, Ian Sena, Rodrigo S. Coelho, Jorge F. dos Santos, Microstructural features of dynamic recrystallization in alloy 625 friction surfacing coatings, *Mater. Manuf. Process.* 33(3) (2018) 270-276, doi:10.1080/10426914.2017.129194
- [10] Hassan, A. K. F., L. S. Mohammed, and H. J. Abdulsamad. 2018. “Experimental and Artificial Neural Network ANN Investigation of Bending Fatigue Behavior of Glass

Fiber/ polyester Composite Shafts.” Journal of the Brazilian Society of Mechanical Sciences and Engineering 40: 201. doi:10.1007/s40430-018-1098-4

[11] H. Darzi Naghibi, M. Shakeri, M. Hosseinzadeh, Neural network and genetic algorithm-based modeling and optimization of tensile properties in FSW of AA 5052 to AISI 304 dissimilar joints, Trans. Indian Inst. Metals 69 (2016) 891– 900.

[12] Kadaganchi R, Gankidi MR and Gokhale H. Optimization of process parameters of aluminium alloy AA2014-T6 friction stir welds by response surface methodology. Def Technol 2015; 11: 209–21

[13] Kadhim K Resan, Abbas A Alasadi, Muhannad Al-Waily and Muhsin J. Jweeg 2018 Influence of Temperature on Fatigue Life for Friction Stir Welding of Aluminum Alloy Materials (International Journal of Mechanical & Mechatronics Engineering) vol 18 no 2

[14]. K. Badheka, V. Badheka, Friction surfacing of aluminium on steel: an experimental approach, Mater. Today: Proc. 4 (9) (2017) 9937–9941, doi.org/10.1016/j.matpr.2017.06.297.

[15] K. Bahrami, M.K.B. Givi, K. Dehghani, N. Parvin On the role of pin geometry in microstructure and mechanical properties of AA7075/SiC nano-composite fabricated by friction stir welding technique Mater. Des., 53 (2014), pp. 519-527

[16] Kim D, Rhee S and Park H. Modelling and optimization of a GMA welding process by genetic algorithm and response surface methodology. Int J Prod Res 2002; 40: 1699–1711.

[17] K. Krasnowski, C. Hamilton, S. Dymek Influence of the tool shape and weld configuration on microstructure and mechanical properties of the Al 6082 alloy fsw joints Arch. Civ. Mech. Eng., 5 (2015), pp. 133-141

[18]. Kosturek, R.; ´Snieszek, L.; Wachowski, M.; Torzewski, J. The influence of post-weld heat treatment on the microstructure and fatigue properties of Sc-modified AA2519 friction stir-welded joint. Materials 2019,12,583.

[19]. K. Prasad Rao a, *, A. Veera Sreenu, Tool steel and copper coatings by friction surfacing – A thermography study, Journal of Materials Processing Technology 212 (2012) 402–407.

- [20]. Kumar Ravi, Somnath Chattopadhyaya, Aniruddha Ghosh, Grzegorz M. Krolczyk, Pedro Vilaca, Ratnesh Kumar, Madhulika Srivastava, Mohammad Shariq, Rupam Tripathi, Characterization of friction surfaced coatings of AISI 316 tool over high-speed-steel substrate, *Trans. FAMENA* 41(2) (2017) 61-76, doi:10.21278/TOF.41206
- [21]. Lin, H.; Wu, Y.; Liu, S.; Zhou, X. Effect of cooling conditions on microstructure and mechanical properties of friction stir welded 7055 aluminium alloy joints. *Mater. Charact.* 2018,141, 74–85.
- [22]. Martinsen, K.; Hu, S.J.; Carlson, B.E. Joining of dissimilar materials. *CIRP Ann. Manuf. Technol.* 2015,64,679–699.
- [23] M.H. Shojaeefard, A. Khalkhali, M. Akbari, P. Asadi Investigation of friction stir welding tool parameters using FEM and neural network *Proc. Inst. Mech. Eng. Part L J. Mater. Des. Appl.*, 229 (3) (2015), pp. 209-217
- [24]. M. J. R. Stegmueller, P. Schindele, and R. J. Grant, *J. Mater. Process. Technol.* 216, 430 (2015).
- [25] M. Mourabet, A. El Rhilassi, M. Bennani-Ziatni, A. Taitai, *Univ. J. Appl. Math.* 2, 84 (2014)
- [26]. Moradi, M.M.; Jamshidi Aval, H.; Jamaati, R. Effect of pre and post welding heat treatment in SiC-fortified dissimilar AA6061-AA2024 FSW butt joint. *J. Manuf. Process.* 2017,30, 97–105.
- [27] Muhsin J Jweeg, Kadhim K Resan, Esraa A Abbod and Muhannad Al-Waily 2018 Dissimilar Aluminium Alloys Welding by Friction Stir Processing and Reverse Rotation Friction Stir Processing (IOP Conference Series: Materials Science and Engineering) vol 454, International Conference on Materials Engineering and Science
- [28] N.D. Ghetiya, K.M. Patel, A.J. Kavar Multi-objective optimization of FSW process parameters of aluminium alloy using Taguchi-based grey relational analysis *Trans. Indian Inst. Met.*, 69 (4) (2016), pp. 917-923
- [29] N.D. Ghetiya, K.M. Patel, *Procedia Technol.* 14, 274 (2014)

- [30]. Patel V, Badheka V, Li W and Akkireddy S 2019 Hybrid friction stir processing with active cooling approach to enhance superplastic behavior of AA7075 aluminum alloy Arch. Civ. Mech. Eng. **19** 1368–80
- [31]. Patel V, Li W, Vairis A and Badheka V 2019 Recent development in friction stir processing as a solid-state grain refinement technique: microstructural evolution and property enhancement Crit. Rev. Solid State Mater. Sci. **44** 378–426
- [32]. Patel V V, Badheka V and Kumar A 2016 Friction stir processing as a novel technique to achieve superplasticity in aluminum alloys: process variables, variants, and applications Metallogr. Microstruct. Anal. **5** 278–93
- [33] R. Winiczenko, "Effect of friction welding parameters on the tensile strength and microstructural properties of dissimilar AISI 1020-ASTM A536 joints," Int. J. Adv. Manuf. Technol., vol. 84, no. 5–8, pp. 941–955, 2016.
- [34] Sadiq emad Sadiq, Sadeq Hussein Bakhy and Muhsin Jaber Jweeg 2020 Effects of Spot Welding Parameters on the Shear Characteristics of Aluminum Honeycomb Core Sandwich Panels in Aircraft Structure (Test Engineering and Management) vol 83 pp 7244-7255
- [35]. Safarbali, B.; Shamanian, M.; Eslami, A. Effect of post-weld heat treatment on joint properties of dissimilar friction stir welded 2024-T4 and 7075-T6 aluminum alloys. Trans. Nonferrous Met. Soc. China (Engl. Ed.)2018,28, 1287–1297.
- [36] Sathiya P, Ajith PM and Soundararajan R. Genetic algorithm-based optimization of the process parameters for gas metal arc welding of AISI 904 L stainless steel. J Mech Sci Technol 2013; 27: 2457–2465.
- [37]. Seidi, E., & Miller, S. F. (2021). Lateral friction surfacing: experimental and metallurgical analysis of different aluminum alloy depositions. Journal of Materials Research and Technology, 15, 5948-5967.
- [38]. Senthil Kumar, V.S., Lokesh, R., Rathinasuriyan, C. and Shankar, R. (2015) Multi Response Optimization of Submerged Friction Stir Welding Process Parameters Using TOPSIS Approach. IMECE2015-50353: V02BT02A032

- [39]. Shariq Mohammed, Madhulika Srivastava, Rupam Tripathi, Somnath Chattopadhyaya, Amit Rai Dixit, Feasibility study of friction surfaced coatings over non-ferrous substrates, *Proc. Eng.* 149 (2016) 465-471, doi:10.1016/j.proeng.2016.06.693
- [40]. Sharma V, Prakash U and Kumar B V M 2015 Surface composites by friction stir processing: a review *J. Mater. Process. Technol.* 224 117–34
- [41]. Singh, R.K.R.; Prasad, R.; Pandey, S.; Sharma, S.K. Effect of cooling environment and welding speed on fatigue properties of friction stir welded Al-Mg-Cr alloy. *Int. J. Fatigue* 2019,127, 551–563.
- [42] S.M. Verma, J.P. Misra Study on temperature distribution during friction stir welding of 6082 aluminum alloy *Mater. Today, Proc.*, 4 (2) (2017), pp. 1350-1356
- [43]. S. Ravisekhar, V. Chittaranjan Das, D. Govardhan, Friction surfaced deposits for Industrial applications, *Mater. Today: Proc.* 4(2) (2017) 3796- 3801, doi:10.1016/j.matpr.2017.02.276
- [44]. Surya Prakash Rao, G. and Balunaik, B. (2015) Effect of Liquid Nitrogen on Friction Stir Welded Joint of Magnesium Alloy Az31b. *International Journal of Applied Engineering and Technology*, 5, 40-44
- [45] S. Verma, J. Misra A critical review of friction stir welding process DAAAM International Scientific Book (2015), pp. 249-266
- [46] T. Udayakumar, K. Raja, A. Tanksale Abhijit, P. Sathiya, J. *Manuf. Process.* 15, 558 (2013)
- [47]. V. Fitseva, S. Hanke, J.F. Dos Santos, Influence of rotational speed on process characteristics in friction surfacing of Ti-6Al-4V, *Mater. Manuf. Process.* 32 (5) (2017) 557–563,
- [48]. Wahid, M.A.; Khan, Z.A.; Siddiquee, A.N. Review on underwater friction stir welding: A variant of friction stir welding with great potential of improving joint properties. *Trans. Nonferrous Met. Soc. China (Engl. Ed.)* 2018,28, 193–219.
- [59]. Wang, W.; Wang, G.; Hu, Y.; Guo, G.; Zhou, T.; Rong, Y. Temperature-dependent constitutive behavior with consideration of microstructure evolution for as-quenched Al-Cu-Mn alloy. *Mater. Sci. Eng.* 2016,678, 85–92.

- [50] Wang, Z. H., D. Y. Gong, X. Li, G. T. Li, and D. H. Zhang. 2017. "Prediction of Bending Force in the Hot Strip Rolling Process Using Artificial Neural Network and Genetic Algorithm (ANN-GA)." *The International Journal, Advanced Manufacturing Technology* 93: 3325–3338. doi:10.1007/s00170-017-0711-5.
- [51] Worood Hussein and Mohsin Abdullah Al-Shammari 2018 Fatigue and Fracture Behaviours of FSW and FSP Joints of AA5083-H111 Aluminium Alloy (IOP Conference Series: Materials Science and Engineering) vol 454, International Conference on Materials Engineering and Science
- [52] Y. Zhang and X. Xu, "Predicting the material removal rate during electrical discharge diamond grinding using the Gaussian process regression: a comparison with the artificial neural network and response surface methodology," *Int. J. Adv. Manuf. Technol.*, pp. 1527–1533, 2021.
- [53]. Zeng, X.H.; Xue, P.; Wu, L.H.; Ni, D.R.; Xiao, B.L.; Wang, K.S.; Ma, Z. Microstructural evolution of aluminum alloy during friction stir welding under different tool rotation rates and cooling conditions. *J. Mater. Sci. Technol.* 2019,35, 972–981.
- [54] Zhang HJ, Liu HJ and Yu L. Microstructure and mechanical properties as a function of rotation speed in underwater friction stir welded aluminum alloy joints. *Mater Des* 2011; 32: 4402–4407.