An Investigation into Interdependencies in Electrical Machines Involving Deformable Materials: A Model-Based Multi-Objective Framework

By

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A thesis submitted in partial fulfilment of the requirements for the degree of
Doctor of Philosophy

The University of Sheffield
Faculty of Engineering
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29th September 2023

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An Investigation into Interdependencies in Electrical Machines Involving Deformable Materials: A Model-Based Multi-Objective Framework
Ph.D. Dissertation, 29th September 2023
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Acknowledgements

I want to express my gratitude to God, the individuals and institutions who have made contributions, to the completion of my thesis.

First and foremost, I am truly grateful to Professor Ash Tiwari, who has been my supervisor. His unwavering guidance, insights and continuous support throughout this journey have played a role in shaping the direction of my research. I would also like to extend my thanks to Dr. Payam Soulatiantork, who has served as my second supervisor. His thoughtful feedback, suggestions and encouragement have greatly enhanced the quality of this work. His guidance has been invaluable in refining the details of my research.

I would like to express my gratitude to Dr. Divya Tiwari and Dr. Michael Farnsworth for their discussions and guidance, which have greatly contributed to the development of the ideas, presented in this thesis. Their mentorship has played a role, in refining, and shaping this work. Their combined wisdom and guidance have played a role in honing and clarifying the ideas presented in this thesis.

Furthermore, I would like to express gratitude, towards The University of Sheffield and the Department of Automatic Control and Systems Engineering for providing an environment and necessary resources that have facilitated the smooth progress of this research.

Also, I deeply appreciate the financial support provided by the Mexican Government with CONAHCYT (Consejo Nacional de Humanidades, Ciencia y Tecnología). The assistance they have provided as it has not only allowed me to pursue this research, but also highlights our collaborative effort to advance science and technology.

Lastly, I want to express my appreciation to my parents, Roman and Alma Rosa, my brother Aland, my friends and my fiancée Araceli. Your constant love, encouragement and understanding have been the driving force behind my perseverance and success throughout this journey. To all those who have been a part of this experience I am truly thankful for your contributions, guidance and unwavering belief in me. This accomplishment would not have been possible, without the support you have provided.

Abstract

The increasing popularity of the green industrial revolution has led to a rise, in the production and use of Electric Vehicles (EVs) and their associated parts, like motors, generators and transformers [1]. This surge was driven by a growing emphasis on sustainability and the need to shift towards alternatives especially in transportation [2]. However meeting the growing demand for these parts while maintaining production standards presents a challenge. To address this challenge it is important to improve manufacturing processes by prioritizing early detection of faults to reduce End of Line (EoL) tests and ensure efficient production.

The efficiency and cost control of Electrical Machines (EM) greatly depend on the interactions, between components and subsystems. The inclusion of deformable materials such as copper wire introduces complexity owing to their nature. This study suggests various frameworks to improve efficiency by minimising the need for tests and effectively handle deformable materials during the manufacturing process.

In this research, a framework that utilises Discrete Event Simulation (DES) was presented to investigate the interrelationships in EM manufacturing specifically focusing on the coil winding process. Through experiments, connections between winding speed, wire thickness, bobbin shape and variations in resistance were discovered. These findings highlight the importance of control features. Additionally, this study introduced an improved DES framework that combines the original DES model with a Supervised Machine Learning (SML) algorithm via Knowledge Distillation (KD). This integration significantly reduced simulation times while still maintaining accuracy.

Lastly, a new approach was introduced with the aim to optimise the linear coil winding process by considering multiple objectives. The goal was to minimise production costs and decrease faults by examining the connections between these objectives. Advanced techniques like the NSGA-II algorithm were utilised to find a balance between faults and production costs resulting in enhancements, in operational efficiency and cost reduction.

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List of Acronyms

ANN - Artificial Neural Network

DES - Discrete Event Simulation

DSM - Design Structure Matrix

DT - Decision Tree

EM - Electrical Machines

EoL - End of Line

EV - Electric Vehicles

FCM - Fuzzy Cognitive Mapping

FEA - Finite Element Analysis

FMEA - Failure Modes and Effects Analysis

KD - Knowledge Distillation

KNN - K-Nearest Neighbours

KPI – Key Performance Indicator

MAE - Mean Absolute Error

MBSE - Model-Based System Engineering

MCDM - Multi-Criteria Decision-Making

MODM - Multi-Objective Decision-Making

MOEA - Multi-Objective Evolutionary Algorithms

MOEA/D - Multi-objective Evolutionary Algorithm Based on Decomposition

MSE - Mean Squared Error

NB - Naïve Bayes

NSGA-II - Non-Dominated Sorting Genetic Algorithm II

PGE - Product Generation Engineering

QFD - Quality Function Deployment

RF - Random Forest

RRTM - Resin-Rich Transfer Moulding

SML - Supervised Machine Learning

SPEA2 - Strength Pareto Evolutionary Algorithm 2

SVM - Support Vector Machine

VPI - Vacuum Pressure Impregnation

WSM - Weighted sum method

Declaration

I, Izhar Oswaldo Escudero Ornelas, confirm that the Thesis is my own work. I am aware of the University's Guidance on the Use of Unfair Means (www.sheffield.ac.uk/ssid/unfair-means). This work has not previously been presented for an award at this, or any other, university.

Sheffield, 29th September 2023

Izhar Oswaldo Escudero Ornelas

List of Publications

Published:

I. O. Escudero-Ornelas, D. Tiwari, M. Farnsworth, and A. Tiwari, "*Modelling interdependencies in an electrical motor manufacturing process involving deformable material*". In Advances in Manufacturing Technology XXXIV: Proceedings of the 18th International Conference on Manufacturing Research, Incorporating the 35th National Conference on Manufacturing Research, 7-10, University of Derby, Derby, UK (Vol. 15, p. 291). IOS Press, 2021, doi: 10.3233/ATDE210051.

I. O. Escudero-Ornelas, D. Tiwari, M. Farnsworth, and A. Tiwari, "*Modelling interdependencies in an electric motor manufacturing process using discrete event simulation*" Journal of Simulation, pp. 1–22, 2023, doi: 10.1080/17477778.2023.2202338.

I. O. Escudero-Ornelas, D. Tiwari, M. Farnsworth, Z. Zhang, and A. Tiwari, "*Hybrid Computational Framework for Early Fault Detection in Coil Winding Manufacturing Process Using Knowledge Distillation.* 2023 IEEE 21st International Conference on Industrial Informatics (INDIN), 17-20, 2023, Institute industrial IT of Technische Hochschule Ostwestfalen-Lippe and Fraunhofer IOSB-INA, Lemgo, Germany, doi: 10.1109/INDIN51400.2023.10218260.

In Preparation:

Journal: Escudero-Ornelas, I. O., Tiwari, D., Farnsworth, M., & Tiwari, A. (2023). *Understanding Interdependencies for an Effective Multi-Objective Optimisation Approach in Linear Winding Processes.* IEEE Transactions on Evolutionary Computation.

CHAPTER I: INTRODUCTION

1.1 Background

The global shift towards sustainable and eco-friendly technologies has given rise to the green industrial revolution, a movement that the United Kingdom has eagerly embraced [1]. Consequently, there has been an exponential surge in demand for electrical products, particularly EVs [2]. At the heart of this rapidly evolving landscape is the manufacturing of EM, including motors, generators, and transformers. To satisfy the market's demands for high-quality and cost-effective products, significant advancements in the manufacturing processes of EM are imperative. Manufacturing EM presents numerous challenges, such as striking a balance between the escalating demand and maintaining quality [2]. The intricate manufacturing process often leads to faults being detected at the end of production, resulting in costly and time-consuming EoL tests [3]. Consequently, early fault detection and mitigation are vital for maintaining production efficiency and product quality. To support the green industrial revolution's growth and development, efficient and cost-effective manufacturing processes are crucial.

One crucial aspect that significantly impacts the performance and dependability of EM are the interdependencies among different components and subsystems. It is vital to strike the balance between these interdependent elements to maximise efficiency and minimise production costs. To ensure manufacturing processes and deliver high quality EM it is crucial to understand and manage these interdependencies effectively. The inclusion of materials in the manufacturing process adds another layer of complexity due to their unpredictable behaviour during production. This unpredictability makes it challenging to simulate and anticipate how these materials will interact with the product. The unique difficulties presented by these materials emphasise the need for approaches, in addressing them throughout the manufacturing process.

This PhD research aims to delve into the aforementioned challenges, examining the intricate relationships between various factors contributing to the cost and quality of EM manufacturing. By conducting a comprehensive analysis of existing methods and technologies, the research proposes innovative solutions to enhance efficiency, reduce reliance on costly EoL tests, and better manage the interdependencies and deformable materials involved in the manufacturing process.

1.2 Motivation

The motivation for this thesis is rooted in the necessity to enhance the efficiency and effectiveness of EM manufacturing processes, with a focus on minimising defects and maximising product quality. Achieving control over the production process is a critical aspect of reducing production defects and ensuring efficiency. As such, this research aims to develop a novel framework that seeks to understand the relationship between input parameters and the generation of faults. By gaining a deeper comprehension of these relationships, the proposed framework will enable better control over the production process, ultimately minimising defects and contributing to the overall improvement of EM manufacturing. The insights gained from this research will not only enhance the competitiveness of the EM industry but also support the broader goal of fostering a greener and more sustainable future.

1.3 Research problem

Existing literature demonstrates that understanding and modelling the interdependencies between parameters and outputs can yield significant benefits. However, it is important to note that, to date, no established methodologies or frameworks have explored the process characteristics of deformable materials and their impact on EM faults. Therefore, this research tries to answer the following question: *"How can a novel framework that understands the relationship between input parameters and the generation of faults be developed to enable better control over the production process, minimise defects, and contribute to the overall improvement of EM manufacturing?".* Consequently, this PhD research addressed this gap by developing a framework that encompasses the process characteristics of deformable materials and their influence on faults, thereby contributing to the optimisation of EM manufacturing processes.

1.4 Research aim and objectives

The main aim of this research was to develop a model-based framework of the interrelationships among the various components of a shop floor manufacturing process in order to identify the source of defects or flaws in a real-world example from the electrical machine manufacturing industry involving deformable material. To accomplish this goal, four primary objectives were designed:

a) Identify and apply techniques that determine the key process characteristics in an EM during an error-prone manufacturing process, detecting interdependencies that lead to defects downstream.
b) Develop a framework by using modelling techniques to understand how a combination of process variables influences the creation of defects.
c) Integrate the established framework with a supervised learning algorithm to enhance the efficiency and reliability of quality control tests by predicting component states and accounting for interdependencies in the process.
d) Establish a model-based framework for integrated fault detection and parameter optimisation in production processes.

1.5 Research methodology

An in-depth methodology was developed by examining each objective and determining the best approach to accomplish it, outlining the specific steps required for completion. This methodology was composed of three frameworks (further discussed in sections 1.5.3 to 1.5.5), each designed to solve a specific objective. Within each framework, various methods were employed (expanded upon in Chapter III), with a predominant focus on modelling interdependencies, to accomplish their respective objectives effectively. The research methodology that directs this PhD thesis was illustrated in Figure 1.1, which included the workflow, research objectives, and their corresponding thesis chapters.

1.5.1 Literature review

In this chapter a literature review was presented, which played a vital role in any research. It entails a thorough and systematic exploration of existing scholarly work that pertains to the research question or topic being investigated. The purpose was to understand what is currently known, identify any gaps or inconsistencies in the existing literature and build upon previous research findings. To do this, literature from various sources such as books, journal articles, conference proceedings and online databases were gathered. It was crucial to ensure that the sources used were reliable and up to date so that they provide a foundation, for this research.

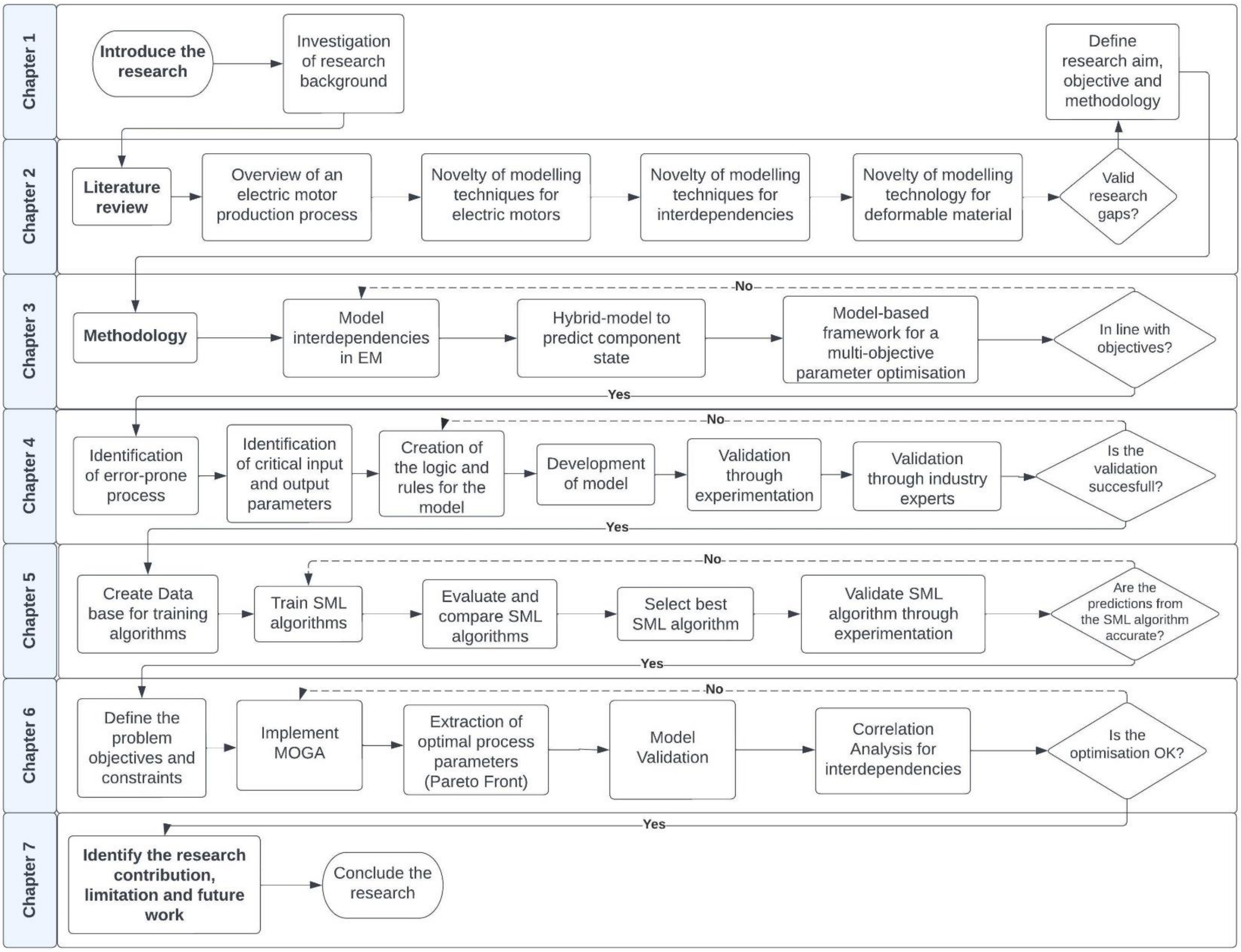


Figure 1.1. Research Methodology

1.5.2 Main steps

This chapter outlined the methodology employed in the research, providing a detailed explanation of the approach taken to achieve the research objectives. The selection of an appropriate research methodology was crucial for ensuring the validity, reliability, and generalisability of the study's findings. This research methodology encompasses topics such as modelling interdependencies, hybrid computational models and multi-objective optimisation.

1.5.3 Interdependency modelling framework

This chapter focused on developing a framework that models interdependencies between process variables, particularly in the context of EM involving deformable materials, to understand their influence on the occurrence of defects. The framework encompasses the identification of relevant process variables, the establishment of relationships among them, and the use of computational techniques for simulating the influence of these variables on the defect formation in EM.

Identification of Relevant Process Variables

The first step in developing the framework involved identifying the relevant process variables that have a significant impact on the occurrence of defects in EM with deformable materials. These variables included:

- **Material properties:** Characteristics of the deformable materials used, such as elasticity, plasticity, and thermal conductivity, that could influence the behaviour of the material during the manufacturing process and contribute to defect formation.
- **Manufacturing parameters**: Factors like temperature, pressure, and processing time could affect the material deformation and subsequent defect occurrence.
- **Geometrical factors:** The design and dimensions of the electrical machine components could impact the material deformation and contributed to defect formation.

Establishment of Relationships among Process Variables

Once the relevant process variables had been identified, the next step was to establish relationships among them to model the interdependencies. This might involve:

- Developing mathematical equations or empirical models that describe the relationships between the identified process variables.
- Conducting experimental studies or analysing existing data to validate the proposed relationships and identify any correlations or patterns between variables.
- Identifying potential causal mechanisms that explained the influence of one variable on another and how they collectively contribute to defect formation in EM with deformable materials.

Computational Techniques for Simulating the Influence of Process Variables on Defect Formation

After establishing the relationships among process variables, computational techniques could be employed to simulate their influence on defect formation in EM. Some potential techniques included: Finite Element Analysis, Assembly Techniques and DES.

Validation and Refinement of the Framework

The developed framework should be validated and refined using experimental data or real-world cases to ensure its accuracy and reliability. This might involve:

- Comparing the predicted occurrence of defects with the actual observations or experimental results.
- Identifying any discrepancies between the predictions and observations, and adjusting the framework or its parameters accordingly.
- Iteratively refining the framework based on feedback from the validation process until a satisfactory level of accuracy and reliability was achieved.

1.5.4 Hybrid computational framework

This chapter delved into the integration of the established model into a hybrid computational framework that improves the efficiency and reliability of quality control tests by predicting component states and accounting for process interdependencies. The framework combined the model of interdependencies between process variables with other computational techniques and quality control methodologies to create a comprehensive approach to defect prediction and quality control in EM involving deformable materials.

Integration of the Model with Other Computational Techniques

To create a hybrid computational framework, the established model can be integrated with other computational techniques relevant to the context of quality control tests. Once the established model is integrate it with other computational techniques, quality control tests can be selected to be reduced or diminished based on the resulting hybrid computational framework. This new hybrid framework should aim to:

- Detect defects at an early stage, minimising the need for rework or scrapping of defective components.

- Continuously monitor and control the manufacturing process to maintain product quality and reduce the occurrence of defects.

Implementation and Validation of the Hybrid Computational Framework in Quality Control Tests

The developed hybrid computational framework should be implemented in real-world quality control tests and validated to ensure its effectiveness, efficiency, and reliability. This may involve:

- Conducting a case study in an industrial setting, where the hybrid computational framework can be applied to the quality control tests of EM involving deformable materials.
- Comparing the performance of the hybrid computational framework with traditional quality control methods, assessing improvements in defect detection rates, process optimisation, and overall manufacturing efficiency.

1.5.5 Multi-objective optimisation framework

This chapter focused on developing a model-based framework that utilised a multi-objective optimisation approach to integrate interdependencies between fault detection and parameter optimisation in production processes. The aim was to simultaneously achieve efficient fault detection, minimise the occurrence of defects, and optimise process parameters, resulting in improved product quality and production efficiency.

Identification of Key Objectives and Constraints

The first step in developing the model-based framework was to identify the key objectives and constraints related to fault detection and parameter optimisation in production processes. These objectives included:

- Minimising the occurrence of defects in the production process.
- Maximising the efficiency of fault detection mechanisms.
- Minimising the costs associated with the production process and quality control.
- Maximising the overall productivity and throughput of the production process.

Constraints may include limitations in available resources, such as time, budget, or equipment, as well as safety and environmental considerations.

Formulation of the Multi-Objective Optimisation Problem

Once the key objectives and constraints have been identified, the multi-objective optimisation problem can be formulated. This involves:

- Defining the decision variables, which may include process parameters, fault detection settings, and quality control strategies.
- Developing objective functions that quantify the performance of the production process with respect to each identified objective. These functions should account for the interdependencies between fault detection and parameter optimisation, as well as their impact on the overall production process.
- Defining the constraints, which may involve limits on the values of decision variables or specific requirements imposed by safety or environmental regulations.

Selection of Optimisation Techniques

The next step is to select suitable optimisation techniques to solve the formulated multi-objective optimisation problem. Some potential techniques include:

- Evolutionary Algorithms
- Multi-objective Metaheuristics
- Decision-Making Methods

Implementation and Evaluation of the Model-Based Framework

Upon selecting the appropriate optimisation techniques, the model-based framework can be implemented and evaluated using real-world production processes. Validation of the results of the optimisation process can be achieved by comparing the predicted outcomes with observations from the production process. Through the implementation of a correlation analysis, interdependencies among variables can be better understood by researchers, allowing for the identification of potential causal relationships, as well as an assessment of the strength and direction of these relationships.

1.6 Thesis structure

This section presents an outline of the thesis structure, providing a comprehensive overview of the chapters and their contents:

Chapter 1: Introduce the background, aim and objectives, and the methodology of this research.

Chapter 2: Provide a review of relevant literature concerning interdependencies in EM involving deformable material, the state-of-the-art research, and identify any research gaps.

Chapter 3: Outlines the methodology employed in the research, providing a detailed explanation of the approach taken to achieve the research objectives.

Chapter 4: Develop a framework that models interdependencies between process variables, particularly in the context of EM involving deformable materials, to understand their influence on the occurrence of defects.

Chapter 5: Integrate the established model to create a hybrid computational framework that improves the efficiency and reliability of quality control tests by predicting component states and accounting for process interdependencies.

Chapter 6: Develop a model-based framework that utilises a multi-objective optimisation approach to integrate interdependencies between fault detection and parameter optimisation in production processes.

Chapter 7: Discussion and conclusion of this research and its contribution to knowledge, as well as provision of information on its limitations and future work.

CHAPTER II: LITERATURE REVIEW

2.1 Introduction

The detection and modelling of interdependencies among input parameters during the manufacturing of EMs that contain copper wire as a deformable material are crucial in the modern industrial world [4]. The increasing demand for reliable and efficient motors, coupled with technological advancements, requires companies to keep up with the latest developments in this field to stay competitive [1]. During the manufacturing process, defects or faults are developed, sometimes they are accumulated creating a negative impact on the quality of the finished product [5]. Understanding how crucial input process parameters and their interdependencies affect the occurrence of faults is essential for identifying the faults early in the process [6].

Thus, this literature review focusses on exploring interdependencies during the manufacturing process and the creation of faults in EMs. When it comes to researching the production of EM there are several challenges that arise due to the use of flexible materials like copper wire. These materials can be tightly wound around stator cores, but this also brings complications during the manufacturing process. It becomes crucial to manage the deformation of copper wire to ensure optimal performance of EMs as it can affect their electrical resistance and efficiency [5].

Understanding how stages in electrical manufacturing especially in stator fabrication are interconnected is a complex task. These interconnected stages can have an impact on outcomes and potentially lead to faults making it difficult to model the processes while considering time-based dependencies. Moreover, detecting faults in materials like copper wire is challenging because their deformation and subtle internal defects make them difficult to identify using EoL tests. Using innovative approaches such as Artificial Neural Networks (ANN) faces obstacles when dealing with deformable processes and lacks sufficient training data, which hinders fault detection in such scenarios [7].

Furthermore, incorporating a multi-objective approach in linear winding processes introduces complexities when it comes to adjusting and optimising the manufacturing process. The various interdependencies create cause and effect relationships that make it challenging to strike a balance, between reducing costs and minimising faults. Additionally, factors such as speed limitations and wire gauge have an impact on the optimisation process. Achieving the desired objectives requires consideration in dealing with these constraints. Selecting the suitable algorithm for research purposes adds another layer of complexity as there is no universal solution that fits all scenarios. Each algorithm has its advantages and disadvantages making it crucial to make well informed decisions for successful research outcomes. It is essential to address these challenges in order to advance the field of EM production while improving the manageability and optimisation process by reducing costs and minimise faults. This will ultimately result in enhanced efficiency, reliability and quality, within manufacturing processes.

This literature review discusses some areas where further research is needed in the field of fault detection and parameter optimisation in EM production processes specifically regarding interdependencies. Firstly, there is a need for better techniques to identify the characteristics and connections within the process that result in defects. Secondly, there is a lack of modelling techniques that can effectively understand the relationships between various parameters in real time manufacturing processes and predict the chances of defects occurring.

Using a DES approach combined with machine learning algorithms shows promise in this area [8]. Thirdly, it is important to develop an integrated framework that considers interdependencies for both fault detection and parameter optimisation to enhance manufacturing operations efficiency and effectiveness. Addressing these research gaps will contribute significantly to developments in electrical machine manufacturing.

2.2 Overview of electrical motors

Manufacturing of electrical motors is a complex process that involves the design, fabrication, assembly and testing elements. This process requires a high level of precision and accuracy in order to create a reliable, efficient and safe product. As Hagedorn et al. [5] mention, as technology advances and electrical motors become increasingly complex, the need for specialised knowledge and expertise in the field of electrical motor manufacturing continues to grow. In this section, the basics of electrical motors manufacturing are discussed, including the main components, processes and techniques involved.

2.2.1 **Components within an electrical motor**

EMs are essential for industrial and consumer applications, consisting of a housing, stator, rotor, and shaft as shown in Figure 2.1. Kißkalt et al. [9] state that the housing protects internal components, while the stator produces a rotating magnetic field using coils. The rotor, containing permanent magnets, rotates in response to the stator's magnetic field, and the shaft transfers this motion to external loads. Lauro et al. [10] mention that traditional manufacturing processes create these components, with the stator being the most complex and prone to defects. Nevertheless, Tiwari et al. [11] point out that the stator must be precisely designed and manufactured to withstand forces and deformations for optimal performance.

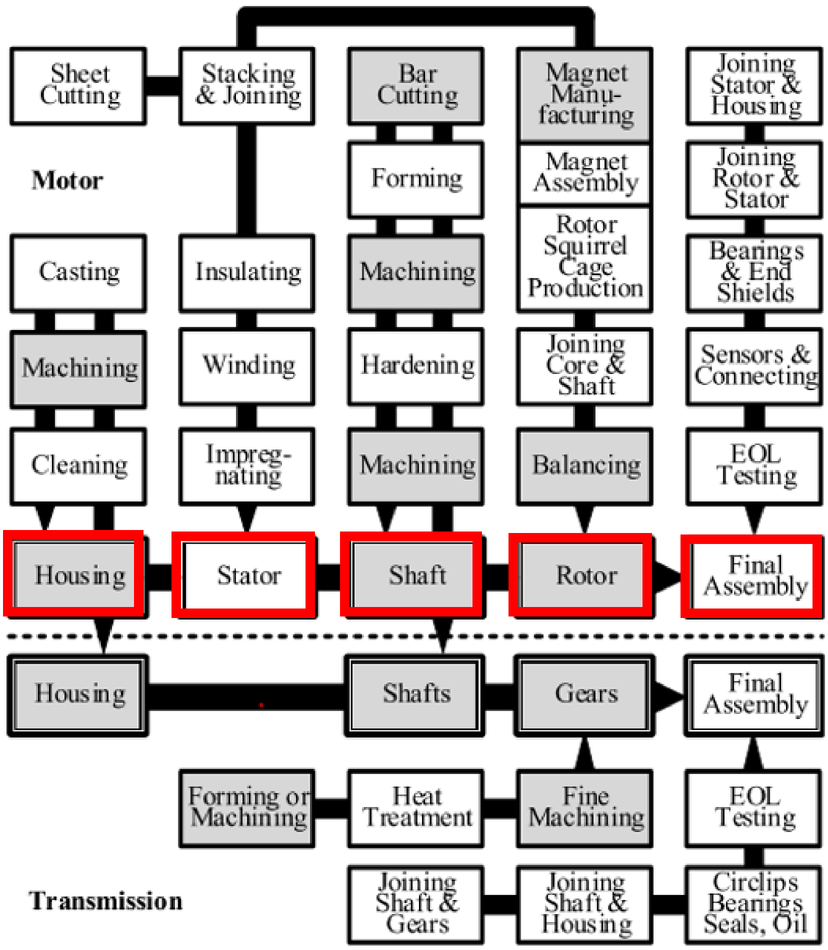


Figure 2.1. Main components and manufacturing steps for an EM [9].

A. Housing

The housing is crucial for electromagnetic motors, providing protection and heat transfer support. Typically made of metals like aluminium and steel, the housing is produced using pressure die-casting and machining operations, such as turning, milling, and drilling. These methods ensure precise shapes, sizes, and structural strength for the stator housing [12]. As Grabowski et al. [13] mention, modern fabrication techniques enable more complex shapes and higher structural integrity. Achieving small tolerances with high precision is vital for the assembly process, as misalignments can cause motor vibrations. Consequently, Mayr et al. [12] highlight that research on housing design, fabrication, and performance is essential for ensuring an EM's motor durability, performance, and safety.

B. Rotor

The rotor is the rotating part of an EM, interacting with the stator's magnetic field to produce torque, generating rotational motion [5]. It is typically mounted within the stator and features a cylindrical steel lamination core with an internal copper winding. Wrobel & Mecrow [14] state that this winding comprises insulated copper conductors arranged in a coil to conduct electricity and create a magnetic field. As evidenced in Wu & El-Refaie's [15] research, rotor design and construction are critical for the motor's successful operation, requiring proper design for specific environments, torque, and speed requirements. The winding must meet the stator's electrical specifications, and various configurations have been researched to maximise rotor performance. Careful rotor construction ensures motor quality and reliability.

C. Shaft

Shafts are crucial components of EMs, providing support and enabling proper functioning [9]. Made from materials like steel and aluminium, these cylindrical shafts allow the rotor to spin, generate power, and support stator windings. They also insulate windings from the core, prevent energy leakage, and absorb vibrations and impacts giving smooth motor operation [16]. Dong et al. [17] support the idea that manufacturing techniques such as machining, extrusion, forging, and casting can be suitable for producing shafts, with the choice depending on motor requirements such as materials, tolerances, and production quantities.

D. Stator

The stator is a vital component in an EM, responsible for producing a magnetic field that interacts with the rotor to create rotational motion [18]. It typically comprises a laminated core made of thin steel plates and windings wrapped around the core [19]. Nau et al. [19] explains that the stator's purpose is to generate a stable magnetic field, allowing the motor to convert or transform electrical energy. The core consists of insulated steel plates, while the winding is made of conductive materials like copper wire. As demonstrated in the research by Guo et al. [20], the stator’s design directly influences motor efficiency and performance, making proper component selection crucial for maximising performance. Oliveira et al. [21] agree that choosing the right component arrangement is essential for ensuring efficient and reliable stator performance.

E. Final assembly

The assembly of the motor is performed automatically or semi-automatically. The stator and the rotor, which already contain the lamination core and the shaft, are put together. To ensure good efficiency, Kißkalt et al. [9] suggest that the air gaps need to be kept as narrow as possible during assembly. In fact Tiwari et al. [11] support the idea that precision is essential to prevent any misalignments that result in vibration, decreasing the motor's efficiency and leading to malfunctions. The motor is then given a final inspection to check for any faults or defects and to ensure that it meets the required specifications.

2.2.2 Common manufacturing processes used for EMs

The manufacturing process of an EM is a complex operation involving a number of steps to ensure a high-quality product [9]. This literature review focuses on the typical manufacturing process steps of stators used in EMs. Stators are an essential component of an EM, and they play a critical role in converting electrical energy into mechanical energy [5]. However, they are also subject to a range of potential issues that can impact their performance, including deformation, vibration, and electrical faults [6]. Understanding and mitigating errors earlier in stators is crucial for ensuring the reliability and longevity of mechanical systems [4]. Furthermore, if not addressed promptly, these errors can lead to catastrophic failures, expensive repairs, and operational downtime [3][4][6].

The fabrication of stators involves manufacturing steps such as sheet cutting, stacking, joining, insulation, winding, impregnation, assembly, and contacting, as shown in Figure 2.2.

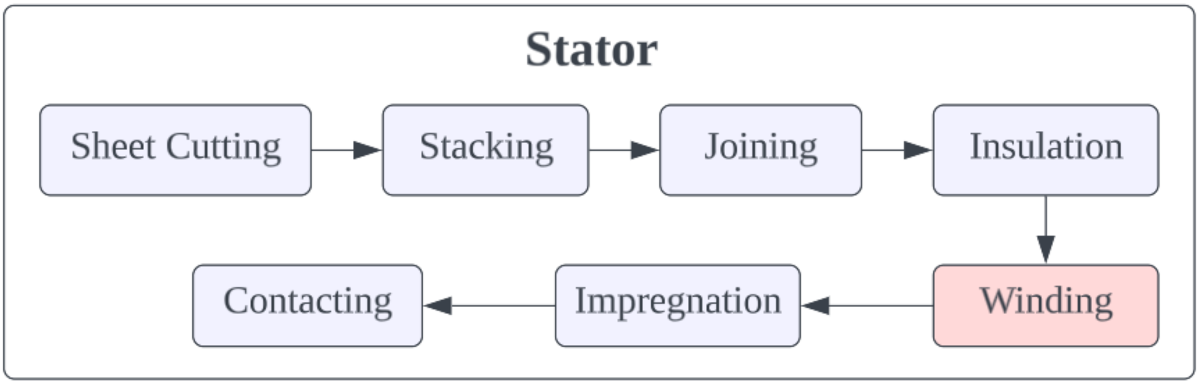


Figure 2.2. Overview of manufacturing steps used to fabricate a stator.

A. Sheet cutting

Sheet cutting is the first process step used for fabricating a stator, which involves cutting sheets of material into specific shapes and sizes to create the individual components of the stator [6]. This process is commonly used in the production of stators made from laminated cores, which are typically composed of thin sheets of electrical steel or other magnetic materials [22]. Bayraktar & Turgut [23] point out that sheet cutting includes techniques such as punching and laser cutting. Urbanek et al. [16] explain that punching is widely used for EMs, while laser cutting offers accuracy for smaller-scale production. These techniques can alter the material structure near the edge, with degradation levels dependent upon the cutting method and input parameters. To mitigate risks, the cutting process must be carefully designed and optimised using appropriate parameters and tooling [6].

B. Stacking

Stacking is a step in stator manufacturing, involving the placement of laminations, spacers, and insulators in their designated positions [24]. The process begins with aligning the lamination stack, which can be done manually or by machines [25]. Next, spacers and insulators are set, providing insulation between laminations and mechanical stability. The final step is compressing the stack, ensuring proper contact and alignment, typically using a hydraulic press. Once completed, the stator coil is ready for testing and installing in the motor.

C. Joining

Joining is a process used during the fabrication of stators to connect the individual components of the stator together into a cohesive whole. Mayr et al. [26] suggest that joining is a critical step in stator manufacturing, ensuring structural integrity. Common joining techniques include welding, adhesive bonding, clinching, and fastening [27]. As proposed by Husain et al. [24] welding is a popular joining technique for stator manufacture due to its minimal setup time, accuracy, and repeatability. Regardless of the technique used, De Oliveira et al. [28] explain that post-processing tests like mechanical fatigue testing and non-destructive testing (NDT) are crucial for ensuring joint quality. Inspecting joints for visual anomalies helps identify potential failures, ultimately maintaining the structural integrity and reliability of the stator [11].

D. Insulation

Insulating involves applying insulating materials to the various components of the stator to prevent electrical losses and protect against electrical breakdown [29]. The process includes several steps, such as applying a lacquer coating to protect against abrasion and mechanical damage [24]. Insulation paper wraps around the stator, isolating it from the external environment and reducing the risk of short circuits and electrical noise. A layer of synthetic rubber, silicone, or other material adds an extra barrier against short circuits and provides thermal insulation, improving efficiency. Finally, a protective coating safeguards against environmental factors such as rain, dust, and corrosion. Zoeller et al. [30] support the idea that proper insulation is crucial for the efficient and reliable operation of the stator.

E. Winding

Winding is the process of placing insulated wire around a core to create an electrical coil as shown in Figure 2.3. The winding process typically involves the use of specialised winding machines, which are designed to wind the wires around the stator core in a precise and consistent manner [31]. Hofmann et al. [32] point out that computer-controlled machines ensure uniform wire winding while achieving the desired amount of electrical current to flow through the stator and motor. The winding process concludes with the installation of electrical connections and insulation [33]. Then, the completed stator is ready for integration into the motor system.

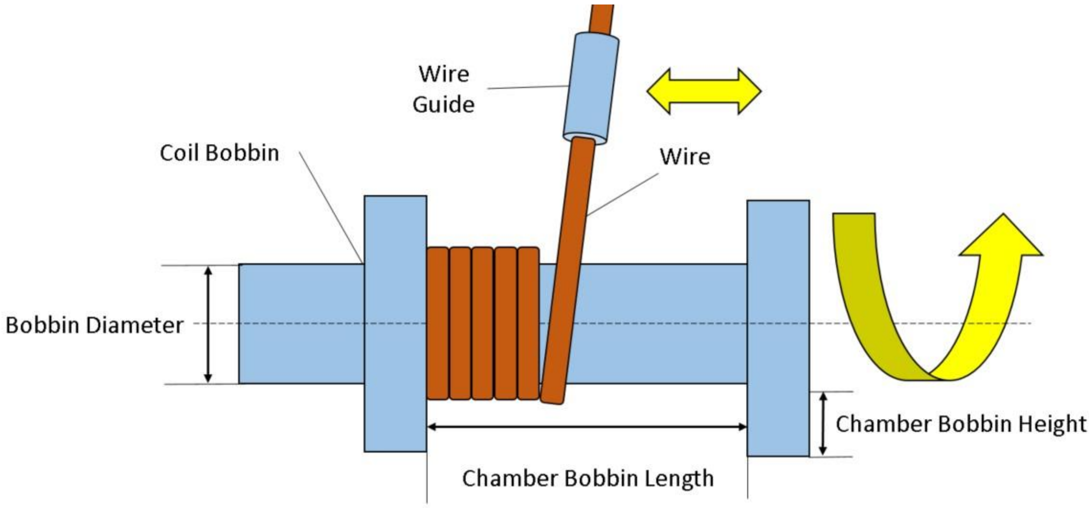


Figure 2.3. Representation of the linear winding process, adapted from Hagedorn et al. [5].

The winding process in EM is of particular interest because it is the process that involves a deformable material and contributes to the highest number of faults [6]. The amount of force applied to a wire has an impact on how the wire bends and its electrical resistance. When the force is increased the wire stretches temporarily without causing any changes. This temporary stretching causes the electrical resistance to increase proportionally. However, if the force goes beyond a yield limit the wire bends permanently and its shape changes resulting in an irreversible increase in electrical resistance. Figure 2.4 shows how the relationship between wire force and bending shifts from temporary to permanent at a point. This emphasizes the

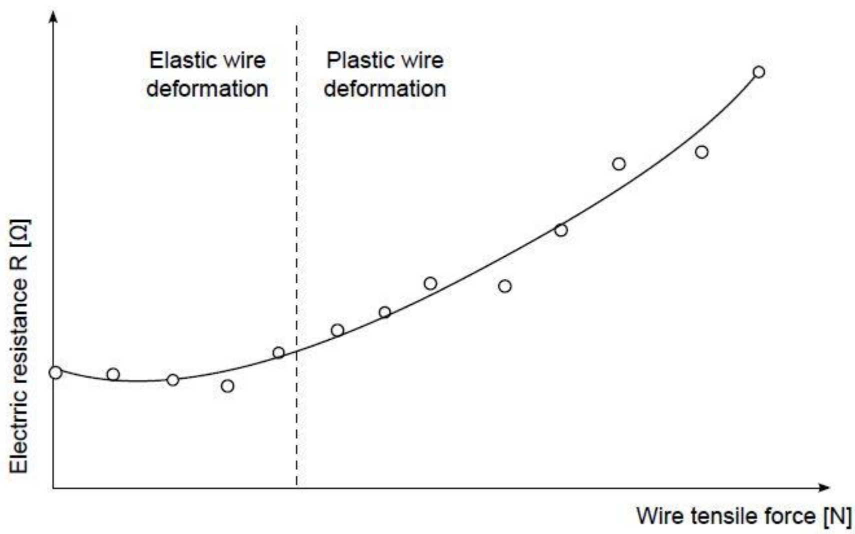


Figure 2.4. Influence of the wire tensile force and the copper wire deformation on the electrical resistance [5].

importance of managing tension to prevent any negative effects, on both the wire itself and the overall performance of EM.

During the winding process, several factors can contribute to faults, such as the deformation of the wire, the formation of voids, and poor electrical insulation [3][6]. These faults can result in reduced efficiency, increased maintenance, and a decreased lifespan of the electrical machine. Therefore, Bermúdez et al. [34] argue that understanding the winding process's intricacies is crucial for improving the reliability and performance of EM.

Escudero-Ornelas et al. [4] emphasise the importance of the use of advanced modelling and simulation techniques that can aid the development of better winding processes. These techniques allow for a more detailed analysis of the winding process and enable the researcher to identify potential issues before they arise. Additionally, Abdallah & Benatman [35] mention that these techniques can be used to optimise the winding process to improve efficiency and reduce the number of faults.

Classification of winding faults

To ensure optimal performance and reliability of EMs, it is crucial to detect and classify faults in the coil-winding process [5]. Different types of faults can have varying impacts on motor performance, making the understanding of their classification important for improving overall quality [6]. Based on geometry in each turn and layer, Sell-Le Blanc et al. [3] identified and categorised faults in the coil-winding process. These faults include double winding, gap, cross-over, flange winding, loose wire, and bulgy turn, as shown in Figure 2.5. Double winding occurs when a wire shifts into one of the layers above, while gap happens when a wire turn is missing in a layer. Crossover results from a change in the feeding direction, and flange winding only happens at the beginning of a layer when there is a missing or defective first winding. Loose wire can arise at the end of the winding process when tension is low, and bulgy turn results when the winding is not tight enough due to tension variation, causing the wire to swell and have a curved appearance.

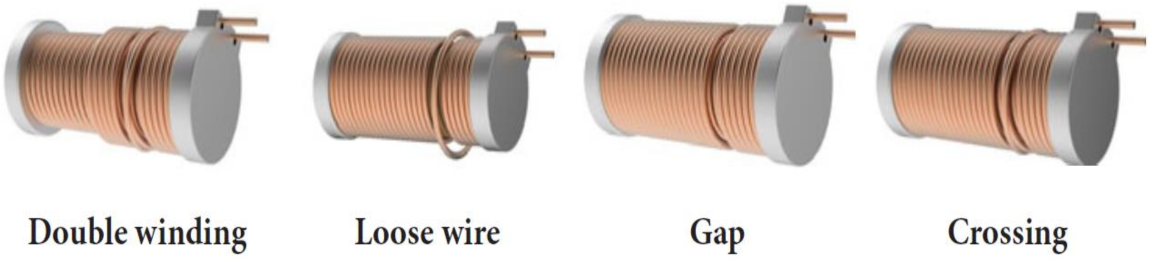


Figure 2.5. Classification of typical layering winding defects [3].

The occurrence of faults during the winding process can be linked to changes in winding pressure, which can result in variations in direction and physical properties [36][37]. A reduction in diameter can lead to increased electrical resistance in the bobbin, and variations in tension can cause the winding scheme to become deformed, resulting in issues such as bulging, convexity, concavity, or bending [38]. To prevent such faults, Vater et al. [39] discuss that it is important to analyse the interdependencies between the contributing factors of the process, including the machine, materials, environment, personnel, and method, in order to determine the underlying cause.

To better understand and analyse these interdependencies, Sell-Le Blanc et al. [3] developed a matrix based on data obtained from workshops that perform winding operations, as shown in Figure 2.6. The parameters that influence the creation of faults during winding can be systematically represented, analysed, and studied through the use of the matrix which assigns values to each parameter. Prior to this classification, there was no specific focus on winding parameters. This matrix provides an efficient and methodical approach for assessing the factors that affect the occurrence of faults during the winding process.

The matrix, composed of rows and columns, has been used to analyse the influence of faults during the winding process. The upper row of the matrix represents the faults classified into four categories related to electrical properties, wire properties, winding scheme, and dimensions. The first column holds parameters divided into categories such as process, wire, and coil bobbin, while values have been assigned to each parameter according to each fault. The analysis of the matrix revealed that the wire tension has the strongest influence on the outer diameter leading to faults in the winding process, as shown by the interference value between faults and parameters in the last row and column.

		Winding Fault	Deviation Range (0-5)	Electric proteries			Wire prop.		Winding scheme			Dimension		
				Faulty electric resistance	Short circuit	Defective hv-resistance	Wire damage	Wire fracture	Winding scheme (wild)	Loose winding	Concision of winding	Defective outer diameter	Defective inner Diamater	Weighted cross interaction of parameter and winding fault
		Weight(1-6) / Parameter		6	5	6	5	5	5	6	5	6	5	
Process	Machine	Winding speed ramp up	0	1	1	1	1	1	2	3	0	2	0	0
Process	Machine	Machine damping	4	1	1	1	1	1	2	2	0	2	0	244
Process	Machine	Machine intertia	4	1	1	1	1	1	2	2	0	2	0	244
Process	Machine	Castor angle	2	1	1	1	1	1	3	3	1	3	0	166
Process	Machine	Wire feeding speed	2	1	2	2	1	1	3	1	1	3	0	164
Process	Machine	Wire feed turning point	3	1	2	2	1	1	3	3	1	3	0	282
Process	Machine	Exit angle	0	3	3	3	3	3	3	3	3	3	3	0
Process	Machine	Winding speed	1	3	3	3	3	3	3	3	3	3	3	162
Process	Wire	Wire tension (global)	4	3	3	3	3	3	3	3	3	3	3	648
Process	Wire	Wire tension (local)	5	3	3	3	3	3	3	3	3	3	3	810
Process	Wire	Cross osscilation	3	1	2	2	2	2	2	2	1	2	3	306
Process	Wire	Longitudinal osce.	3	1	2	2	2	2	2	2	3	2	3	336
Process	Wire	Transversal ossc.	4	1	2	2	2	2	2	2	3	2	2	428
Process	Wire	Free wire length	1	2	3	3	3	3	3	3	3	3	3	156
Process	Wire	Anti frction coating	2	3	3	3	3	3	3	1	1	3	3	280
Wire	Geometry	Outer wire gauge	2	3	1	1	1	1	3	3	1	3	2	210
Wire	Geometry	Inner wire gauge	2	3	1	1	1	1	3	3	1	3	2	210
Wire	Geometry	Plastic deformation	4	3	3	3	3	3	3	1	3	3	3	600
Wire	Geometry	Linear expansion	4	3	3	3	1	1	2	3	3	2	3	524
Wire	Geometry	Lateral contraction	4	1	3	3	1	1	2	1	1	2	2	368
Wire	Geometry	Defect of ovality	1	2	1	1	1	1	3	1	0	3	0	72
Wire	Geometry	Degree of insulation	1	1	3	3	3	3	1	1	0	1	0	86
Wire	Mechanical properties	Wire hardness	1	3	3	3	3	3	3	3	3	3	3	162
Wire	Mechanical properties	Poisson ratio	1	1	1	1	1	1	1	1	1	1	0	49
Wire	Mechanical properties	Youngs-Modul	1	0	1	1	1	1	3	1	2	3	3	85
Wire	Mechanical properties	Failure strain	1	3	3	3	3	3	3	3	3	3	3	162
Wire	Mechanical properties	0,2% Yield Point	1	3	1	1	1	1	1	3	2	1	2	88
Wire	Mechanical properties	Tensile strength	1	3	3	3	3	3	3	3	3	3	3	162
Wire	Mechanical properties	Srping back behavior	2	3	3	3	3	3	3	3	3	3	1	304
Wire	Mechanical properties	Dynamic bending behavior	2	3	3	3	3	3	3	3	3	3	3	324
Wire	Mechanical properties	Static bending behavior	2	3	3	3	3	3	3	3	3	3	2	314
Coil bobbin	Geometry	Winding ground	3	0	3	3	3	3	3	1	0	3	0	306
Coil bobbin	Geometry	Length	4	0	1	1	1	1	1	1	2	1	3	252
Coil bobbin	Geometry	Width	2	3	3	3	3	3	3	2	2	3	3	302
Coil bobbin	Geometry	Aspect ratio	3	3	3	3	3	3	3	1	2	3	3	435
Coil bobbin	Geometry	Winding width	3	0	1	1	3	3	3	3	1	3	3	336
Coil bobbin	Geometry	Radius of curvature	3	3	3	3	3	3	3	2	3	3	3	468
Coil bobbin	Mech. Prop.	Youngs-Modul	3	0	0	0	1	1	1	1	0	1	3	126
Coil bobbin	Mech. Prop.	Mech. stability	4	1	2	2	1	1	3	1	2	3	3	408
Coil bobbin	Mech. Prop.	Friction	1	0	1	1	1	1	1	3	2	1	3	75
Cross interaction of a winding fault with parameters				990	1010	1212	930	930	1170	1158	850	1404	1000	

Figure 2.6. Matrix by Sell-Le Blanc presenting the relationship between process parameters and faults during winding [3].

F. Impregnation

Impregnation is a process where a fluid material such as resin is applied to fill the empty spaces between the laminations and windings of the stator core [40]. Vacuum Pressure Impregnation (VPI) and Resin-Rich Transfer Moulding (RRTM) are commonly-used methods that offer several advantages such as improved electrical insulation, mechanical strength, and heat dissipation [5]. During VPI, the stator core is placed in a vacuum chamber and impregnated with resin from a heated reservoir, with the pressure caused by heating the chamber forcing the resin into the empty spaces. RRTM, on the other hand, offers superior electrical insulation, mechanical strength, and heat dissipation. According to Liu et al. [41]

both methods involve a vacuum and pressure, and offer benefits that contribute to the proper functioning and longevity of the stator in its intended application.

G. Contacting

The contacting process involves connecting the various electrical components of the stator to each other in order to form a complete electrical circuit [33]. Riedel et al. [42] mention that thermal crimping is a common technique due to its fast crimping times, tight seal, and reliable connections. In contrast, Hagedorn et al. [5] explain that welding is also common but has limitations such as increased hysteresis losses and corrosion. Soldering is another technique that uses metal heated to join wires and connectors, but it can lead to electrical losses and damage to the protective coating [5]. Proper contacting ensures the stator's efficient and reliable operation, and Alani et al. [43] support the idea that choosing the appropriate technique depends upon specific requirements and considerations such as cost, environment, and expected performance.

2.2.3 Condition monitoring and fault detection in electrical motors

The search for more efficient and reliable ways to identify potential problems in production processes, with the advancement of technology, has led to the development of analytical tools and approaches for identifying the sources of errors [44][45]. The focus of this section is on the condition monitoring and fault detection in EMs by way of identifying the most useful methods and techniques that aid the identification of error-prone manufacturing steps as presented in Figure 2.7. Advantages and disadvantages of the various techniques and methods, as well as their potential applications, are also considered.

The selection of Assembly Sequence Planning, Precedence graphs, Liaison graphs and Petri Nets as techniques for condition monitoring was based on their ability to accurately model assembly processes and identify stages that may be prone to errors. This aligns with the research objective of identifying manufacturing errors. Similarly, fault detection techniques such as FMEA and Quality function deployment were chosen due to their proven track record in systematically identifying and prioritising potential failure modes while also implementing quality measures (further discuss in section 2.2.3 B). This aligns with the research focus on ensuring reliability and efficiency in electrical production processes. These techniques were preferred over other options because they have been extensively studied in the field of electrical

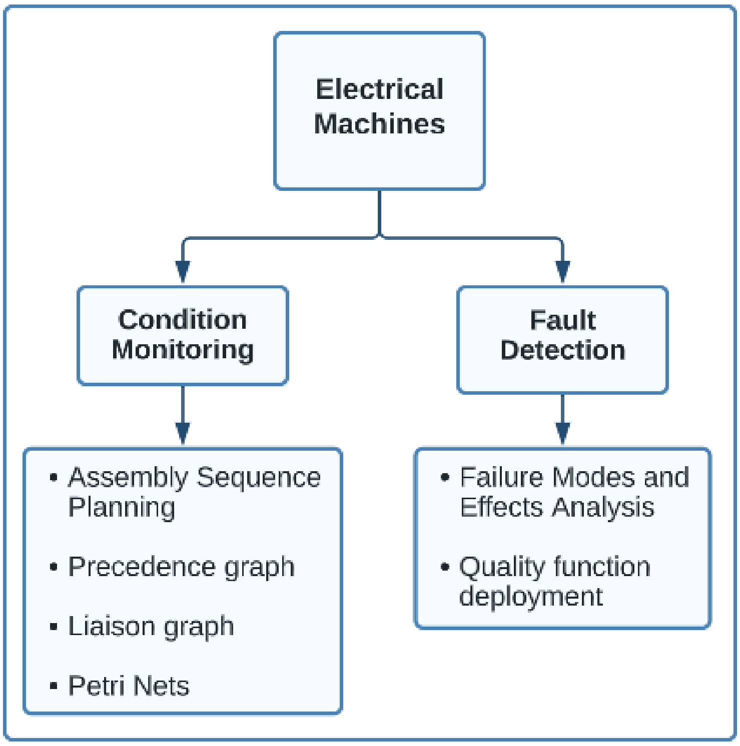


Figure 2.7. Flowchart of the condition monitoring and fault detection techniques implemented in EMs.

manufacturing and have shown success, in similar scenarios (Sections 2.2.3 A and B).

A. Conditional monitoring in electrical motors

i. Assembly Sequence Planning (ASP)

ASP is a set of methodologies used in industry to optimise the design of a product assembly sequence [46]. Ghandi & Masehian [46] mention that ASP uses a working model to create a sequence of steps to reduce errors in the manufacturing process. The ASP model considers the overall design of the product, the manufacturing process, and the resources required to produce the product, and creates an optimal assembly sequence that is error-free [47]. As Prajapat & Tiwari [47] discuss, the main objectives of ASP are to improve manufacturability, assembly, and reduce costs while maintaining essential product functions. This approach has proven to be highly beneficial in mapping a manufacturing process and isolating complex product assemblies into a limited number of subassemblies as presented in Table 2.1 [47][49].

As De Oliveira et al. [28] point out, the monitoring of faults in EM is essential to ensure optimal performance and prevent costly downtime. Various studies have reported the use of

Table 2.1. Comparison table of condition monitoring techniques.

Condition monitoring techniques	Advantages	Disadvantages
Assembly sequence planning	-Optimises assembly sequence to reduce errors. -Improves manufacturability and assembly. - Helps identify potential faults and reduce assembly errors. - Reduces the cost of faulty products.	- May not be effective in representing operations involving deformable materials and their interdependencies.
Precedence graph	-Identifies error-prone manufacturing steps. -Provides an optimized sequence of operations. -Suitable for agile assembly.	-Inadequate in representing processes with deformable materials and their correlations. -Assumes independent operations, not suitable for highly interdependent tasks.
Liaison graph	-Analyses complex problems and relationships between causes and effects. -Helps determine efficient component arrangement and optimisation.	-Limited applicability in manufacturing processes and fault detection for EMs.
Petri nets	-Provides a formal model to describe and analyse information flow and fault scenarios. -Used for reliability analysis in EM design and operation.	-Time-consuming and not statistically representative. -Does not consider the combined effect of multiple faults.

ASP in monitoring faults in EM [46]. For instance, in a study by Ghandi & Masehian [46], ASP was used to optimise the assembly process of an electrical connector where deformable and flexible parts were involved while detecting assembly faults. The authors reported that ASP helped them in identifying potential faults and reduce assembly errors. Similarly, in a study by Guo et al. [48], ASP was employed in the disassembly of electronic appliances and electromechanical/mechanical products implementing methodologies from the Industry 4.0, which allowed them to reduce the cost of faulty products. Ultimately, the authors reported that ASP aided in detecting potential faults and improved the overall reliability of the system.

ii. Precedence graph

Precedence graphs are a method used to identify error-prone manufacturing steps [49]. It involves a graphical representation of the product design, the sequence of operations required to produce the product, and the resources needed. Burggräf et al. [50] suggest that the graph can be used to create an optimised sequence of operations to reduce errors in the manufacturing process. This method has been applied in EMs to model the sequence of operations, capturing the characteristics of an electric vehicle by providing an agile assembly. However, Burggräf et al. [50] describe that this technique has been shown to be inadequate in representing operations such where deformable material is involved, and establishing correlations between them due to the constant change of the components.

Echoing Burggräf, Riggs et al. [51] demonstrates that a precedence graph is inadequate in representing these processes because it assumes that each operation is independent and can be performed in isolation. This is not the case for magnet assembly and winding processes, as they are highly interdependent and must be performed in a specific order. For example, if the magnet assembly is done before the winding process, it may be difficult to wind the wires correctly around the magnets, leading to an incorrect final product [9]. Establishing correlations between these processes is also critical for ensuring the optimal performance of the electrical machine [6]. However, a precedence graph does not provide an effective way to represent these correlations. For instance, the quality of the final product may be affected by the number of turns in the winding process, which, in turn, affects the magnetic field produced by the machine [5]. Rocha & Ramos [49] emphasise that these correlations cannot be accurately represented by a precedence graph, as it only shows the sequence of operations and not the interdependencies between them.

iii. Liaison graph

The Liaison graph is a tool used to analyse the connections between the causes and effects of a complex problem. It has been applied in engineering design to analyse the order of components when assembling them to reduce difficulty and identify any relationships between their shape and size [52]. Pintzos et al. [52] provide the example where this method was used in the assembly of a wind-driven generator to determine the most efficient arrangement due to the large scale and load of the components. Drawing on the work by Giorgio et al. [53] it can be stated that the use of a Liaison graph allows for the creation of a model with the necessary instructions to construct the generator quickly and securely while also revealing the relationships between each component, allowing for optimisation of the output.

iv. Petri Nets

Petri nets are a graphical, formal and abstract model used to describe and analyse the flow of information [54]. Pamuk [54] suggests that this model can capture and represent relationships between different scenarios in which a system may encounter faults. This technique has been applied in the realm of EV design to increase reliability through the mapping and evaluating of faults with Petri nets and fault tree analysis [55]. Utilising Petri nets allows for the construction of a reliability analysis tailored to the motor's characteristics [56]. Therefore, due to the goal of increasing reliability in EM production, Gaied et al. [57] mention that Petri nets have been used to map the operation sequence of EV, trains, and even winding machines. The downside of this technique is that it is time-consuming and not statistically representative, and it fails to take into account the combined effect of multiple faults [57].

B. Fault Detection in electrical motors

i. Failure Modes and Effects Analysis (FMEA)

FMEA is a method used to analyse a process and understand the relationship between its errors and output. Abhilash et al. [58] point out that FMEA is applied to identify and prevent errors in the early stages of development and improve product quality by assessing the severity, frequency, and detectability of possible failures. FMEA has been widely used in industries such as engineering, automotive, and aerospace, and has been explored from its historical roots in quality control to contemporary applications in risk management [59]. Jhorar & Kumawat [60] explain that this technique has been applied to identify parameters in a fractional horsepower AC motor failure and subsequent fault-proofing procedures developed using the Poka-yoke concept. Despite some limitations such as lack of standardisation and structure, FMEA is a widely-used method for evaluating potential failure modes and associated risks [58]. Its benefits outweigh any limitations and there is a large amount of literature available to explore its applications and potential improvements.

ii. Quality Function Deployment (QFD)

QFD is a widely used approach in product planning, design and quality management, which incorporates customer feedback into the development process by ranking product characteristics based on customer requirements [61]. Hariri et al. [62] proposed that QFD allows for a quick and efficient identification of relationships between customer requirements and product characteristics, making it useful for detecting process issues and satisfying customer needs. According to Anwar et al. [63] QFD has been implemented in various industries, including the automotive sector, especially in the design of electric cars. However, challenges associated with QFD include difficulty in obtaining customer feedback, lack of standardisation, and resource constraints such as the need for skilled personnel and time [64]. Despite these challenges, QFD is a useful tool for ranking process characteristics, but other techniques and expert opinions are necessary to detect correlations as QFD cannot take into account interdependencies [62].

2.3 Interdependencies in electrical motors

Interdependencies in a manufacturing process entail the intricate relationships and interactions among diverse components, processes, and systems included in producing goods [6]. Mayr et al. [2] explain that these interdependencies profoundly influence the quality, efficiency, and cost-effectiveness of the manufacturing process. Following Mayr's line of reasoning, Escudero-Ornelas et al. [4] further explain that interdependencies are a critical aspect in the engineering field and a vital topic for enhancing the manufacturing process's efficiency. A comprehensive analysis of these interdependencies is necessary to optimise the manufacturing process and ensure that the final product meets the required specifications.

The success of a manufacturing process depends on considering the specific dependencies and constraints of each component being assembled to produce the final product [65]. For example, Mayr et al. [2] discussed that in the case of an electrical motor, integration of multiple components such as the housing, stator, rotor, and shaft requires a comprehensive understanding of the interdependencies between these components. Neglecting these interdependencies can lead to delays, poor quality, and high costs [3][5]. Nishino et al. [66] proposed that incorporating interdependency analysis into the manufacturing process optimisation strategy is crucial to ensure efficiency and improve quality while reducing costs. This analysis can identify critical components and processes that need optimisation, and potential bottlenecks that may cause delays or quality issues [11]. Therefore, it is of great importance to accurately identify all existing interdependencies in EMs in order to determine the most relevant parameters and to monitor them efficiently in order to avoid any potential faults.

2.3.1 Techniques for measuring interdependencies

Interdependencies in manufacturing processes can be measured through a variety of techniques. Mayr et al. [26] describe that these techniques are employed to understand the complex relationships between different variables and how they interact with each other during the manufacturing process. In electrical machine manufacturing, Sell-Le Blanc et al. [3] demonstrated that interdependencies exist among various factors and stages playing a critical role in determining the efficiency and effectiveness of the overall system. Therefore, measuring these interdependencies is essential for improving the performance of EM processes.

A. Correlation analysis

Correlation analysis is a widely used statistical technique that measures the strength and direction of the relationship between two variables. In the field of electrical engineering, Shevkunova et al. [67] have employed the correlation analysis as a useful tool for measuring the interdependencies between different parameters in EM, such as voltage, current, speed, and torque. For example, Irhoumah et al. [68] point out that a correlation analysis can help identify the relationship between the input voltage and the output power of an EM. One of the main advantages of correlation analysis is that it provides a quantitative measure of the relationship between variables, making it useful for identifying the strength of interdependencies between different EM parameters [67]. Additionally, it is easy and quick to perform, making it a useful tool for researchers working with EM.

However, there are also some limitations to using correlation analysis. Sasikala et al. [69] mention that one potential drawback is that correlation does not necessarily imply causation, meaning that a correlation between two variables does not necessarily indicate that one causes the other. Furthermore, correlation analysis assumes that the relationship between variables is linear, which may not always be the case in EMs [69]. Nonlinear relationships may require more complex techniques such as nonlinear regression analysis or machine learning algorithms.

B. Regression analysis

Regression analysis is another statistical technique used to measure the relationship between a dependent variable and one or more independent variables in EM. This technique can help identify the impact of variations in the input voltage or frequency on the electrical machine's output power and critical parameters affecting the overall performance of the machine [69]. Glučina et al. [70] state that this technique's advantages include providing a measure of the causal relationship between variables, identifying critical factors that impact the machine's performance, and determining the direction of the relationship between different parameters. However, Murthy & Kumar [71] argue that the regression analysis's limitations include assuming a linear relationship between variables and not accounting for other unmeasured factors that may impact the electrical machine's performance.

2.3.2 Techniques for modelling and simulating interdependencies

Modelling and simulating techniques have become increasingly important in the field of engineering, particularly in the study of interdependencies between different components and systems [72], [81]. Laprie et al. [74] state that the ability to accurately model and simulate complex systems allows for a better understanding of their behaviour and performance, as well as the identification of potential issues before they arise. In the context of EM, interdependencies between different components and systems are critical for achieving optimal performance and reliability. As such, Hawer et al. [75] mention that modelling and simulating techniques are becoming more prevalent in the design, manufacture, and maintenance of EM. Therefore, this section will explore the different modelling and simulating techniques used in the study of interdependencies in EM, their advantages and limitations, and the potential future developments in this field.

The development of EMs has increased in recent years with new technologies and materials being utilised [1]. To produce high quality, reliable, and cost-effective motors, it is important to understand their behaviour [76]. Modelling EMs enables simulation of their behaviour in different scenarios and prediction of changes in process parameters [4], [36]. Currently, modelling and simulation tools are being used to study the behaviour of components such as the stator, resulting in cost and time savings [36], [77]. There are various modelling techniques as shown in Figure 2.8. The application areas and restrictions of these modelling techniques must be explored in the literature to compare and assess them. By using modelling techniques, more reliable motors with fewer faults can be produced [28], [78], [79].

The choice of selecting these techniques for modelling and simulating electrical machines and their interconnections was based on a thorough literature research approach [4],[28]. These methods, as shown in Figure 2.8 have been carefully selected after reviewing existing literature,

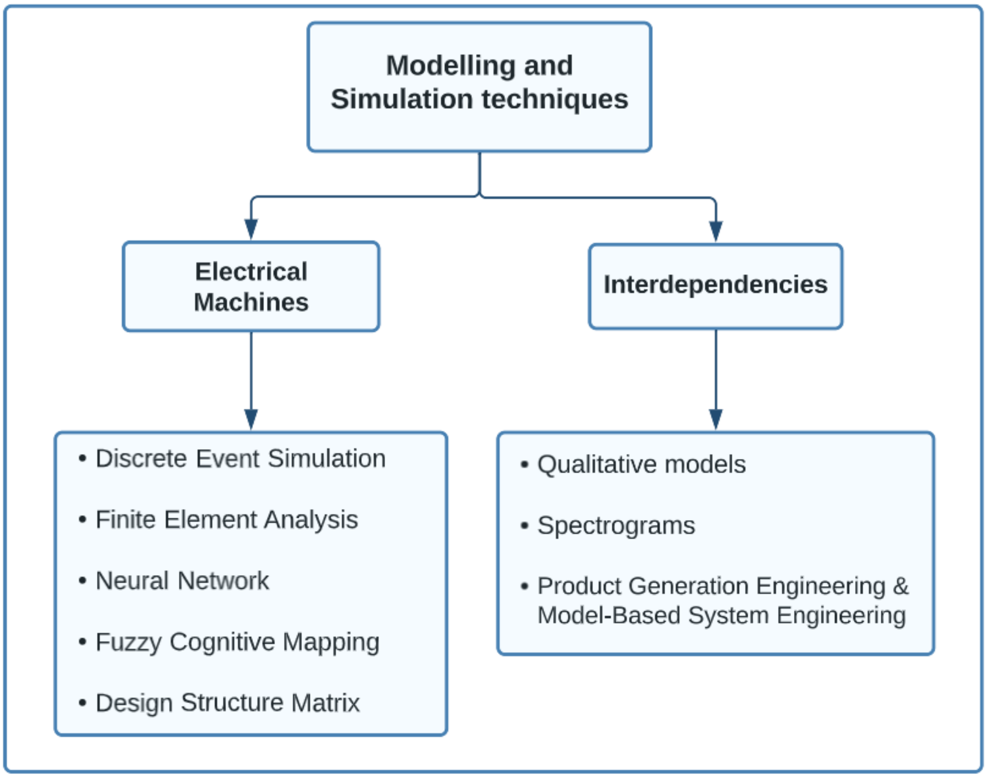


Figure 2.8. Flowchart of techniques capable of modelling and simulating EMs and interdependencies.

consulting the latest high-level academic journals and gathering valuable insights from the industrial and electric motor manufacturing stakeholder experiences. Each technique has been chosen considering its suitability in capturing aspects of interdependencies and electrical machines. This diverse selection is a combination of theoretical foundations, empirical evidence and practical considerations to ensure a robust approach to modelling interdependencies, in the context of electrical machines.

A. Techniques for modelling an electric motor manufacturing process

i. Discrete Event Simulation (DES)

DES is a widely used and versatile method for decision-making in various aspects of the business world, particularly in the manufacturing industry [47]. Budgaga et al. [80] mention that DES evaluates systems where events change their state at periodic intervals and introduces random variables through discrete probability distributions. It provides valuable insights into system performance and has been used for fault detection and predictive maintenance in wind turbines, and for predicting energy consumption [8][81]. Greasley & Edwards [82] point out that the capability of DES to model discrete events and introduce random variables makes it a suitable tool for analysing complex systems and processes in the manufacturing industry. DES is well-suited for creating a model that simulates the process flow and examines faults as discrete events to determine which parameters have the highest influence upon them.

According to Prajapat et al. [83] DES is recommended in the literature as a beneficial technique for modelling process characteristics in manufacturing due to its adaptability. According to Albers et al. [72] they found that there is potential in utilising DES and combined it with the features offered by Industry 4.0 like simulation to analyse and understand how different aspects of a manufacturing process are interconnected. They explained that by modelling these relationships it becomes possible to achieve a level of control and stability, in the manufacturing process. In their study Capocchi et al. [89], employed a DES to simulate the parts of an electric motor, including the rotor and stator. They found that DES had shown potential as presented in Table 2.2, in detecting faults at a stage in a three-phase wound rotor induction machine, which led to its application in this research. The application of DES continues to grow as researchers and practitioners explore its potential to improve system performance, reliability, and safety [47], [84], [85].

ii. Finite Element Analysis (FEA)

FEA is an accurate technique for modelling the behaviour of structurally complex components in engineering. Weigelt et al. [86] highlighted that FEA involves creating a 3D environment with a finite element mesh to represent changes in component behaviour when an applied load is imposed. Critical parameters can be identified through calculations and Computer-Aided Design (CAD) software when used in conjunction with FEA to create a model [32]. FEA is a numerical technique that can handle complex problems in areas such as deformable bodies, heat transfer, and fluid mechanics. Zaeh & Siedl [87] make the case that FEA can model both static and dynamic behaviour, including nonlinear outcomes, and generate time-dependent simulations .

FEA has been widely used for examining faults in EMs, primarily in stators and rotors, and is capable of conducting structural analysis during winding when faults are more probable [32], [88]. FEA has also been used in combination with other techniques such as Monte Carlo simulation to predict the relationship between nucleus density, stored energy, and temperature [89]. However, Kazeminezhad et al. [89] explain that its limitations include its inability to identify long-term interdependencies across a manufacturing process and its high cost, as well as the need for more advanced programming techniques compared to other techniques like DES.

iii. Neural Networks (NNs)

NNs are modelling techniques that use algorithms to identify relationships in sets of data from stochastic and predominantly non-continuous manufacturing processes. NNs have the ability to learn autonomously and generate an output independent of the input, and can perform multiple tasks without affecting system performance [90]. They are currently used in various fields such as image and language processing, route detection, speech recognition, and forecasting [91]. Raja et al. [92] point out that NNs have also been used for quality testing in EMs to identify defects in the stator winding. Fischer et al. [7] discussed that attempts have been made to combine NNs with other modelling techniques such as DES to develop surrogate models of intricate systems, but it requires a large data set for training and takes a long time to process. Nevertheless, Gletter et al. [93] state that NNs are faster than FEA and more accurate than analytical modelling, but require a significant amount of training and are typically constructed for a specific type of electrical machine.

iv. Fuzzy Cognitive Mapping (FCM)

FCM is a modelling technique that uses a cognitive map to represent the relationships between elements in a system [79]. It calculates weighted edges to reflect the cause-and-effect relationships between elements, allowing for the modification of external influences and the creation of dynamic models. FCM has been applied in various fields, including business, economics, education, health, project planning, and engineering, and has been used in EMs for fault identification and control, improving performance through consideration of functional correlations in the process [94]. However, Groumpos [94] argues that constructing a model with FCM requires considerable effort and specialist skills, and it may not be suitable for nonlinear outputs. Despite its limitations, FCM has been demonstrated as a useful tool for analysing interdependencies to achieve optimal changeability in factory design.

v. Design Structure Matrix (DSM)

DSM is a modelling technique that provides insight into complex systems composed of interconnected components [95]. It can be used to optimise architecture in products, organisations, and manufacturing processes. By decomposing a system into subsystems, a static or time-based model can be studied to better understand the relationships between parameters and how they affect system behaviour [96]. Lu & Sundaram [97] describe how a DSM has been applied to a range of applications – providing an example from the *Boeing Commercial Airplane Group* where they implemented a DSM as a foundation for developing a software tool to analyse the relationships between parameters and components of a wing. However, Browning [95] emphasises that DSM has limitations as shown in Table 2.2, as it can only model one single process flow at a time and cannot identify overlapping operations or interdependences among components, such as those in electronic manufacturing.

Table 2.2. Comparison table for modelling techniques for EM.

Technique	Advantages	Disadvantages
Discrete Event Simulation (DES)	- Provides valuable insights into system performance and fault detection.	- May not effectively represent long-term interdependencies.
	- Suitable for analysing complex systems in manufacturing.	- High cost and requires advanced programming techniques.
Finite Element Analysis (FEA)	- Accurate in modelling structurally complex components.	- Limited in identifying long-term interdependencies.
	- Handles deformable bodies and dynamic behavior.	- High cost and requires advanced programming techniques.
	- Used for examining faults in EMs.	
Neural Networks (NNs)	- Can identify relationships in non-continuous manufacturing processes.	- Requires a large dataset for training and long processing time.
	- Faster than FEA and more accurate than analytical modeling.	- Constructed for a specific type of electrical machine.
Fuzzy Cognitive Mapping (FCM)	- Represents cause-and-effect relationships in a system.	- Requires considerable effort and specialist skills.
	- Used for fault identification and control in EMs.	- May not be suitable for nonlinear outputs.
Design Structure Matrix (DSM)	- Provides insight into complex interconnected systems.	- Can only model one single process flow at a time.
	- Used to optimize architecture in products and manufacturing processes.	- Cannot identify overlapping operations or interdependences among components.

B. Techniques for modelling interdependencies

i. Qualitative models

Qualitative models proposed by Laprie et al. [74] demonstrated the potential to model process characteristics associated with failures in electric and information infrastructures as presented in Table 2.3. Various tools are available to identify key process characteristics and interdependencies, including the Ishikawa Diagram and the Fuzzy Cognitive Map [94][98]. Pal et al. [98] describe that the Ishikawa Diagram is particularly useful due to its functionality and adaptability, but it has limitations as it can only consider a single variable at a time. Groumpos [94] points out that the Fuzzy Cognitive Map is a widely utilised tool to analyse interdependencies in a system Qualitative models have several limitations when used to model interdependencies in a manufacturing step [74]. Firstly, they tend to focus on individual components rather than how they interact with each other [75].

Table 2.3. Comparison table of techniques use for modelling interdependencies.

Technique	Advantages	Disadvantages
Qualitative models	- Potential to model process characteristics associated with failures.	- Tend to focus on individual components rather than their interactions.
		- Assume linear and predictable manufacturing processes.
		- Rely on historical data for predictions.
		- Can be complex and time-consuming.
		- May not consider the human element in manufacturing.
Spectrograms	- Visualise interdependencies and identify key factors causing test failures.	- Requires a smart production system for automatic root cause identification.
		- Cannot take corrective action on its own.
Product Generation Engineering (PGE) and Model-Based System Engineering (MBSE)	- Leverages Industry 4.0 technology for comprehensive knowledge base.	- Manual extraction and entry of process parameters can be time-consuming and inconvenient.
	- Analyses process parameters and risk associated with their utilization.	
	- Establishes relationships between process characteristics.	

Secondly, qualitative models assume that the manufacturing process is linear and predictable, whereas it can be highly dynamic and subject to unexpected changes [60]. Thirdly, qualitative models often rely on historical data to make predictions, which may not be sufficient for modelling interdependencies. Fourthly, qualitative models can be complex and time-consuming to develop and implement. Lastly, they may not account for the human element of manufacturing, such as operator skill or decision-making, which can significantly impact the final product's quality [98].

ii. Spectrograms

Identifying the root causes of faults is an essential step in preventing rejections in the manufacturing process [3] [99]. As products become increasingly complex, and processes interdependent, Baier et al. [99] developed a method to visualise interdependencies using spectrograms. This tool allows them to identify key factors contributing to EoL test failure [11]. Spectrograms have been found to reduce time for root cause analysis by half. However, a smart production system is still necessary in order to automatically identify root causes and take corrective action such as altering input parameters, as this technique cannot do this itself [99].

iii. Product Generation Engineering (PGE) and Model-Based System Engineering (MBSE)

Albers et al. [72] propose a technique for modelling interdependencies which seeks to leverage the potential of Industry 4.0 technology. This technique analyses relevant product and process system characteristics using a three-level matrix to generate a comprehensive knowledge base. Subsequently, a PGE model is utilised to determine the effects of process parameters and the risk associated with their utilisation. Finally, MBSE is used for ascertaining relationships between process characteristics at the early stages of the process. Despite the effectiveness of this approach, Albers et al. [72] mention it is worthwhile noting that a limiting factor is the time-consuming and inconvenient manual extraction of all process parameters and their subsequent entry into the model.

2.4 Optimisation process considering interdependencies

Simulation models are used to analyse complex systems, such as manufacturing processes, that can be challenging to study using traditional analytical methods [100]. Although simulation models are powerful tools for understanding such systems, they can be computationally intensive and require a considerable amount of time to execute [101]. Wang & Boyd [102] mention that simulation models should be designed to run as fast as possible for industrial settings in order to ensure a high level of accuracy and efficiency. Therefore, in this section, strategies and techniques were discussed for significantly optimising simulation models considering interdependencies to make them more efficient and effective.

2.4.1 **Model optimisation**

Model optimisation approaches are techniques used to improve the performance and accuracy of machine learning models, as shown in Figure 2.9. Thompson et al. [101] point out that model optimisation is an important aspect of machine learning as it can significantly improve the model's ability to make accurate predictions on new, unseen data.

The choice to integrate parallel computing, analytical models and supervised machine learning as part of a model optimisation approach was based on a thorough analysis of existing literature (further explore in sections 2.4.1 A, B and C). These selected techniques provided adaptable approaches for optimising models. They allow for an understanding of system dynamics, scalability in handling large scale simulations and the ability to capture complex relationships between variables. By utilising these recognised and validated techniques, a strong foundation can be established for this research ensuring that the findings are credible and rigorous.

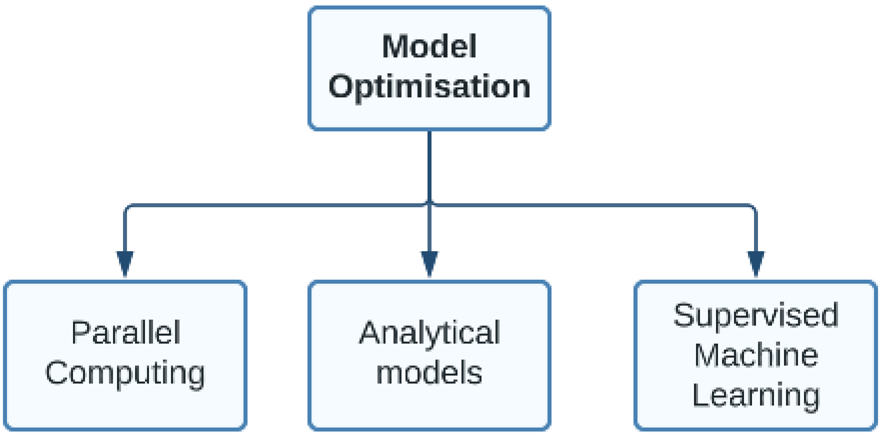


Figure 2.9. Flowchart of model optimisation approaches that consider interdependencies.

A. Parallel computing

Parallel computing has greatly impacted scientific research by reducing simulation time and speeding up the pace of research. It enables processing of a single task in multiple threads, leading to more complex simulations being run in shorter periods of time [103]. Furthermore, parallel computing technology allows multiple cores to work on the same task simultaneously, leading to an increased number of simulations run in a shorter timeframe. Eddelbuettel [104] explains that this has allowed researchers to quickly test and analyse research scenarios and make more informed decisions. One example of its application is provided by Deepak et al. [103] where an assembly sequence simulation time was reduced by a factor of ten by implementing parallel computing, leading to faster design iterations and better product performance. Another study is presented by Skowron et al. [105] in which they developed neural detectors and classifiers to help them enable an automatic model to distinguish between the stator and rotor winding faults for supplying various voltage frequencies and load torque values. By using parallel computing, the computing time was reduced by 50% compared to a sequential algorithm.

B. Analytical models

Analytical models are a cost-effective and time-saving approach used in research to understand the behaviour of complex systems or problems [65]. They use mathematical equations to describe the behaviour of a system, enabling researchers to identify important features and trends, debug and refine simulations, investigate the system under different conditions, and predict behaviour without running simulations. Analytical models have been applied in various fields, including the thermal analysis of stators in EM [106]. Studies have shown good agreement between the results of analytical models and experimental data, demonstrating their accuracy [107]. They have been used to optimise the cooling systems of stators, improving their cooling performance and reducing maximum temperatures [41].

Analytical models are used to optimise a system based on mathematical computations but have several limitations. They rely on simplifying assumptions that may not fully capture the complexity of the system, are computationally expensive and time-consuming to develop, and may be limited in their ability to capture dynamic changes in the system [65]. Abdulah et al. [108] mention that they may also require large amounts of data to develop and validate, and be limited in their ability to account for uncertainty in the system being modelled.

C. Supervised Machine Learning (SML)

SML algorithms are becoming increasingly popular in the manufacturing process of EMs, particularly in the production of stators [109]. This is because these algorithms can model the interdependencies between variables, which affect the quality and efficiency of the final product [90]. Singh et al. [90] describe that by using a labelled dataset to train a model, the best performing design can be selected, reducing the time and effort required for optimisation and selection. Echoing this idea, Chen [110] makes the case that SML algorithms can also identify the key parameters that affect the quality and efficiency of the final product, thereby improving the accuracy of predictions.

SML has been used before in EMs as an efficient model optimisation technique with multiple examples such as the one provided by Chen et al. [121] in which SML was implemented to obtain the optimal design and performance of a double stator with a multi-excitation flux-switching machine. Another example was provided by Prajapat et al. [83] where the key parameters affecting the quality of the final product were identified using a DT model that was trained on a dataset of a turbine assembly. Overall, SML algorithms present several benefits in the EM manufacturing process as previously discussed, but they also have some limitations. A major limitation is mentioned by Parekh et al. [112] in which a large, labelled dataset is required to train the model, and the accuracy of the model depends on the quality of the labelled dataset.

Supervised learning paradigms

Supervised learning paradigms are techniques that involve training a model on data to predict or classify future observations, as shown in Figure 2.10. In supervised learning, the model is trained on a dataset that includes both input data and the corresponding output data or labels [90]. The goal is to learn a mapping between the input data and the output data to predict or classify future observations accurately [110].

One of the most common supervised learning paradigms is regression analysis, which involves predicting a continuous numerical output variable based on one or more input variables. Another popular supervised learning paradigm is classification, which involves predicting a categorical output variable based on one or more input variables. Regression and classification models were selected because they have proven to be effective in supervised learning scenarios [90]. In supervised learning the models learn from labelled data to make

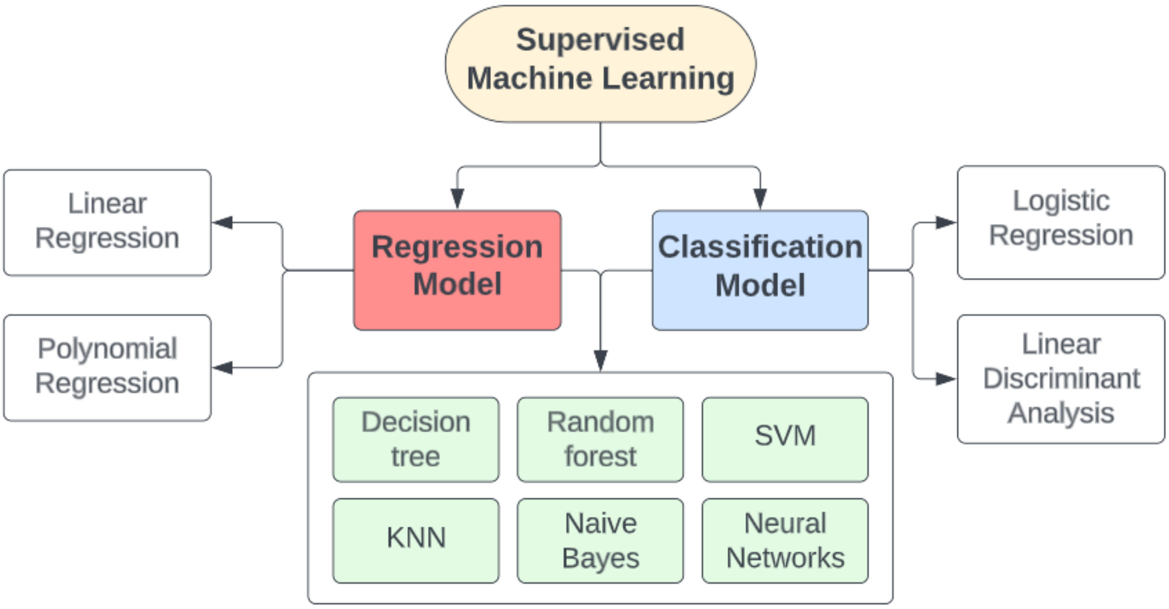


Figure 2.10. Flowchart of the most common SML paradigms.

predictions or classifications. Although there are other techniques available, for example, clustering algorithms for unsupervised learning or reinforcement learning for sequential decision-making [113], regression and classification were chosen as they are capable of handling both continuous and categorical output variables. This choice aligns well with this research objectives and characteristics of the dataset.

Regression model

A regression model in SML predicts a continuous numerical output based on one or more input variables. It uses algorithms like linear regression, polynomial regression, and support vector regression to learn a mapping between input and output data for accurate predictions on new data. Regression models are easy to interpret and can handle both linear and non-linear relationships, but they often assume a linear relationship which may not always be accurate [90]. The quality of their predictions depends heavily on the quality and representativeness of the input data.

In the realm of EMs, regression models are used to identify dependencies and predict energy consumption, aiding energy optimisation efforts [113]. Common models used include linear regression, Support Vector Machines (SVM), Random Forest (RF), and XGBoost [90]. They can predict electric load and consumption in buildings, helping with energy-saving initiatives.

However, these models face challenges relating to data quality, complexity of factors influencing energy consumption, scalability, linearity assumption, and model selection. Data pre-processing is essential to ensure the validity of regression models, and, as the number of variables increases, the reliability of regression models decreases. Therefore, choosing the appropriate regression model for a specific application can also be challenging.

Classification model

A classification model in SML predicts a categorical output variable based on one or more input variables. It aims to learn a mapping between input and output data to accurately classify new, unseen data. In the context of EMs, classification models are used to detect and identify electrical appliances in real-time based on their electrical parameters [7]. These models aid in monitoring and controlling the operation of electrical devices, improving energy efficiency and reducing consumption [113]. They can also analyse the driving power and dependence of power infrastructure components, like substations, to support network analysis and management. Furthermore, they can be used in the design and application of EMs, helping to optimise performance and ensure reliability.

Classification models have the advantage of handling categorical output variables with multiple categories and non-linear relationships between input and output variables [47]. However, they require a large amount of labelled data for training, and the quality of predictions is highly dependent upon the quality and representativeness of the input data.

i. Popular supervised learning algorithms

Supervised learning algorithms have many applications, including predicting customer behaviour, detecting fraud, image classification, and natural language processing [90]. They can learn complex patterns in data and make accurate predictions or classifications. However, Chen [110] discussed that they require a large amount of labelled data for training and can be susceptible to overfitting if the model is too complex or if the training data is too limited. Some of the most popular SML algorithms include DT, RF, SVM, K-Nearest Neighbours (KNN), Naïve Bayes (NB) and neural networks.

The decision to use DT, RF, SVM, KNN, NB and neural networks to model interdependencies in the manufacturing process of electrical machines was based on their proven effectiveness, versatility and applicability across a wide range of data scenarios (expand upon in this section). After conducting an extensive literature review research and examining real world evidence [90],[110-113], these algorithms were found to be a well-rounded choice because they offer interpretability, accuracy, versatility, performance and the ability to handle complex relationships. This ensures an approach to modelling interdependencies while maintaining computational efficiency. Hence, these algorithms were selected as the suitable options for capturing the diverse and intricate interdependencies during the manufacturing process of electrical machines. In addition, it is important to note that as the field progresses, new or more advanced algorithms may be considered for future research endeavours.

Decision trees (DT)

DT are a form of machine learning that is used in electrical machine simulations to reduce simulation times and improve accuracy [114]. By classifying and predicting outcomes based on data, DT can determine optimal operating conditions for EM more efficiently than traditional methods [114] [115]. They also provide a visual representation of the machine's behaviour and interactions between components, enabling engineers to make informed decisions and improve efficiency. Several studies have applied DT in stator manufacturing for fault prediction with high accuracy and better understanding of the underlying process mechanisms [116]. Despite its advantages, Géron [115] describes that DT can suffer from overfitting and bias towards dominant classes, and researchers can use ensemble methods to improve performance.

Random Forests (RF)

RF is a machine learning approach that can be used to speed up the simulation of EMs, such as stators, by providing accurate predictions of the system's behaviour in various conditions [117]. RF are a collection of DT that analyse the behaviour of the system from different viewpoints and identify the most important features for predicting that behaviour. By combining and weighing the predictions of the individual DT, an accurate and faster prediction of the system's behaviour can be obtained, reducing the simulation time of the stator [90]. As Peña-Graf et al. [118] describe, RF also identify outliers in the data and can be used to identify which parameters have the most impact on the system's behaviour, allowing for better understanding and design optimisation.

In a study by Marinov et al. [117], a RF algorithm was applied to decision making when designing power electronic converters, and achieved an accuracy of 97.45%, outperforming other machine learning algorithms. It has also been used for process simulation in stator manufacturing to identify potential problems and optimisation opportunities. In a study by Thornton & Edward [113], a RF model was developed to simulate the winding process of a stator in an electric induction motor, with excellent results, showing comparable outcomes when validated against actual manufacturing data. However, RF require a large amount of data and can be computationally intensive, and the interpretability of the model may be reduced.

Support Vector Machines (SVMs)

SVMs are a popular technique capable of reducing the number of simulation iterations required by producing a more accurate model, leading to a reduced number of simulations for refinement [90]. The improved accuracy of the model also allows for more accurate performance predictions and better decision-making during the design process. SVMs can also reduce computational time by using algorithms such as kernel methods. Géron [115] explains that they are capable of predicting the stator's behaviour in different operating environments and under varying loads, further reducing the time and resources required for simulation.

SVMs have been applied in several studies for stator fault prediction and efficiency prediction. For example, Cano-Lengua et al. [119] used an SVM-based model for stator winding inter-turn short circuit fault diagnosis, achieving a high accuracy of 96.15%. Géron [115] discusses the use of an SVM-based method for diagnosing stator winding faults in permanent magnet synchronous motors, while, in comparison, Singh et al. [90] used SVMs to predict the efficiency of stator windings in an axial flux permanent magnet synchronous motor with high accuracy.

K-Nearest Neighbours (KNNs)

A KNN algorithm is a data mining technique that is used to reduce simulation time and improve the accuracy of results. It works by finding the k-nearest neighbours to a test point in a dataset and using those neighbours to approximate the desired output. KNNs have been used in several studies to predict winding temperature and classify stator faults [120]. The algorithm outperformed other machine learning models, such as Artificial Neural Networks and SVM, in the prediction of winding temperature [121]. Similarly, it was able to accurately classify stator faults based on vibration signals [122]. However, KNNs have some limitations, including the requirement for a large number of training examples and poor performance in high-dimensional spaces, which need to be considered when applying the algorithm in practice [123].

Naïve Bayes (NB)

NB algorithms are used to reduce simulation time and improve accuracy by quickly identifying the most important parameters. The algorithm uses Bayesian probability theory to identify the most significant parameters and exclude those that have the least impact on the output [116]. The algorithm's simplicity and fast training time make it suitable for real-time applications like fault diagnosis [115]. However, the accuracy of the classifier depends on the quality and quantity of input data and the assumption that the input features are independent of each other may not be true in some cases. Studies have shown that NB algorithms provide more accurate results and are effective in diagnosing different types of faults in stator windings in induction and permanent magnet synchronous motors [116].

Artificial Neural Networks (ANNs)

ANNs are a type of artificial intelligence that can be used to simulate the behaviour of electrical systems, such as stators, to reduce the simulation time [28][90]. ANNs can learn the relationship between electrical parameters and the stator behaviour, allowing for real-time approximation. The use of ANNs for simulation time reduction is a novel application of AI and has the potential to significantly reduce the time required for simulating complex electrical systems [90]. However, ANNs have a high computational cost, can be considered black boxes, and are susceptible to overfitting [91]. Researchers should consider these limitations when applying ANNs to real-world problems.

ii. Performance Metrics and Evaluation

In SML, the performance of a model is usually evaluated using various performance metrics that are appropriate for the task at hand and the type of problem being solved. Some of the most commonly used performance metrics for SML algorithms are presented in Table 2.4 [90] [91].

Table 2.4. Performance metrics employed during SML to evaluate the model’s performance and accuracy [125].

Evaluation Metric	Description
Accuracy	It is the most commonly used performance metric and is simply the ratio of the number of correct predictions made by the model to the total number of predictions. It is a good metric for balanced datasets but can be misleading for imbalanced datasets.
Confusion Matrix	A table summarises the performance of a classification model by showing the number of true positives, false positives, true negatives, and false negatives. The confusion matrix provides a more comprehensive view of the model's performance, including its ability to make correct and incorrect predictions.
Precision	It is the ratio of true positive predictions to the total number of positive predictions made by the model. It measures the model's ability to avoid false positive predictions.
Recall	It is the ratio of true positive predictions to the sum of true positive and false negative predictions. It measures the model's ability to detect all positive instances.
F1-Score	It is the harmonic mean of precision and recall. It provides a balance between precision and recall and is a good metric to use when both precision and recall are important.
ROC Curve and AUC	ROC Curve is a plot of the true positive rate against the false positive rate for different threshold values. AUC is the area under the ROC curve and provides a single number summary of the model's performance.
Mean Squared Error (MSE) and Mean Absolute Error (MAE)	These are common performance metrics for regression problems, where the goal is to predict a continuous numerical value. MSE and MAE measure the difference between the true values and the predicted values.

These are some of the most commonly used performance metrics in SML. The choice of metric depends upon the type of problem being solved and the desired trade-off between accuracy and other factors, such as precision, recall, and computational cost.

2.4.2 **Process optimisation**

Process optimisation refers to the action of improving a specific process to achieve the desired outcomes more efficiently, effectively, and reliably [124]. Duan et al. [125] suggest that the winding process in an EM can be considered a multi-objective optimisation problem because it involves several parameters that need to be optimised simultaneously. The winding process needs to balance several objectives, including achieving the desired magnetic field, minimising energy consumption, reducing fault rates, and improving efficiency [5].

A multi-objective problem refers to a situation where multiple, conflicting objectives must be optimised simultaneously. This type of problem is common in real-world applications, including in EMs regarding stators [111][125]. Optimising the design of a stator, for instance, requires balancing multiple objectives such as reducing weight, increasing efficiency, and maintaining structural integrity. These objectives are often interdependent and require trade-offs to find the optimal solution.

The process optimisation of stators focuses on finding a set of solutions that balance multiple objectives such as reducing manufacturing costs, decreasing fault creation, and improving process efficiency. Solving multi-objective problems can be challenging as the objectives may conflict and be difficult to balance [126]. Costantino et al. [127] point out that traditional optimisation techniques, such as linear and non-linear programming, are not suitable for these problems as they can only optimise a single objective.

Specialised techniques, such as multi-objective optimisation algorithms and metaheuristics, have been developed to address this challenge. The optimisation problem can be approached using various techniques, as shown in Figure 2.11, including evolutionary algorithms or scalarisation, which aim to find a set of non-dominated solutions that represent a trade-off between conflicting objectives.

This research meticulously considered and selected these process optimisation techniques, based on its proven effectiveness in addressing optimisation challenges [125-127]. These challenges include converting multi-objective problems into single objective ones, evaluating alternative solutions systematically, identifying patterns, combining multiple approaches and dealing with conflicting objectives. Moreover, these techniques offer adaptability to optimisation scenarios. Furthermore, their track record of success in research studies and

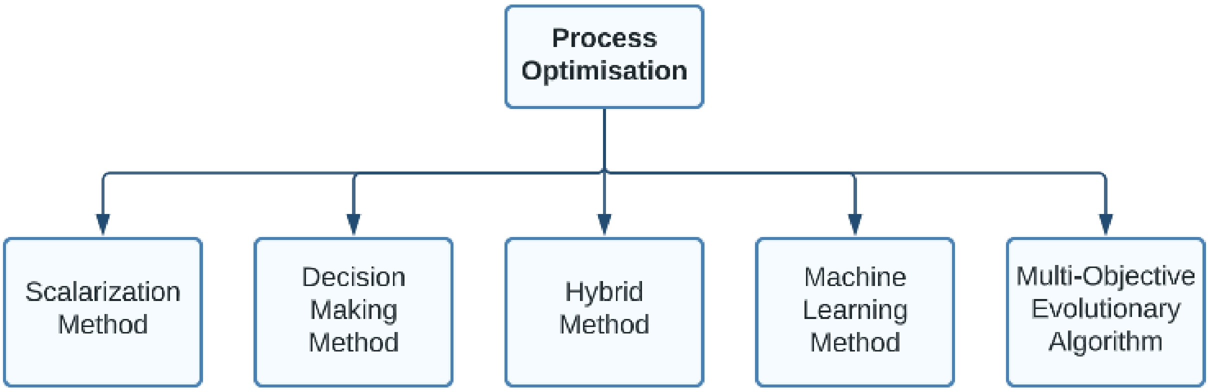


Figure 2.11. Diagram of multiple approaches for process optimisation when dealing with a multi-objective problem.

practical applications (more insight offer in this section) offers confidence in their capability to provide outcomes. Lastly, by combining these techniques it is possible to address optimisation challenges using a holistic view to achieve efficient solutions.

A. Scalarisation method

This method converts a multi-objective problem into a single objective problem by defining a scalarisation function. The most popular scalarisation method is the weighted sum method (WSM). The WSM is a commonly used approach for solving multi-objective problems by aggregating multiple objectives into a single objective function by assigning weights to each objective [128]. WSM has been applied to optimise stator design, balancing conflicting objectives such as minimising weight and cost while maximising efficiency and structural integrity [129].

Several studies have shown the effectiveness of WSM in optimising stator design [129], [130]. However, WSM has limitations, including difficulty in selecting appropriate weights for the objectives and difficulty in handling non-convex or non-linear problems [129]. To address these limitations, modifications such as the use of multi-objective evolutionary algorithms and fuzzy decision-making approaches have been proposed to improve the performance of WSM [131].

B. Decision-making method

Decision-making methods are techniques used to solve multi-objective problems by determining the best solution among a set of alternatives. They can be based on mathematical models, expert judgment, or both. Common approaches include multi-criteria decision-making

(MCDM) methods [62], which help weigh the relative importance of conflicting objectives, and multi-objective decision-making (MODM) methods [61], which use various techniques to find optimal solutions. Data-driven approaches, like machine learning, can enhance these methods by incorporating historical data to improve accuracy. Decision-making methods offer a systematic and structured approach to problem-solving and can be customised to suit each problem and decision-maker's needs.

C. Hybrid methods

Hybrid methods combine multiple optimisation techniques to solve multi-objective problems, leveraging the strengths of different methods to overcome individual limitations. Techniques such as genetic algorithms, particle swarm optimisation, and artificial neural networks can be combined for improved performance [132] [133]. Hybrid methods efficiently and effectively solve multi-objective problems, addressing trade-offs between competing objectives and handling complex, non-linear relationships [134]. They can manage problems with multiple constraints and uncertainties by incorporating various optimisation techniques suited to different problem types. Hybrid approaches provide robust and accurate solutions in various applications, including the optimisation of EM like stators [135].

D. Machine learning methods

Machine learning methods offer a computational approach to solve multi-objective problems by optimising multiple conflicting objectives, applicable to real-world situations such as stator design in EMs [39]. These algorithms learn from past data, identifying patterns and making predictions about system behaviour, which aids in optimising objectives like cost reduction and efficiency increase [116]. Techniques like DT or neural networks can determine optimal design parameters, considering trade-offs between conflicting objectives.

Reinforcement learning can optimise system behaviour by learning from past actions to make decisions that maximise a set of reward functions [90]. Combining machine learning with multi-objective optimisation algorithms can lead to more sophisticated problem-solving methods [136]. However, machine learning methods can also pose challenges, such as the need for large data amounts, difficulties in interpreting complex models, and the risk of overfitting to the training data [137].

E. Multi-Objective Evolutionary Algorithms (MOEAs)

MOEAs are a class of optimisation algorithms that are designed to solve multi-objective problems. MOEAs are based on the principles of evolutionary algorithms and genetic algorithms, which mimic the process of natural selection to find an optimal solution [135]. MOEAs are specifically designed to handle multiple conflicting objectives and generate a set of non-dominated solutions that represent a trade-off between the conflicting objectives. The non-dominated solutions are known as the Pareto front and provide a comprehensive representation of the trade-off between the objectives [138].

In the context of multi-objective optimisation, MOEAs can be used to find the optimal trade-off between multiple conflicting objectives. For example, in the design of EM such as stators, MOEAs can be used to minimise weight and manufacturing costs while maximising efficiency and structural integrity [111] [139]. MOEAs can also handle complex and non-linear relationships between objectives, which makes them well suited for solving multi-objective problems [126].

MOEAs use various strategies such as selection, crossover, and mutation to generate a new population of solutions [140]. The solutions are evaluated based on their performance with respect to the objectives, and the best solutions are selected for the next iteration. This process continues until a satisfactory set of non-dominated solutions is found. The use of MOEAs can provide a comprehensive representation of the trade-off between conflicting objectives, making it easier to identify the best trade-off for a particular application [135]. Overall, MOEAs are a powerful tool for solving multi-objective problems and provide a comprehensive representation of the trade-off between conflicting objectives.

i. Multi-Objective Optimisation Techniques

Multi-objective optimisation techniques can optimise complex systems with multiple objectives to be met simultaneously, such as EM that require efficiency, reduced losses, and minimised noise and vibrations [141]. Such machines have complex interdependencies between different parameters, requiring optimisation techniques that consider them simultaneously. Examples include NSGA-II, SPEA2 and MOEA/D as shown in Figure 2.12, which use mathematical models to simulate machine behaviour and optimise design parameters

[136][142]. Multi-objective optimisation techniques can handle trade-offs between different objectives and interdependencies between parameters, leading to more optimised designs.

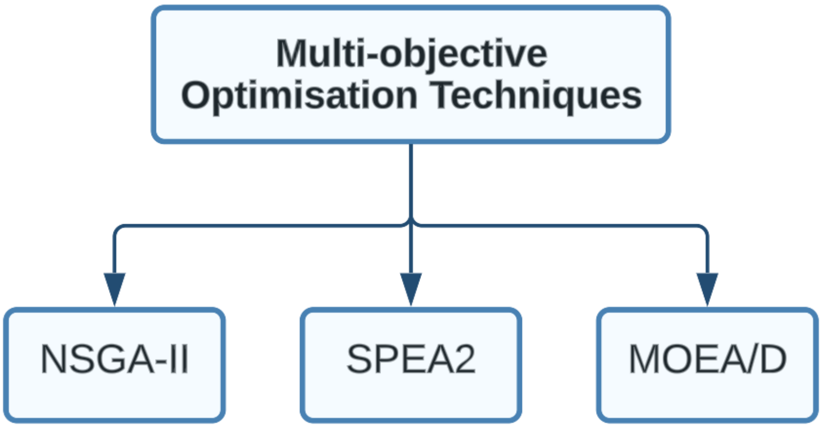


Figure 2.12. Diagram of the optimisation techniques used in multi-objective problems.

However, they can be computationally expensive and rely on the accuracy of mathematical models [143].

The selection of techniques such as NSGAII, SPEA2 and MOEA/D were chosen over other algorithms in this field was because they have shown to be effective when dealing with problems that involve multiple objectives [138],[141-143]. These algorithms helped in generating solutions that are robust and can effectively balance conflicting goals. They have also been proven to perform effectively in generating Pareto optimal solutions, which provides valuable insights, into complex optimisation scenarios and allows decision makers to explore different trade-offs productively.

Non-Dominated Sorting Genetic Algorithm II (NSGA-II)

The NSGA-II, a multi-objective optimisation algorithm based on the genetic algorithm framework, is widely used in stator manufacturing research. The algorithm has been applied to optimise the design of stator winding for various types of EMs, as demonstrated in studies by Thornton & Edward [113] and Malagoli et al. [144]. In Thornton & Edward's [113] study, an NSGA-II was used to balance multiple objectives, such as torque, efficiency, and power factor during the inspection of apparatus with high flexibility for permanent magnet synchronous motors.

The algorithm was successful in finding multiple Pareto-optimal solutions that met the desired objectives. Similarly, in Malagoli et al.'s [144] study, an NSGA-II was successfully applied to a stator as part of an asynchronous machine to obtain the optimal design variables and therefore minimise the cost of materials, taking into account multiple objectives including torque, efficiency, and flux-weakening capability. The results showed that the NSGA-II was able to identify the optimal winding configuration that achieved the desired trade-off between the conflicting objectives.

Strength Pareto Evolutionary Algorithm (SPEA2)

An SPEA2 is a multi-objective optimisation technique that has the objective of finding a set of Pareto-optimal solutions, where one solution cannot be improved in one objective without sacrificing performance in another objective [143]. The algorithm works by maintaining a population of candidate solutions and using a fitness function to evaluate each solution's performance. Through selection, crossover, and mutation operations, the population is evolved over multiple generations to reach the optimal set of solutions. Nevertheless, the "niching" problem, which describes how challenging it is to keep a variety of solutions across the Pareto front, is one prominent drawback. Despite the fact that SPEA2 employs a density estimation approach to promote diversity, it could still have trouble keeping a diverse population of solutions. This might result in the loss of some of the Pareto front, particularly if the Pareto front is complex or discontinuous.

An SPEA2 has been used in stator manufacturing research to optimise various design aspects, such as slot configurations and winding layouts. For example, Frutos et al. [143] used an SPEA2 to optimise the operations scheduling under machine availability constraints of a permanent magnet motor. Liu & Zhang [145] improved the SPEA2 algorithm with a local search for multi-objective investment decision-making with an application to permanent magnet synchronous motors. In both studies, the SPEA2 was able to identify multiple Pareto-optimal solutions that achieved the desired objectives [145].

Multi-Objective Evolutionary Algorithm Based on Decomposition (MOEA/D)

A MOEA/D is a well-regarded multi-objective optimisation algorithm that relies on decomposing the objective functions into smaller sub problems. It has been utilised in research on EM to optimise various aspects such as the design, slot configuration, and material selection [152]. For instance, Farnsworth et al. [152] applied a MOEA/D to optimise the design of a programmable microelectromechanical bandpass filter, while Garcia & Trinh [146] utilised a MOEA/D to optimise the modular cell design. Garcia & Trinh [146] point out various limitations with this algorithm such as it demonstrates sensitivity to its parameters and scalability issues, especially with an increasing number of objectives, and it struggles to maintain diverse solutions for problems with complex Pareto fronts. It also exhibits dependency on the decomposition method used, faces challenges in handling complex constraints and dynamic problems, and can demand significant computational resources, particularly for high-dimensional or many-objective problems.

2.5 Challenges encountered during stator manufacturing

The production of an EM requires the fabrication of a stator, but issues may arise during the manufacturing process due to various factors such as material selection, machining accuracy, lamination quality, coil winding accuracy, assembly quality, and testing reliability [3]. Poor lamination quality can lead to excessive electrical losses and weakened mechanical integrity, while incorrect coil winding can result in lower efficiency and increased sound levels [20]. Additionally, unreliable testing can lead to incorrect measurements and hinder optimal performance [21].

Sell-Le Blanc et al. [22] pointed out that these issues can significantly affect the stator's performance, resulting in reduced efficiency, increased electrical losses, weakened mechanical strength, and the production of higher sound levels. Therefore, as Yang et al. [23] mention, it is crucial to address these issues during the manufacturing process to ensure the stator's efficient and reliable operation.

Deformable material

Deformable materials, such as copper wire, play a significant role in the production of EMs [1]. These materials possess mechanical properties that enable them to be easily shaped and bent into specific forms during the manufacturing process, allowing them to be wound tightly around a stator core or other components [24]. Komodromos et al. [25] stated that the deformability of these materials is due to their inherent ductility and malleability, which allow them to withstand the forces involved in the winding process without breaking or cracking. Sell-Le Blanc et al. [26] pointed out that the mechanical properties of these materials can be influenced by various factors such as the type and purity of the material, the temperature of the environment, and the specific manufacturing techniques used. Understanding the properties of these materials is crucial for ensuring the efficient and reliable operation of EMs [27].

Coil winding is a complicated process used during the fabrication of stators that involves winding the copper wire onto the stator core while maintaining the wire's integrity [3]. The copper wire's capacity for ductility and deformation is essential in this process. However, the deformation of copper wire can cause issues in the winding process, leading to high electrical resistance or reduced efficiency as discussed by Hagedorn et al. [3]. To prevent these issues, several techniques have been proposed, including annealing, lubrication, variate winding tensions, and dynamic deformation methods [3][28]. Proper maintenance and inspection of the coils are also crucial in identifying any deformation issues and preventing further damage [19]. Overall, properly managing copper wire deformation during the winding process is crucial to achieve optimal performance from the EM [4].

Modelling interdependencies

Interdependencies, within electrical manufacturing processes present a challenge as they necessitate an understanding of how input parameters and process outputs relate potentially leading to faults [3]. Specifically in the fabrication of components such as stators, there are interconnected stages involved, such as the insertion of copper wire into coils. The key challenge lies in comprehending how these interdependencies impact the outcome and identifying any signs of trouble before faults arise. Additionally, processes involving deformable materials further complicate matters since alterations made during steps can have repercussions on subsequent ones. Modelling processes while accounting for the time-based dependencies within each step is indeed complex. An example would be coil winding, where the shape of the copper wire undergoes changes throughout the process due, to these interconnected relationships.

Reduction of End of the Line tests

The current quality tests known as the EoL tests, which are typically used to identify faults during the manufacturing of stators have proven to be inefficient and result in increased costs and longer production times [1]. Particularly when it comes to identifying faults in materials, like copper wire, traditional techniques face challenges [4]. The reason for this difficulty lies in the dynamic nature of deformation the fast pace of manufacturing as well as the presence of subtle internal defects. Additionally, limitations in sensor technology and the absence of models further complicate matters. Moreover, when it comes to using machine learning for fault detection in scenarios there are obstacles to overcome. These include a lack of training data issues with overfitting and difficulties, in dealing with non-linear deformable processes.

Multi-objective optimisation involving interdependencies

The use of a multi-objective approach in linear winding processes involves various interdependencies that lead to complex cause and effect relationships. As a result, making adjustments and optimising the process becomes challenging [6]. Finding the balance between reducing production costs and minimising faults is also difficult because improvements in one aspect may have negative consequences elsewhere. Additionally, there are constraints related to the achievable speed and wire gauge, which limit the range of possible solutions and impact the optimisation process. Lastly selecting a suitable algorithm, for research poses a challenge since there is no universal solution that fits all scenarios, and each algorithm comes with its strengths and weaknesses.

2.6 Research Gaps and developed solutions

This section aims to identify research gaps in the field of fault detection and parameter optimisation in production processes for EM where interdependencies has a major influence. The purpose is to provide a foundation for future research to address the limitations of existing research and develop more advanced and integrated approaches to improve the efficiency, reliability, and quality of EM manufacturing processes. The role of interdependences is crucial in this field, and research gaps has been identified with this in mind.

Gap 1: Firstly, there is a lack of understanding and effective methods when it comes to identifying and implementing techniques that can accurately determine the characteristics of processes in the manufacturing of EM especially when dealing with defects or errors. In particular, the ability to detect the connections between factors that result in defects further, down the line is still not well developed and has not been adequately addressed.

Solution 1: To address this identified gap and the first objective of this thesis (section 1.4), the existing literature offers techniques like Precedence Graphs, Liaison Graphs, Petri Nets and Graph Data Models [57] [59] [61]. This work utilised the Precedence Graph technique because it provides a visualisation of the system and the order of activities, which is crucial for understanding interdependency behaviour. To decompose activities, it is necessary to begin with those related to the material specifically the copper wire coil. The purpose of the graph data model was to extracted process parameters and faults from existing literature. By analysing the graph, interdependencies between input parameters and faults were uncovered. Each fault was then ranked using severity, occurrence and detection scales to reveal how interdependencies affected outputs during coil winding. Insights were gained into how interdependencies manifested at stages of a process and may contribute to faults.

Gap 2: Another gap was a need for modelling techniques that can effectively capture the complex relationships between different parameters, in the manufacturing process. Additionally, these techniques should be capable of providing real time predictions on the likelihood of defects occurring. Attempts have been made to model the behaviour of deformable material and its interdependencies during manufacturing [89]. However, these attempts often focus on specific steps rather than analysing the entire sequence to identify relationships.

Solution 2: To study the interdependencies in a process involving deformable materials, a framework that utilises a DES approach was developed. The simulation model focussed on the process of noncircular orthocyclic coils in a linear manner. The DES model has the capability to identify faults and areas with higher resistance known as "hotspots". To validate the DES model accurately, experiments were conducted on a linear coil winding machine. Thanks to this model, the second objective of this thesis (section 1.4) was achieved, which focuses on creating a modelling framework to gain insights, into how different process variables interact and impact the occurrence of defects in processes involving materials that can be deformed. This solution enables an examination of the process by simulating interactions and optimising parameters leading to a reduction in defects and improved efficiency, in EM.

Gap 3: There is a lack of research on how the developed framework can be integrated with a SML approach. This integration was anticipated, to allow for predicting the state of a component and reducing the time needed for online quality control tests by identifying how different factors, within the process affect each other. Numerous studies have explored ways to address the gap that was identified earlier. In the manufacturing industry, it is practice to conduct multiple quality tests after each step to identify any faults or defects [9].

However, this approach can be costly and time consuming. Traditional tests for coil quality often involve using Dowell’s equation and winding resistance tests to spot anomalies in resistance [3]. While these methods can be effective, they require an amount of time and expertise. Additionally, pattern recognition has been used to detect coil faults [99]. It does not consider outputs from previous manufacturing steps, which indicates a gap in existing research. These attempts have been valuable and underscore the need for a more integrated and efficient approach to detecting faults and ensuring quality control, in manufacturing processes.

Solution 3: The proposed approach utilised a KD approach combining the DES model with a SML algorithm. It aims to overcome challenges in KD by using architecture search and data augmentation methods to enhance the generalization capabilities of the student model (SML algorithm). By employing the DES model to generate training data for the SML algorithm this framework greatly improves fault detection and prediction in machine manufacturing. Therefore, achieving the third objective of this research (section 1.4) which focus on combining the known framework, with a supervised learning algorithm in order to enhance the effectiveness and dependability of quality control tests. By predicting the states of components and taking into account the interdependencies, within the process.

This framework holds promise, for reducing manufacturing time enhancing stator quality and ultimately improving reliability and safety. Furthermore, the developed framework plays a role, in real time monitoring by potentially being capable of acting as a digital twin. The use of a digital twin as an online model offers several advantages compared to relying solely on offline models such as the DES model. Offline models are valuable for analysis and prediction. However, they have limitations when it comes to real time monitoring and control of the manufacturing process. One significant drawback is their inability to promptly respond to changes or anomalies in the production environment since they are typically updated periodically based on data.

In contrast a digital twin serving as an online model can mirror the actual production environment with great accuracy and provide continuous monitoring and control capabilities allowing for real time adjustments and interventions. To transform the current models into a digital twin, integration with sensors on the actual winding machine would be necessary, enabling real-time data collection and feedback. This aspect could be considered as potential future work, as it would enhance the model's ability to accurately reflect the current state of the manufacturing process. As a result, manufacturers could identify faults and predict outcomes as they happen enabling proactive measures for maintaining quality and efficiency.

Gap 4: Lastly, there is a gap in the literature regarding a multi-objective framework for integrating fault detection and parameter optimisation where interdependencies plays a crucial role in the production processes. There is a need to develop and successfully implement such framework that has the potential to greatly improve the efficiency and effectiveness of manufacturing operations. There are methods available to tackle complex problems at multiple levels, such as evolutionary learning, parallel and distributed algorithms, and the island model genetic algorithm [145]. These approaches have mostly been utilised in design optimisation rather than process optimisation, where a hierarchical approach is necessary.

Solution 4: Evolutionary algorithms, which is a level scheme has demonstrated its effectiveness in optimising multi-objective problems by maintaining some level of independence between populations. To optimise the manufacturing process, it has been proposed to use the NSGA-II algorithm. This algorithm has shown great performance in solving multi-objective problems [123] [153]. The focus with the NSGA-II was on two objectives at both the component and process levels: reducing costs and improving quality.

Taking a multi-objective approach to balance and optimise these objectives within linear winding processes is an innovative solution to challenges faced in this field and solving the last objective of this research, which focussed on establishing a model-based framework for integrated fault detection and parameter optimisation in production processes (section 1.4). In addition, by creating correlation matrices from optimised models, insights into interactions could be gained and assessed how optimised input parameters correlate within resulting system faults. Utilising the NSGA-II algorithm to minimise interdependencies within the system, can aid in enhancing manageability and optimisation while also lowering expenses and mitigating faults.

2.7 Summary

In this literature review, a comprehensive overview of EMs and their components has been provided, with special emphasis placed on the challenges encountered during the manufacturing of the stator when deformable material is involved. Common manufacturing processes have been explored, and the classification of winding faults, as well as the condition monitoring and fault detection techniques prevalent in the industry, have been discussed. To understand the complex interdependencies in EMs, various measuring and modelling techniques, along with simulation strategies, have been analysed.

A detailed study on SML has been presented, with different supervised learning paradigms and the most popular supervised learning algorithms being explored, which have potential applications in enhancing the process optimisation and fault detection in EMs with deformable materials. This literature review lays a solid foundation for the potential development of a novel approach to model the interdependencies in electrical motors, especially where deformable materials are involved. Moreover, an exhaustive examination of process optimisation has been conducted, considering interdependencies. A variety of optimisation techniques, with a focus on Multi-Objective Evolutionary Algorithms like the NSGA-II, SPEA2, and MOEA/D, have been explored, with their merits and demerits highlighted.

CHAPTER III: TECHNIQUES AND METHODS

The goal of this chapter was to provide a detailed understanding of the methodology employed whilst exploring interdependence modelling in an EM manufacturing process involving deformable materials. Three primary frameworks were outlined:

- An interdependency modelling framework was created to further study the interdependencies, by modelling and simulating multiple stages of the coil winding process allowing for the detection of abnormalities in the winding scheme and fault creation scenarios such as increased electrical resistance, commonly known as 'hotspots'.
- A hybrid computational framework for early fault detection in coil winding manufacturing process was created using a KD approach. This framework utilised a KD approach as a method to address the challenges associated with the technique and optimised the student model's performance by employing architecture search and data augmentation.
- A multi-objective optimisation framework involving dependencies was created. This framework dealt with complex issues related to optimal decision-making using advanced multi-objective optimisation techniques as a method that generated solutions while balancing competing priorities simultaneously.

Finally, the last framework was reinforced by implementing a novel correlation analysis method, which identified variable relationships by calculating an interdependency value between different system components. Multiple statistical methods for calculating and interpreting correlation coefficients and testing for statistical significance were also discussed (further discussed in Chapter VII) . The goal of this research was to develop a comprehensive and rigorous methodology composed of multiple frameworks with their own specific methods and techniques that contributed a valuable insight into the field of EMs and interdependencies, promoting further investigation.

3.1 Proposed framework for modelling interdependencies

As new technologies emerge across various industries today, modelling techniques has become increasingly relevant for simulating real-world manufacturing systems and processes. The value of such models lies in their ability to provide insight into how these systems may perform under varying circumstances. Given that there are correlations between input/output characteristics that affect error formation whilst producing goods, they must be taken into consideration whenever building out a digital representation of such environments. Figure 3.1

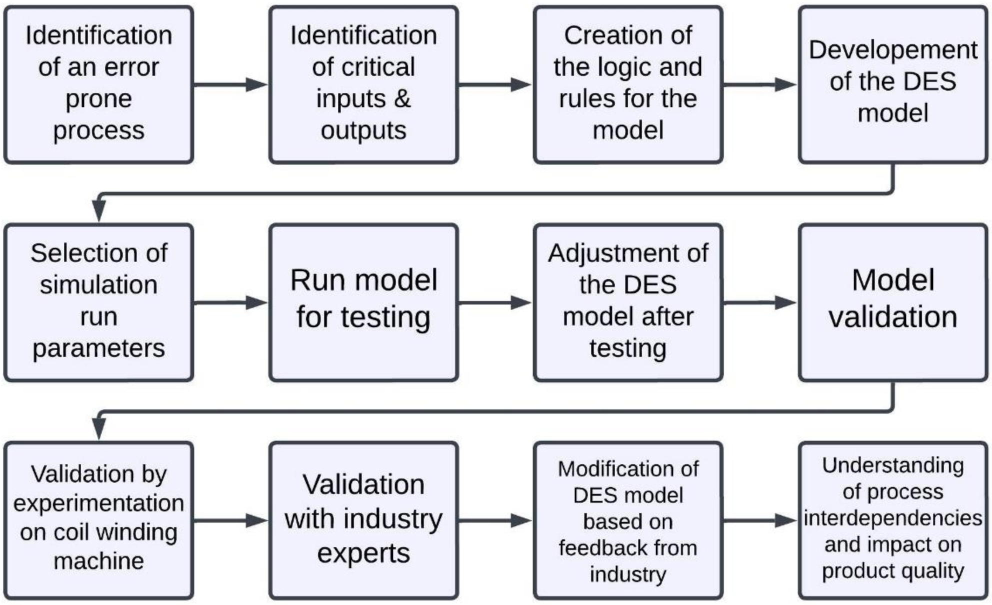


Figure 3.1. Research methodology for developing a framework capable of modelling interdependencies where deformable material was involved.

provided an example of the research methodology used when devising a specific simulation model approach capable of modelling interdependencies.

3.1.1 Identification of an error-prone manufacturing process

A thorough literature review has revealed that producing an EM involves a complex procedure that comprises multiple steps [3][5]. Each phase of production was analysed, even those involving deformable materials. To provide an accurate understanding of the manufacturing process of an EM, a precedence graph was included depicting how each process fits together (Figure 3.2). Despite all key processes involved in an EM's manufacture being shown on this graph, it is worth noting that errors occur most frequently when making stators, requiring them to be looked at more closely.

To better understand these error's origin points during stator production, every manufacturing step in the fabrication of the stator was examined thoroughly – from sheet cutting to the assembly of discrete parts. Copper wire, which is commonly used for making coils and classified as "deformable material", was identified as part of this problem, which gets its shape altered throughout the winding process due to operating tension inputs leading to a defective product [147]. Consequently, the process of coil-winding was selected as the starting

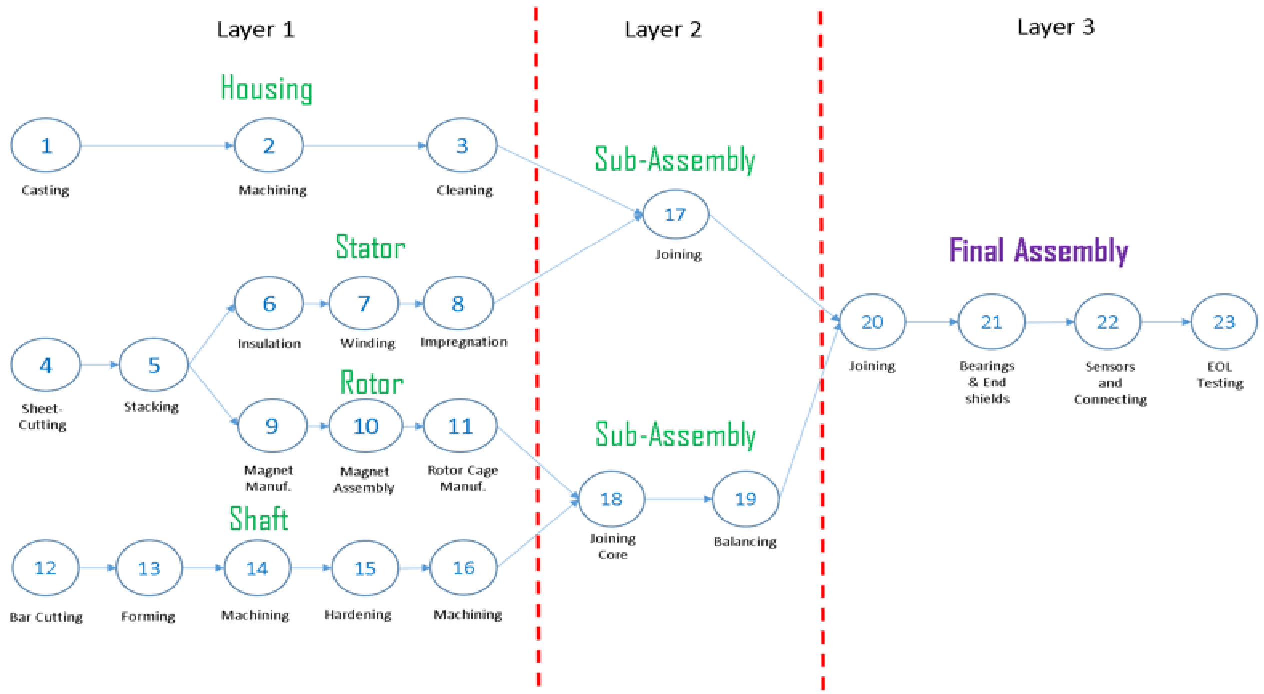


Figure 3.2. Precedence graph of an EM manufacturing process.

point for the identification and elucidation of interdependencies in processes involving deformable material.

3.1.2 Identification of critical inputs & output parameters

Developing a robust simulation model required establishing vital parameters before formulating a convincing logic. An analysis drawn from a precedence graph (Figure 3.2) and a graph network (Figure 3.3) led to four critical input parameters: wire tension, winding speed, wire diameter, and bobbin shape. These variables create intricate interdependencies resulting in errors later in the coil-winding process indicating that a comprehensive understanding of the process parameters and their impact on the copper wire's physical properties was needed to effectively prevent faults during production processes involving deformable materials. Ensuring that the coil diameters remained consistent was essential, for achieving performance. It necessitated monitoring especially to avoid any deviations, in wire properties that could potentially impacted the quality of the product during production.

Furthermore, parameters such as tension and winding speed were established at the onset of the process, yet variations arise due to interdependencies exerting an effect on the wire. A software called *NEO4J* was utilised to analyse system elements and their relationships by using graph diagrams consisting of nodes (circles) and lines representing relationships between inputs and outcomes in the process. A graph diagram showing connections makes it clear that input parameters such as tension are significant in fault production (Figure 3.3). This information can be utilised to design prevention strategies while maintaining connections to other elements within the system. Employing innovative tools such as graph diagrams, that categorise inputs precisely for effective modelling as a strategy, have shown important benefits for this research.

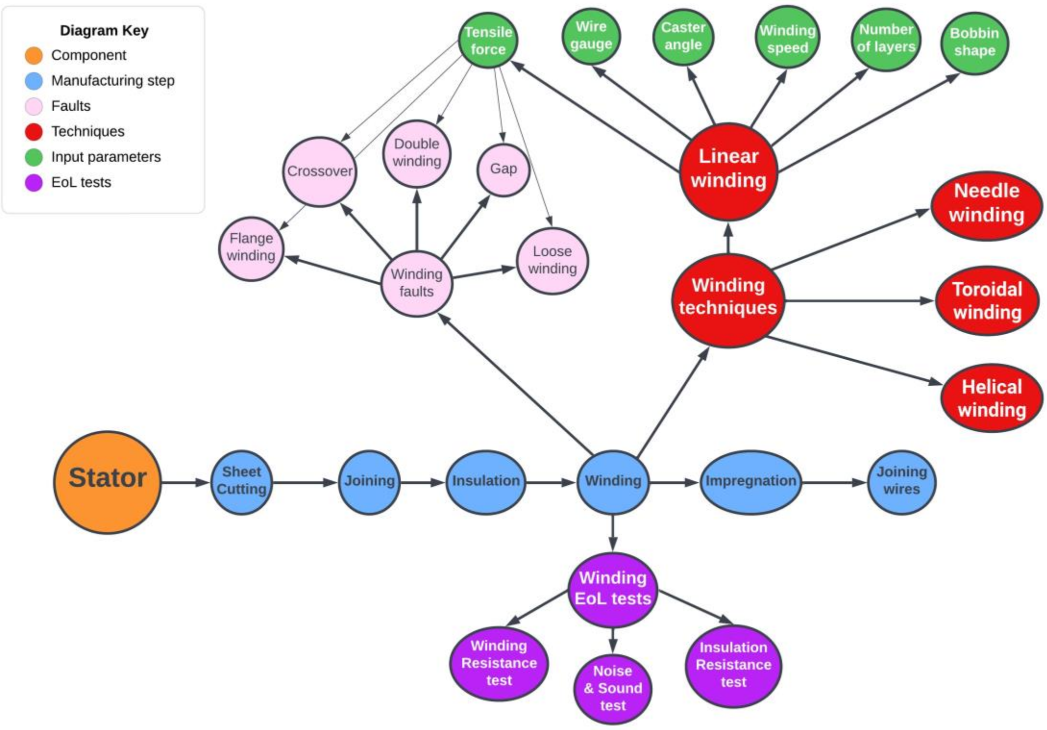


Figure 3.3. Graph diagram of a stator representing the underlying relationship between the input parameters and the creation of faults during the winding step.

3.1.3 Creation of the logic and rules

To identify the causes of faults occurring during winding processes, this framework was guided by relevant literature to represent interdependencies between process parameters and faults during the winding process [5][148]. The corresponding logic developed for this framework was depicted visually through a flowchart, displayed as Figure 3.4. According to Hagedorn et al.'s [5] findings, initial wire touch points with bobbin surfaces cause the most defects among the first five wire layers during windings before later wires become securely set into grooves formed by previous wires layered just below them. Subsequent cycles saw rising tensions too,

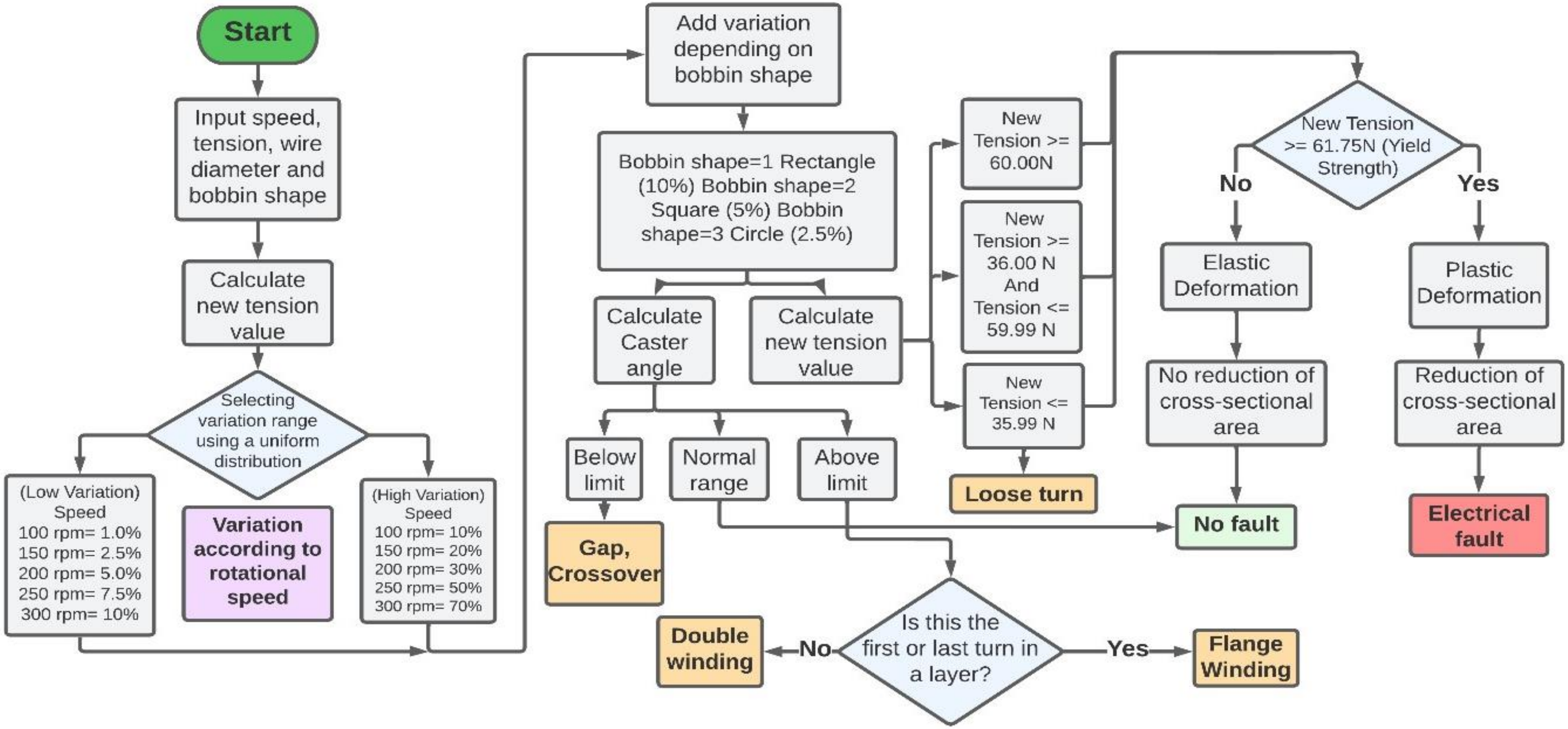


Figure 3.4. Flowchart of the logic used in the DES model that represents a linear winding process.

yielding defects until limits were reached, thus limiting the damage done thereafter on affected coils or their turns, as well depending upon fault characteristics.

Orthocycling design was employed for this research, due to the fact that it is the most popular winding scheme used in the industry, thanks to its high fill factor [5]. The model consisted of five winding layers with each having twenty turns. Each turn applied a variable tension that could either increase or decrease, leading to further faults if exceeding specific yield limits (61.75 Newtons). To overcome these errors efficiently and effectively, a function was embedded within the model to calculate the tension values for every turn in the layer, and to recognise the type of variation (low or high). Elastic deformation would return the wire to its original shape post-withdrawal of the applied load. Conversely, plastic deformation caused permanent deformation to the wires with defects persisting after the release of the applied load.

The probabilities in the model with low variation received only a 20% chance, while potential for high variation was selected at an 80% probability. These probability percentages came from logical assumptions and the literature review [4][6], that indeed suggested that most process variations tend to be of the high variety. Upon receiving information about which variation would be applied during each individual turn, calculating how much variability must be accounted for can easily be done mathematically through usage of normal distribution calculations generated via a random number generator.

Consequently, by adding these adjustments and instructions into the system, new tension values were conjured up through multiplication processes utilising both chosen variation datasets as inputs, as well as initial base tension inputs in some instances. Some geometrical faults were intentionally added into the system such as flange winding, double or multiple winding, cross over, gap, bulgy turn, and loose wire. These potential errors were foreseen early on, leading to research factors surrounding such failures until strict rules were crafted to be followed, as presented in Table 3.1. When under low-tension situations, faults such as bulgy turn formation or loose wire were triggered. These problems arise when elastic deformation occurred in the wire leading it to alter its shape under pressurisation during winding, often then returning to its natural form after pressure was no longer applied. This “spring-back effect” was precisely what triggered these incidents.

Table 3.1. Rules for faults occurrence in the DES model.

Faults	Symbol	Rules	Produces
Flange Winding	F	Only appears at the beginning of each layer when the tension is above the yield limit	Gap, Cross Over and Double
Gap	G	It is produced anywhere in the coil under low or high tension	N/A
Cross Over	C	Occurs only during high tension and it can be located in any turn or layer	Double Winding
Double Winding	D	Is only created after the second layer and when the tension is over the yield limit	Multiple Winding, Gap
Multiple Winding	M	It can be produced after a Double Winding and sometimes by itself after the yield limit is reach	N/A
Bulgy Turn	B	This fault appears when the tension is under the 35 newtons in any layer or turn	Bulgy Turn
Loose Wire	L	It only appears at the end of the winding process if there is a low tension	Problems during contacting

3.1.4 Development and implementation of the DES model

A DES model was developed to replicate how predefined process parameters affected the final wound coil's geometrical and electrical features (e.g., set wire tension relative to winding speed, caster angle of the wire, bobbin shape and aspect ratio) [6]. Witness Horizon simulation software provided by *Royal Haskoning DHV* (2021) was implemented for developing the DES model. This software allowed the user to simulate various discrete events efficiently, addressing intricate industrial issues where time dependence was critical.

The DES model was made up of several process steps during the winding procedure, encompassing wire storage, wire break, and wire guide, as depicted in Figure 3.5. The initial step involved unwinding copper wire from a larger bobbin and transferring it to the winding machine via storage. Any abnormalities that might had occurred during fabrication were accounted for by introducing a minor variation to its cross-sectional area through use of the DES model. This procedure initiates constant tension on the wire. Although precautions were taken during the wire break, fluctuations in process elements like winding speed might impacted the wire's cross-sectional area. The subsequent stage utilised a wire guide designed to direct and position the wire accurately on the bobbin surface in order to minimise the probabilities of spatial disarrangement or geometrical faults that may arise from varying speeds during processes like winding.

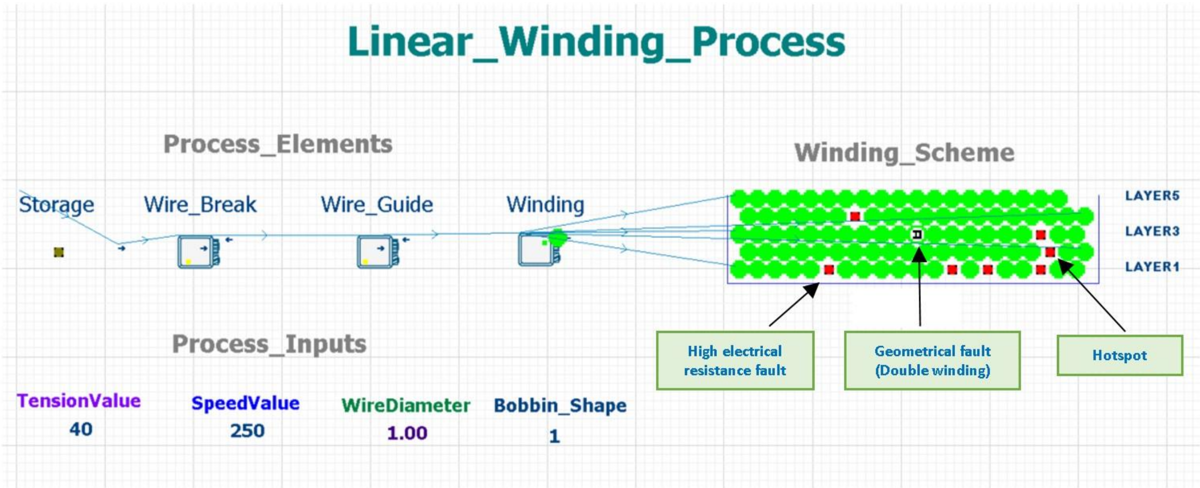


Figure 3.5. The DES model representing the linear winding process.

To ensure precision across multiple turns while minimising space between them (fill factor), a well-structured winding scheme was implemented along with assigning positions to each section through specially programmed orthocycling schemes which boast of higher fill factors than other winding schemes [5]. However, the electrical resistance variation of each turn and the caster angle were also factored into the model, which could instigate geometrical faults during production. Chapter IV provided a detailed explanation on these processes. Expected outputs from the simulation model included:

• A comprehensive mapping guide that models every turn and layer throughout the winding in detail, exhibiting geometrical faults and featuring locations for all turns including clusters like high electrical resistance or hotspot formations.

• The simulation model also generated a database containing information on key parameters such as electrical resistance value, caster angle and geometrical fault display for each turn; this database would allow to pinpoint abnormalities in parameters such as winding speed, tension and wire cross-sectional area at any point in the production process. The harnessing of this data pool would later aid in training supervised learning algorithms during the optimisation process of the manufacturing processes, thus, high product quality was ensured.

3.1.5 Selection of simulation running parameters

In order to assess the effect that key input parameters had on the process output product, it was vital to undertake a systematic approach for the simulation experiments. Based on research, it was found that utilising a full factorial design of experiments approach has been effective in reducing cogging torque in electric motors while remaining cost-effective and adaptable [108].

A 2^3 two-level full factorial design was selected to systematically assess each input parameter's influence on process output. This analysis explored both main effects and interaction effects by varying parameters at low or high levels. Understanding these effects was crucial during optimisation to achieve the desired outputs. Such comprehensive experimental designs provided straightforward interpretation of results while identifying significant factors when variable adjustments impacted process performance. This led to a robust analysis of the system and assisted in uncovering relationships between variables that could go unnoticed with less comprehensive experimental designs. In this case, k = 3 (input parameters), resulting in 2^3 (2 settings high and low) = 8 possible combinations, as shown in Table 3.2.

Table 3.2. A 2^3 two-level full factorial design with high and low levels for different process parameters.

Process Parameters			
Run #	Rotational Speed (rpm)	Bobbin Shape	Wire Diameter (mm)
1	100	Rectangle = 1	0.30
2	800	Rectangle = 1	0.30
3	100	Rectangle = 1	0.71
4	800	Rectangle = 1	0.71
5	100	Square = 2	0.30
6	800	Square = 2	0.30
7	100	Square = 2	0.71
8	800	Square = 2	0.71

A. **Rotational speed** – Linear winding's fundamental process element was influenced by one critical factor: rotational speed – which directly influenced both winding rates and manufacturing times. To account for operational variability commonly faced during production periods, low (100 rpm) and high (800 rpm) limits were established within this spectrum. By analysing how these affected outputs measured by the DES model, as well as other factors present within the experimental design involving rotation pace interactions, a deeper understanding of these dynamics was expected.

B. Shape of the bobbin – The impact of bobbin shape on fault occurrence during winding has been studied by Hagedorn et al. (2018), revealing that square and rectangular-shaped bobbins introduced immense variability due to constantly changing wire length between wire guides and winding positions compared to circular-shaped counterparts which exhibited minimal inconsistency throughout this procedure. Therefore, only non-circular-shaped bobbins underwent experimental testing. Fusion 360 CAD software from *Autodesk* (2022) was utilised to formulate individualised designs for each bobbin; finalised models were 3D printed as illustrated in Figure 3.6.

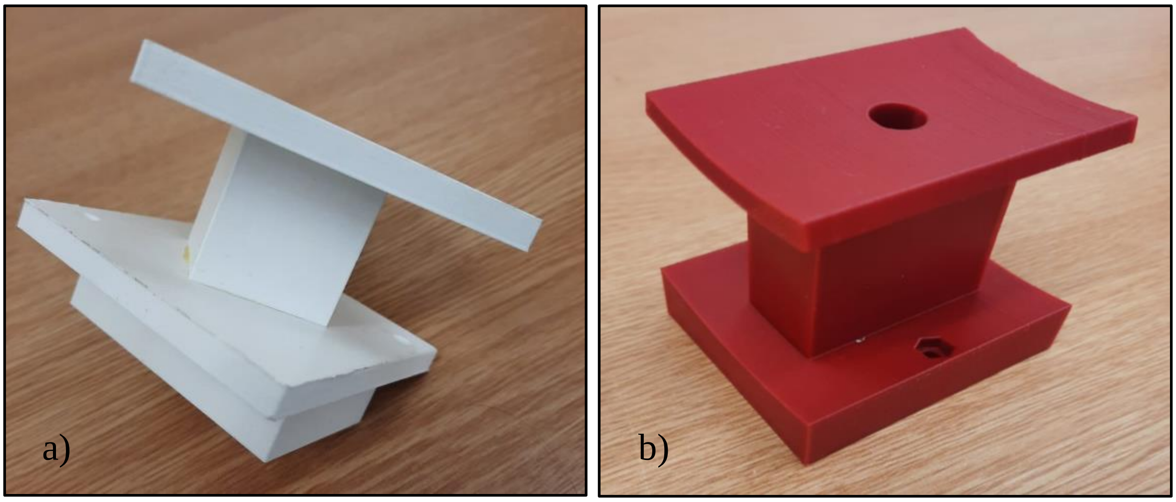


Figure 3.6. a) Squared bobbin shape b) Rectangular bobbin shape

C. Wire diameter – Dobroschke's [150] research highlighted how crucial it was to consider the wire diameter when analysing fault occurrence throughout this process step. Various factors were directly affected by changes in gauge size like the caster angle, yield limit, and spring-back angle. By increasing a wire's diameter, its caster angle and yield limits tend to increase simultaneously resulting in being able to withstand greater tension levels while reducing potential for faults at larger diameters only, or above certain sizes; smaller cross-sectional areas had higher probabilities for geometrical deviations due to more noticeable spring-back angles hence leading one towards potential fault points if overworked during processes.

To gain further insight into how specific diameters affected this stage of production, experiments using various gauges were carried out, which included two commonly found sizes within industries: 0.30 mm and 0.71 mm. These particular wire gauges were often utilised within the industry as they fall within an appropriate range to adequately fit the wire guide located in the machine without applying overwhelming tension on the wire as it proceeds through the nozzle.

3.1.6 Run simulation model for testing

To attain an understanding of the DES model's functionality and efficacy, it required being run for a specific phase or until specific requirements were met (namely, producing one bobbin comprising five layers of 20 turns per layer). During execution, state changes occurred discretely at different times. After execution was complete, data outputs were collected and analysed statistically to establish how modifications in input parameters impacted system efficacy.

3.1.7 Validation of the DES model

In order to validate the model, experiments were conducted on a lab-based linear winding machine following the input and output parameters presented in Table 3.3. By doing so, data could be generated and then compared against the DES model's predictions, thereby identifying any discrepancies that might needed correcting. Only when such corrections had been made, further steps could be taken to refine the model until it effectively mirrors both experimental findings as well as simulated results in an encompassing way. Alongside this empirical validation stage, feedback from industry experts was obtained. Suggestions by industry experts were incorporated into the final product version ensuring trustworthiness through a combined approach consisting of empirical validation alongside expert evaluation.

Table 3.3. Input and output parameters selected for the model.

Input parameters	Range	Output parameters
Winding speed	100-350 RPM	Electrical resistance value
Tension value	40-80 N	Electrical resistance accumulated error
Wire diameter	0.30-1.20 mm	Caster angle
Bobbin shape	1- Rectangular 2-Square 3- Circular	Geometrical faults

A. Validation by experiments on a coil winding machine

The DES model outcomes were verified through a series of experiments conducted on a laboratory-grade linear winding machine used to create an orthocycling winding scheme. The lab-based linear winding machine, known as the **200mm CNC Coil Winder MK4**, was presented in Figure 3.7 (a). Additionally, Figure 3.7 (b) showed the **Coil Winder Controller MKII Software V4.5**, which helps manage various process parameters such as speed, bobbin size, and the number of turns per layer. This particular winding machine has closed-loop motors both on the feeder and bobbin assembly that enhance torque, precision and speed, and reduce losing steps while producing small run quantities of coils or bespoke single-off coils suitable for a wide range of bobbin shapes for electronic projects. The maximum winding speed capability for the machine was 2000 rpm. To validate the findings, a comprehensive factorial design was utilised as suggested in Section 3.1.5.

Figure 3.7. (a) Linear winding machine used for experimentation model "CNC Coil Winder MK4'

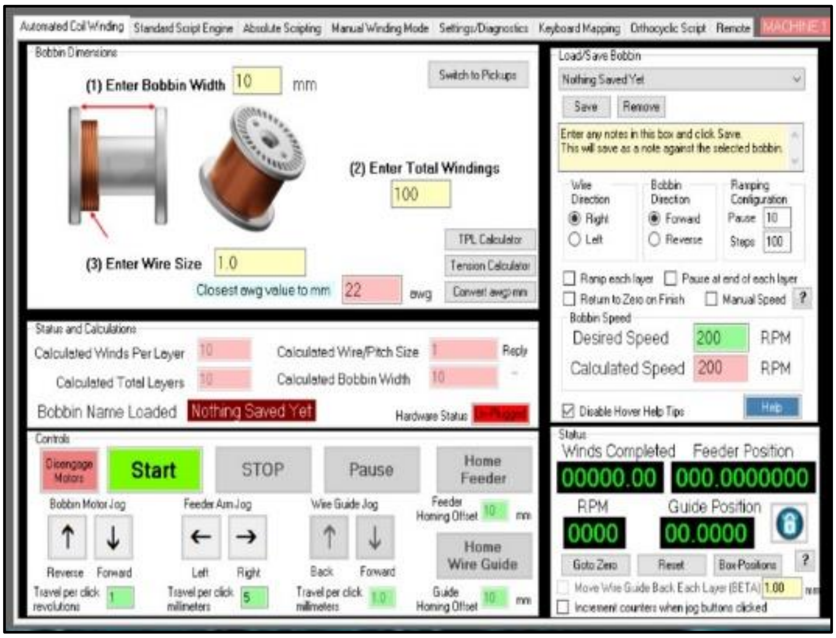


Figure 3.7. (b) Coil Winder Controller MKII Software V4.

B. Validation with industry experts

In this research, validation was conducted by gathering feedback, from four industry experts in multiple sectors. These experts were individuals who represented companies with different ownership structures.

- **Expert 1** represents a public limited company specializing in predictive simulation software and modeling services. Engaged in medium-value, high-volume production of simulation products, this company boasts a workforce of over 100 employees. The expert, serving as a simulation specialist, brings 25 years of extensive industry experience to the table. Their company operates globally, with its main sector revolving around the UK.
- **Expert 2** is associated with a private limited company focused on aerospace and defense products. With a substantial workforce exceeding 1000 employees, this company primarily deals with high-value, low to medium-volume manufacturing. The respondent, occupying the role of director of manufacturing, possesses 20 years of industry experience. Their company operates on a global scale, catering to clients worldwide.
- **Expert 3** represents another private limited company specializing in the manufacture of electrical machines. Engaged in medium to high-value, low to medium-volume production, this company also boasts over 1000 employees. The respondent, serving as a manufacturing specialist, brings 20 years of industry experience to the table. Their company operates globally, with operations primarily based in Italy.

- **Expert 4** is affiliated with a public limited company involved in aerospace and automotive sectors. This company, with a workforce of over 100 employees, focuses on high-value, low-volume manufacturing. The respondent, designated as a technical specialist, brings 8 years of industry experience. Their company operates mainly in the UK, serving clients domestically.

Incorporating insights from industry experts was an integral aspect of validating the DES model effectively. Feedback from EM manufacturing professionals, alongside esteemed members of academia and simulation specialists, was extremely valuable during this process. The goal was to carefully evaluate underlying assumptions concerning the specific system being modelled. These reviewers analysed the logic flow while considering all relevant parameters that serve as structural components of said system towards improving fidelity along with accuracy for real-world operations modelling. Based on their feedback two main changes were made to the model; first the threshold level for identifying a bobbin as scrap was revised to be 10% of accumulated error; secondly, a more efficient method was adopted for storing all information obtained from the model in the form of tables.

3.2 Proposed methodology for developing a hybrid computational framework

The present methodology in Figure 3.8 employed KD to generate a complete framework from the DES model previously developed. This comprehensive framework, also known as the "teacher model", was capable of preparing appropriate datasets to train SML algorithms (the "student model"). Figure 3.9 presented the steps that were followed to develop the student model during the KD approach. Ultimately, this approach sought to enhance the efficiency and accuracy of fault prediction in manufacturing processes involving deformable materials in manufacturing steps such as linear winding.

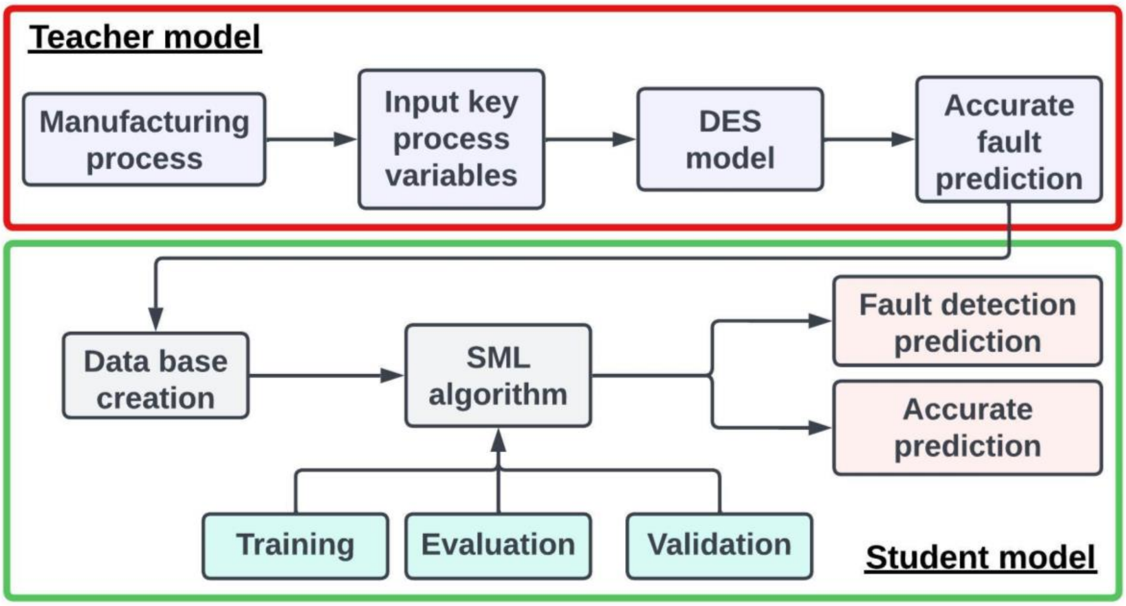


Figure 3.8. Methodology for developing a hybrid computational framework.

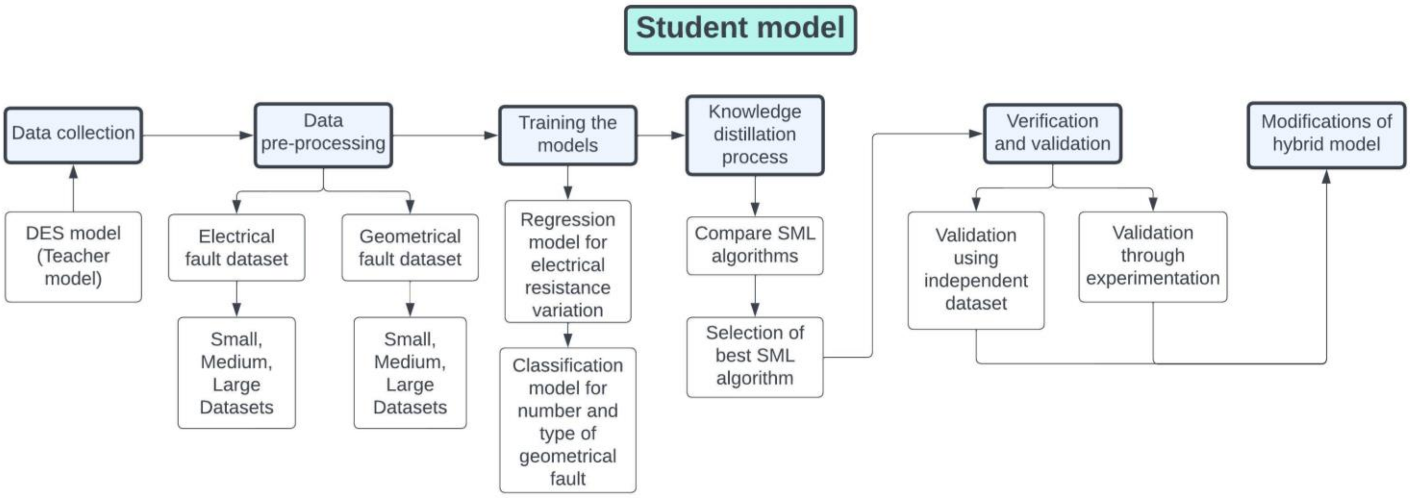


Figure 3.9. Methodology for developing a student model as part of a hybrid computational framework.

3.2.1 Data collection

The first step in gathering data involved systematically extracting a comprehensive dataset from the previously created and validated DES model. This dataset encompassed various parameters and outcomes associated with the coil winding process. Multiple simulations were conducted under different conditions and parameters to collect data from over 10,000 instances. Physical measurements such as tension, rotational speed and other pertinent inputs were included in this dataset. It served as an essential component for training via KD by providing information on potential faults and their associations with input process parameters.

3.2.2 Data pre-processing

As part of the data pre-processing phase, the all-inclusive dataset was then split up into three distinct databases with unique size specifications – the small database containing 10,000 entries; the medium database twice that number (20,000 instances); and the large database having approximately four times (40,000 instances) as many as the small database. Employing an intense partitioning strategy granted the opportunity to obtained performance reliability under varied conditions while also reconciling with administration demands related to test-train segmentation in each subset. Each database was then divided using a 75–25% split, with 75% of the data reserved for training the KD model, and the remaining 25% allocated for testing. This type of split allowed the model to keep a proportionate ratio between datasets, enabling it for validation against those earmarked for training at fixed percentage points.

3.2.3 Training the student model

Effective training of the 'student' model hinges on utilising pre-processed data together with advanced methodologies such as deep neural networks or machine learning models. The goal was for the student model to mimic the teachers (DES model) performance while being computationally efficient. Both models used input parameters such as winding speed, wire gauge and bobbin shape and target labels for training data. In this scenario, the student model learning was supported by incorporating targets such as electrical resistance variation and number of geometrical faults per layer, in its output parameters.

The training loss used for the student model in the KD framework was MSE. This specific loss function calculated the squared difference between the predicted and target values, which helped guide the learning process of the student model. While MSE was simple to implement and computationally efficient it might not fully capture all the subtleties of knowledge transfer as Kullback-Leibler divergence does. This could potentially result in an effective distillation of insights from the teacher model. Additionally, MSE might give much importance to outlier examples and if not carefully balanced, with regularization techniques it could lead to overfitting.

3.2.4 Knowledge distillation process

A comprehensive approach to data analysis during coil winding for the KD process necessitated utilising two models. The initial step involved using a regression model for predicting percentage variation in electrical resistance per turn during coil winding. Next, a classification model forecasted the type of geometrical fault per turn. It was vital to compare actual and predicted resistance outcomes when assessing regression model performance while evaluating how well the classification technique performed.

A. Comparison of SML algorithms

While creating an effective KD process, it was important to consider comparisons of multiple SML algorithms like DT, RF, SVM, KNN, NB and ANN to determine their effectiveness. This included testing algorithms' abilities when it came to capturing essential knowledge from their instructor model while utilising pre-processed data for procedures. To evaluate predictive capabilities effectively, consideration for different performance metrics such as accuracy, dataset size, number of parameters, noise level when handling complex dataset along with simulation timing, was assessed. Analysing results helped to identify the algorithm that outperforms others and thus could inform on the data's complexity pattern more effectively for better decision-making in future learning processes. The rigorous selection greatly enhanced the overall KD process by selecting the more efficient supervising learning algorithm for the student model.

B. Selection of the best SML algorithm

Undertaking the KD process required thoughtful consideration when selecting an appropriate SML algorithm. Multiple algorithms were examined and evaluated based on their efficacy in capturing distilled knowledge. These algorithms were trained with pre-processed data before their performance was assessed through various metrics (more details presented in Section 5.3). After this evaluation, the best suited supervised learning algorithm is chosen to act as the student model, therefore enabling optimum knowledge transfer and better fault detection capabilities.

3.2.5 Verification and Validation

To ensure that a KD approach was successful it was important to evaluate and validate the chosen algorithms. This involved conducting benchmarking against independent datasets using a cross validation technique (Section A), as well as controlled experiments (Section B) in order to assess their reliability, functionality and consistent performance. By taking this approach, it was possible to enhance the efficiency of fault detection, in coil winding, during the KD process by improving its robustness and output generation.

A. Validation process using an independent dataset

To achieve this aim, a 5-fold cross-validation approach was utilised to assess performance levels, as shown in Figure 3.10. In dividing the dataset into five discrete parts, every subset was assigned as either a source of data for training, or a means of conducting validations while all other leftover parts are employed accordingly too. Repeating this process provided reliable indications about an algorithm's abilities; it helped evaluate predictive accuracy levels alongside its generalisation capabilities. The evaluation measures, like accuracy, precision, recall and F1 score, were computed for each iteration. This process generated five sets of evaluation scores. These scores were then averaged to give an assessment of how the model performs across the five different scenarios. This approach provided an estimate of the model’s effectiveness and its ability to generalize beyond specific instances.

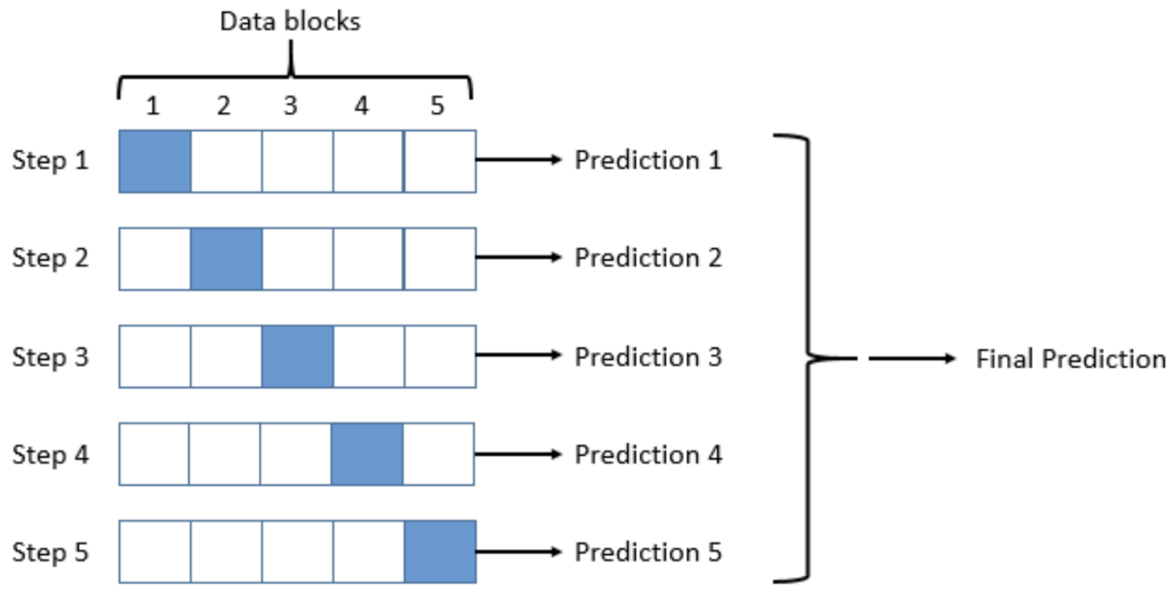


Figure 3.10. Diagram of the 5-fold cross-validation method (blocks in blue represent the testing folds at each step) by [149].

B. Validation process through experimentation on a coil winding machine

To assess their efficiency and accuracy, multiple experiments utilising regression and classification models were conducted on a linear winding machine. By comparing predicted value outcomes from the selected algorithm with corresponding physical ones generated by the same machine, it was possible to determine whether these calculations remained reliable for use in production settings utilising genuine datasets. As testing procedures were exclusively designed for use with this particular type of winding process these procedures cannot thus be directly extended towards other techniques such as needle winding, which presented different characteristics and challenges.

3.2.6 Modification of hybrid model based on feedback

Modifications were made to the hybrid model to improve fault detection by incorporating more data (10% more instances) into their database specifically for faults such as double winding and gaps located at the second layer. It was noticed that the model had difficulty predicting the placement of wires over wires, which resulted in false predictions. To address this issue, the model was modified by adjusting the error probabilities for the creation of faults when speed increased based on results and valuable feedback from the validation process. This refinement process also involved tuning hyperparameters, like increasing the n_estimators and max_depth in order to optimise the accuracy, robustness and generalizability of the model. The ultimate goal was to enhance its performance, in detecting faults within the coil winding process.

3.3 Proposed framework for multi-objective optimisation involving interdependencies

The manufacture of EMs entailed the intricate task of linear winding, which posed numerous challenges relating to costs and fault control. To confront this multi-objective problem, an approach that equally prioritises both aspects while focusing on the intricacies associated with linear-winding techniques was required. Thus, the proposed framework was illustrated in Figure 3.11 as an effective way forward.

In this research, a multi-objective approach was proposed to address the complex challenges related to linear winding. The goal of this research was to make the linear process more cost effective while reducing faults providing a solution to the problems encountered in such processes. However, it is important to note that the current implementation only focuses on optimising two objectives: cost reduction and fault minimisation. The intention was to utilise this as a foundation and in future phases expand this optimisation framework by incorporating a wider range of objectives. These objectives may include energy efficiency, increased production output, reduced material usage and environmental impact mitigating. By expanding the scope in this way, this research aims to continuously improve and strengthen the effectiveness of this optimisation strategy over time.

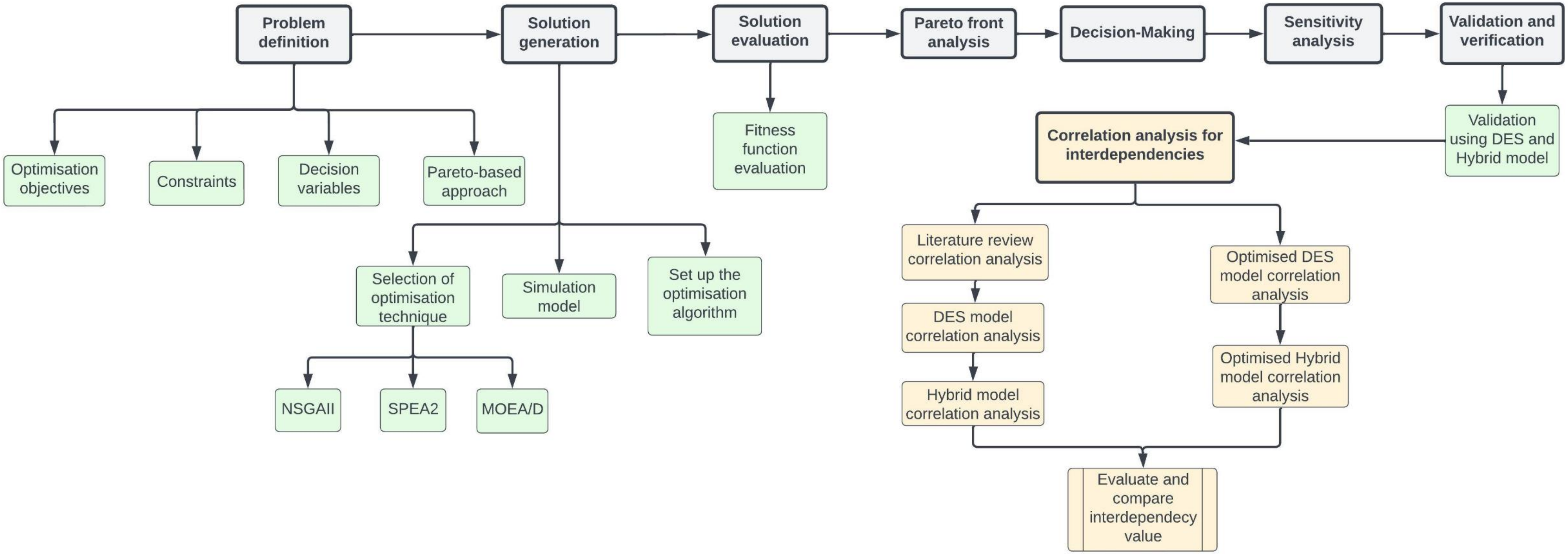


Figure 3.11. Proposed framework for multi-objective optimisation involving interdependencies.

This approach considered the effects that interdependencies has on multiple objectives, together providing a comprehensive framework capable of enhancing efficiency levels while reducing fault rates when winding coils. The subsequent sections introduced several different approaches to solve multi-objective problems showcasing their potential to achieve improved outcomes in terms of cost reduction and fault minimisation in the context of linear winding.

To thoroughly evaluate the impact of multi-objective approaches on system interdependencies, a correlation analysis was conducted. The goal was to uncover the interconnected effects between objectives with a specific focus on the cost function and the number of geometrical faults as key objectives. By performing this analysis, this research aimed to gain insights into how changes in one objective could affect others. Then a Pearson correlation matrix was constructed for this assessment, incorporating results from both the original models and the new optimised models obtained through optimised input parameters derived from a multi- objective algorithm.

3.3.1 Problem definition

Reducing both costs and faults presented challenges that must be accounted for in linear winding processes. By prioritising these objectives, it provides immediate improvements in financial performance and product reliability setting a foundation, for further optimisation efforts. There is a complex trade-off that required optimisation with regard to different variables like speed selection that impact the overall performance. For instance, slower speeds might cause longer production times thereby raising costs while they could also culminate in more frequent cases of malfunctioning products. Meanwhile, faster options considerably assist cost reduction by enabling greater output, but defects were more likely to happen at high winding speed.

Achieving an ideal balance between costs and minimising flaws was key in maintaining smooth operation in the linear winding process. Careful deliberation on how speed, costs, and variations affect each other was necessary for decision-makers aiming to reach a favourable middle ground. By utilising appropriate optimisation techniques alongside multifaceted approaches enables a thorough analysis that resulted in identifying efficient operating conditions consisting of both cost-effectiveness as well as reduced error rates.

A. Optimisation objectives

When determining optimisation goals, it was important to assess the needs of the problem. This included identifying desired results and considering performance indicators like reducing costs while improving quality and effectively utilising resources. To promote cost-effectiveness and attained optimal results within the linear winding process, it was vital to address two essential hurdles: the reduction of production costs and the decrease of fault occurrence as presented in the fitness function in Figure 3.12.

The optimisation objectives for this problem have been expressed as follows:

In this case, x represented the set of decision variables, which included parameters like the rotational speed, tension in the wire, wire gauge, etc.

It was wanted to find the x that solves the following problem:

Minimise F(x) = [f1(x), f2 (x)],

Where:

- f1(x) was the manufacturing cost. This function would depend on the specifics of the linear coil winding process such as energy consumption, rework, scrappage and throughput.
- f2(x) was the number of geometrical faults during linear winding. This function would depend on the number of geometrical faults created per bobbin during the coil winding process.

```
def _evaluate(self, x, out, *args,  **kwargs):
    f1 =clf.predict([[x[0],x[1],x[2],x[3],x[4],x[5]]])
    f2 =regressor.predict([[x[0],x[2],x[3],x[4],x[6]]])
```

Figure 3.12. Example of fitness functions.

B. Constraints on decision variables

To conduct this research accurately whilst upholding necessary standards for performance quality, feasibility of operation, and overall product reliability, it was decided that rotational speed and wire gauge were crucial constraints for analysis. These two factors were chosen with careful consideration on how they impact the linear winding process, keeping safety considerations as a top priority along with adherence to operational/technical specs/capabilities. Through selecting these particular restrictions, it would not only reach desired levels of optimisation within the multi-objective problem but also maintained each crucial standard mentioned previously.

For this research, it was assumed that x[0] represents the rotational speed of winding and x[1] was the wire gauge. The goal was to find the values of x[0] and x[1] that solve this multi-objective problem while respecting certain boundaries on these parameters.

The constraints were expressed as follows:

a <= x0 <= b

c <= x1 <= d

Here **a** and **b** represent the minimum and maximum feasible speed of winding, respectively. Similarly, **c** and **d** represent the minimum and maximum feasible wire gauge. Therefore, in this multi-objective problem it was required to find a solution for the x = [x0, x1] that minimises F(x) = [f1(x), f2(x)] while satisfying the constraints.

In a complete mathematical form, the problem was:

Minimise F(x) = [f1(x), f2(x)]

Subject to

a <= x1 <= b

c <= x2 <= d

or

100 rpm <= speed <= 350 rpm

0.30 mm <= wire gauge <= 1.0 mm

C. Decision variables

Careful consideration of factors having direct impacts on underlying objectives and constraints was essential when selecting decision variables for addressing multi-objective problems. In the representation of the multi-objective problem for the linear winding problem, a significant number of decision variables were utilised. These variables were classified into three categories, as displayed in Table 3.4:

Table 3.4. Definition of decision variables.

Category	**Notation**	**Description**
Input Arguments	Yl	Yield limit
	l	Number of layers
Decision Variables	x[0]	Rotational speed
	x[1]	Wire gauge
	x[4]	Bobbin shape
	x[5]	Caster angle
Output Arguments	C	Cost
	Nf	Number of faults
	Tf	Type of faults
	ERv	Electrical resistance variation value

Input Parameters: Input variables were housed within the simulation model, inaccessible by the optimisation solver. These parameters marked a well-defined operational field, outlining viable boundaries defined by policy and environmental factors.

Decision Parameters: The arrangement of these variables directly affected the performance of the coil winding process, and it was noteworthy that targeted optimisation problems were impacted. These decision parameters come with predetermined values but were adjusted by the optimisation solver. For every combination of decision parameter values, a distinct solution was produced, resulting in an array of possible solutions.

Output Parameters: Output parameters were simulated by activating the model after input parameters and decision variables are provided. The key performance indicators (KPIs) pertaining to the coil winding process and the optimisation objectives being focused on were reflected in the output parameters. To assess their suitability, these KPI values were passed on to the optimisation solver.

D. Pareto-based approach

For addressing multiple objectives at once, implementing a Pareto-based approach appeared more practical given its competence in providing comprehensive examination while simultaneously showcasing the adjustments required among conflicting goals. The problem faced required considering both production cost and the number of geometrical faults per layer. This approach helped generate a set of solutions that found a ground between these two conflicting objectives. Then, the Pareto frontier was carefully explored, which represented the possible solutions were improving one objective would mean sacrificing the other. This exploration allowed for an evaluation of trade-offs and made it possible to select solutions that achieved the best compromise between minimising costs and reducing geometrical faults. Further details about this approach were presented in Chapter VI.

3.3.2 Solution generation

This section has explored how to generate solutions for a problem with multiple objectives where interdependencies played a vital role, it has been broken down into three parts. First, it was discussed how to choose the correct multi-objective optimisation technique. Then, it was explained how to incorporate the already created simulation models (DES and Hybrid model), of the winding problem into the optimisation algorithm. Lastly, the specifics of configuring and implementing the chosen optimisation algorithm to effectively tackle the challenges posed by the objectives was discussed.

A. Selection of optimisation technique

The use of the NSGA-II method was employed due to its superior performance characteristics in this domain. The benefits of using this particular approach included being able to manage multiple objectives adeptly, together with being an extremely efficient sorting mechanism which allows us easier navigation through Pareto’s front towards determining optimal decisions relating to cost versus number of faults necessary in addressing a multi-objective issue.

B. Simulation model of linear winding problem

The development of the NSGA-II for a linear winding process started with identifying the objectives and quantifying them. Next, the solutions were encoded and determined by a fitness function that incorporated specific objectives and constraints of the process. Python version 3.9 within JupyterLab environment version 3.3.2 was implemented as an encoding platform for the development of the optimisation solver alongside its simulation model's creation due to its remarkable flexibility and usability, as well as its robust abilities in relation to data analysis and modelling. These aspects were considered as vital factors in selecting these tools for this research – specifically considering the requirements to produce both accurate as well as efficient levels.

The Pymoo library was chosen for its strong features, user-friendly interface, and specific multi-objective optimisation support during the development of the NSGA-II model in this research. Pymoo constituted an exceptional Python library housing state-of-the-art adaptations of numerous multi-objective optimisation algorithms, most notably NSGA-II. The library's noteworthy feature was the high-level API, marked by adaptability and ease of use in accommodating personalised adjustments. Pymoo stood apart from its peers (DEAP, PyGMO and jMetalPy) since it offered a single point of entry to multiple-optimisation algorithms, thus making it effortless to alternate between approaches or track their relative performance.

For this research, the fitness function for the NSGA-II model was designed differently from how it has been done traditionally. The use of a fitness function was customary in evolutionary algorithms like NSGA-II to measure how well-suited potential solutions were based on their decision variable sets' qualities or "fitness." In most instances, traditional fitness functions rely on mathematical equations that produce scalar fitness values after mapping decision variables appropriately. However, in this particular work's context, an alternative method have been selected by implementing a main component of the previously created hybrid model instead of relying on conventional techniques for determining solution quality.

This novel approach integrated both regression and classification aspects to design an advanced technique for assessing alternatives proficiently. The hybrid model took into account the decision variables set given to it by making predictions (for regression) and classifications (for classification). Using these outputs' combined values ascertains each possibility's overall "fitness". While operating independently from the optimisation solver, the hybrid model does contribute significantly to its process through being incorporated into programming code as a 'function'.

A specific set of decision variables triggered this function and led to a corresponding fitness value output. Such an output served as guidance for the NSGA-II algorithm's search towards optimal solutions. With its classification component, integrating the hybrid model as a fitness function offers far superior assessment than would be possible through traditional mathematical functions alone. In adopting this innovative approach towards multi-objective problem-solving, greater optimisation effectiveness and improved solution quality could be achieved.

After generating an initial population of possible solutions randomly, genetic operators were used such as selection, crossover and mutation. Finally, the NSGA-II ranked solutions based on their fitness and crowding distance, identifying Pareto-optimal solutions. The algorithm followed an iterative process in which it evolved the population to improve the quality of solutions until obtaining a set of near-optimal or optimal solutions for multi-objective problems. This method enabled an optimal control of the linear winding processes while considering multiple objectives.

C. Set-up of the optimisation algorithm

To understand how the NSGA-II algorithm in this research was set up, refer to Table 3.5. This table itemises all configurations used and enables replication or deeper investigation of this methodology going forward.

Table 3.5. Set-up of the NSGA-II multi-objective optimisation solver.

Parameter	Value
Population size	100|500|1000
Number of generations	3|5|10
Migration interval	5
Selection	BinaryRandomSampling
Crossover	TwoPointCrossover
Mutation	BitflipMutation
Mutation probability	prob=0.5, prob_var=0.3

Code for NSGA-II algorithm

In order to understand how the multi-objective optimisation process was implemented, the code for the NSGA-II algorithm is available on an ORDA repository to enhance reproducibility and aid in comprehension (https://figshare.com/s/726d69c203325bac44b0). This code intelligibly outlined each operation with relevant details in sequence; starting from initialisation followed by selection, crossover, mutation, right up until completion. Revealing the code employed in this research facilitates transparency and replication by peers.

3.3.3 Solution evaluation

When faced with multiple goals it could be challenging to find the right path. However, by creating solutions using optimisation algorithms the process could be simplified. Assessing these options based on a set of functions aided in understanding how each solution might impact different scenarios ultimately leading to more effective decision making. To evaluate how well they perform while balancing achievements in areas (Pareto optimality) metrics such as hypervolume, spacing and generational distance could be useful for carefully comparing and ranking possibilities. By conducting experiments and measuring responses based on predefined goals, it became possible to assess the suitability of solutions and their interactions. Statistical analyses, including sensitivity analysis and ranking further guide towards outcomes providing a clear path, for making well informed decisions.

3.3.4 Pareto front analysis

Using a Pareto based approach the research aimed to find the possible solutions for a problem involving multiple objectives. As a result, it discovered a Pareto front that showcased high quality solutions each offering unique trade-offs between the objectives. The process would produce a Pareto front, which illustrated the intricate balance between two factors: the number of geometric faults per layer (X-axis) and production cost (Y-axis). This plot would present the fact that no solution dominated others within this front, highlighting how enhancing one objective without compromising another was simply not possible. Lower values were preferred for both objectives as they indicated faults and lower costs. In assessing cost effectiveness and comparing solutions, reference cost values obtained from existing literature played an important role, in achieving a comprehensive evaluation of this multi objective optimisation problem.

3.3.5 Decision-Making

The process of making decisions would focus on finding a solution that addresses both cost and quality at the time. Along with this, it had to be considered the two constraints; the top winding speed and staying within the range of wire diameters that has been chosen beforehand. By taking this approach, it could be ensured that the solution struck a balance between cost reduction and reducing quality faults, while meeting the operational restrictions.

3.3.6 Sensitivity analysis

To conduct the sensitivity analysis, an approach was followed that involved creating correlation matrices that measured the interdependency value for each model. Initially, ordinal input parameters were used for this purpose. Then, a comparative analysis was performed by repeating the process with optimised parameters. These correlation matrices would provide the tools in quantifying and visualising the relationships between input variables and model outputs. They would provide insights into how changes in parameters influenced the outcomes. By following this two-step process, it was possible to gain an understanding of sensitivity uncovering how modifications, in both input parameter values and optimisation approaches affected the behaviour of the models. (This topic was further discussed in Section 6.7)

3.3.7 Validation and verification of the NSGA-II algorithm

The process for validating NSGA-II, when applied to a challenge involving multiple objectives, comprised various essential stages. Initially, proper functionality was necessary by comparing its execution against established analytical solutions (benchmark test) like prior models created for similar problems such as the DES or the Hybrid model using a. Once this first step proved successful in verifying how well it operates, then it was recommended to proceed to assess whether or not it delivers accurate performance in comparison to anticipated outcomes using a K-Fold cross-validation test for seamless resolution of the specific multi-objective challenge.

3.3.8 Correlation analysis for interdependencies

The incidence of faults during winding and their impact on manufacturing costs could be understood by conducting a correlation analysis. Conducting a correlation analysis was imperative in gaining insight into the problem's dynamics by examining how input parameters correlate with output metrics like the cost and number of faults. This methodology would be employed across five different scenarios to explore various interdependencies.

Firstly, to understand the interdependency value during linear winding, a correlation matrix was adopted based on Sell-Le Blanc's work [3]. His established tool mapped out relationships between factors involved in the winding process granting insight into complexity while identifying potential areas where improvements could have been made, as changes in one factor might influence other factors, thereby creating ripple effects throughout it all. This revised matrix provided theoretical and empirical observations to create a comprehensive view of the findings. Furthermore, by visualising the interdependencies between different parameters in this way, the complexities of the process became more readily understood aiding decision-making towards minimising faults and costs arising from it.

Secondly, a unique approach was utilised – a new correlation matrix for linear coil winding was developed incorporating data from various sources and literature reviews [2][9], the developed DES model, and results from linear winding experiments. Thirdly, another correlation matrix was developed to further understand relationships using the Hybrid model. This model utilised a more diverse modelling technique to explore how different factors influence one another. Finally, correlations established that improved versions of these two models could offer valuable insights into refinement effects concerning the interplay between aspects involved in linear winding.

The process commenced by using optimisation algorithms such as the NSGA-II for generating solution sets with distinct input parameters. After incorporating the output parameters that have been fine-tuned by means of the NSGA-II algorithm, there was an intention to execute models that strive towards a balance between reducing costs without compromising on minimising faults. Thereafter, evaluations on each model's performance shall proceed thoroughly, with special attention given to measuring how effective these new optimised parameter's function. The contemplated evaluations aimed at providing insights regarding areas like the dependability of these models, the success rates achieved through the optimisation process, and how big a part the NSGA-II algorithm played in attaining both cost efficiency and reduced faults in linear winding.

A statistical method such as Pearson's correlation coefficient was then applied for quantifying their relationships (this was further discussed in Chapter VI). With this data available, it became convenient to construct a correlation matrix illustrating co-relations coefficient-wise. Positive co-relations imply both variables move towards a similar direction when changed, while negative coefficients represent opposite directional changes among them. By analysing the patterns emerging from this research, this informs which inputs affect the outcome the most – helping steer decision-making in the right direction, guiding system improvements, and enabling the researcher to get targeted results which are more easily achievable through quick controls, enhancing functionality, and saving resources.

3.4 Summary

This chapter provided an understanding of a methodology composed of three frameworks that include specific methods and techniques used to explore interdependency modelling in an electrical manufacturing process that involved deformable materials. By presenting these frameworks in detail, this research aimed to contribute insights and promote a deeper understanding of electrical processes and their interdependencies. Three key frameworks were central to this research:

The first framework focused on creating a customised model (DES model) to simulate and analysed the interdependencies within the coil winding process. In the manufacturing process of EM, there was a need to develop modelling techniques that could understand the connections, between input parameters. These models should also be able to make real time predictions, about the probability of defects. In the past there have been attempts to model deformable materials and their dependencies. However, attempts mainly focused on rigid material and individual stages instead of analysing the entire sequence to identify relationships.

Therefore, this thorough analysis aimed to identify anomalies and abnormalities with attention given to "hotspots" characterised by increased electrical resistance. To ensure the accuracy of the DES model experiments were conducted on a linear winding machine to validate the model. By examining the coil winding process, this framework aimed to significantly improved the understanding of potential inefficiencies and areas of concern during manufacturing thereby creating opportunities, for optimising these processes.

The second framework played a significant role, in introducing a hybrid framework that improved the early detection of faults, in coil winding while reducing the computational burden. Previous research has acknowledged the need of a framework that anticipates component states and reduce the duration of quality control tests by understanding how different factors influence the process. In the manufacturing industry it is practice to conduct quality tests, which can be expensive and time consuming. While traditional tests like Dowell's equation and winding resistance have been effective, they require a lot of time and expertise. This highlights a research gap that emphasizes the importance of an integrated and efficient approach, to ensuring manufacturing quality control.

To deal with this problem, KD was utilised, which transfers knowledge from a teacher model (DES model) to a simpler student model (SML model). By generating SML training data using the DES model this method greatly improves fault detection and prediction, in machine manufacturing. KD uses architecture search and data augmentation, which improves the generalization of the student model. Furthermore, the framework shows potential for reducing manufacturing time, enhancing stator quality, and improving reliability and safety. Additionally, transitioning to a digital twin could address the limitations of offline models, offering real-time monitoring, control capabilities, and prompt responsiveness to production changes, with integration of sensors on the winding machine being a crucial step for future enhancement.

The third framework focused on an aspect of optimising multiple objectives to understand the connections between input parameters. This was especially important because there is no literature available on a framework that combines fault detection and parameter optimisation for interconnected electrical production processes. It was crucial to develop and implement this framework to improve manufacturing efficiency. Unlike frameworks that mainly focus on design optimisation (evolutionary learning and distributed algorithms) this research utilised techniques such as NSGA-II to generate well balanced solutions with the aim of making optimal decisions by considering interdependencies and multiple priorities (production costs and component quality). This framework also introduced a correlation analysis which calculated interdependency values from correlation matrices derived from optimised models, which helped in identify the relationships between system components and evaluate their behaviour when objectives were minimised. This provided a foundation, for assessing how optimised input parameters can influence system faults enhance manageability, optimise costs and prevent faults.

Overall, when these three different frameworks were combined, they have the power to bring about changes, in how the interdependencies in manufacturing processes are understood and control them. The goal was to create a foundation for understanding more efficient decision-making and improved optimisation strategies, in the field of electrical manufacturing.

CHAPTER IV: DEVELOPMENT AND IMPLEMENTATION OF A SIMULATION MODEL APPROACH TO EXPLORE INTERDEPENDENCIES IN THE COIL WINDING PROCESS OF ELECTRICAL MACHINES FOR ENHANCED OPERATIONS

4.1. Introduction

This chapter is dedicated to present the results from this research concerning interdependency interactions involving deformable materials underscored with specific faults and complexities present in an electrical machine's operations. Firstly, section 4.2 explained the results obtained from the DES model highlighting critical inputs and output parameters identified during this research (Table 4.1). These key variables provided insights into how the interdependencies behaved in the system. Also, the results of the DES model also presented an understanding of how different components within the system are interconnected.

Moving on to the next section, section 4.3 presented the results from the lab-based experiments using a linear coil-winding machine. These experiments aimed to validate the accuracy and predictions made by the DES model focusing on two types of faults; electrical resistance faults and geometrical faults. By comparing the data obtained from the literature [2][3] against the model's predictions, a deeper understanding of how the system responds to these specific anomalies was gained. Finally, in section 4.4 a comparison between the results obtained from the DES model and those obtained through lab experimentation was carried out. This comparative analysis aided in evaluating how accurately and practically applicable the DES model was, in predicting real world behaviours. These discoveries help to gain an insight into how deformable materials were influenced by interdependencies in EM. This knowledge improved the capability to tackle issues and intricacies such as hotspots and geometrical faults that arise during their operations.

4.2. Results from the DES model

The objective of this section was to present and elaborate on the findings obtained from the development and execution of a DES model based on a linear coil winding process. To begin, the DES model allowed for an examination of the interdependencies within the coil winding process filling a crucial gap in previous modelling techniques [2][99]. It provided real time predictions of probabilities, which is vital for quality control in manufacturing. Notably, the model’s ability to consider deformable materials and their dependencies rather than just rigid materials was a noteworthy advancement. The specifications and capabilities of the DES model have been previously discussed in section 3.1.2. However, in this section the significant implications they have in the performance dynamics of the coil winding process in electrical machine manufacturing was understood.

One of the discoveries from these implications was the identification of "hotspots" characterised by increased electrical resistance. This finding has implications for ensuring quality and optimising processes. These hotspots indicated areas during manufacturing where defects or inefficiencies were more likely to occur. By pinpointing these locations, the DES model offered a valuable tool to focus on optimising these specific areas ultimately resulting in improved overall process efficiency. In addition to its role in modelling interdependencies, the DES model's potential as a digital twin lies in its ability to facilitate prompt responsiveness to potential fault creations. Integration of sensors on the winding machine is crucial for future enhancement, as it would enable real-time data collection and feedback, further improving the model's accuracy and its capability for continuous monitoring and control of the manufacturing process.

4.2.1 Identification of critical inputs & output parameters

Drawing inspiration from Sell-Le Blanc et al.'s [3] ground breaking work, an abridged matrix that synthesises essential factors impacting the incidences of faults during the coil winding process was developed. Table 4.1 visually exhibits key process inputs within its columns, and potential faults within its rows; the colours correspond to various forms of faults caused by processes impacting on such inputs. Vital input parameters like wire tension, caster angle of wire, and especially winding speed were considered as critical to this model based on their prominence in previous findings, including those by Hagedorn et al. [5].

In order for the DES model to operate effectively, input parameters must be entered into the system such as winding speed, tension, wire diameter and type of bobbin shape. Based on these inputs, the model generates deviations in the set value of applied tension. Studies have demonstrated that non-circular bobbins with higher winding speeds may have uneven process parameters, which can impact wire tensile force and consequently alter a wire's electrical properties [5].

Table 4.1. Main winding faults and influencing parameters during linear winding adapted from [3]. The influence level informs the impact of a particular parameter on the generation of faults.

Parameter / Winding fault	Process							Wire					Coil bobbin	
	Machine					Wire		Geometry			Mechanical		Geometry	
	Caster angle	Wire feeding speed	Wire feed rate	Exit angle	Winding speed	Wire tension (global)	Wire tension (local)	Outer wire gauge	Inner wire gauge	Plastic deformation	Failure strain	Tensile strength	Length	Width
Faulty electric resistance	M	M	M	H	H	H	H	H	H	H	H	H	L	H
Short circuit	M	M	M	H	H	H	H	M	M	H	H	H	M	H
Reduce High Voltage strength	M	M	M	H	H	H	H	M	M	H	H	H	M	H
Wire Damage	M	M	M	H	H	H	H	M	M	H	H	H	M	H
Wire fracture	M	M	M	H	H	H	H	M	M	H	H	H	M	H
Winding scheme (wild)	H	H	H	H	H	H	H	H	H	H	H	H	M	H
Loose winding	H	M	H	H	H	H	H	H	H	M	H	H	M	M
Concision of winding	M	M	M	H	H	H	H	M	M	H	H	H	M	M
Defective outer diameter	H	H	H	H	H	H	H	H	H	H	H	H	M	H
Defective inner diameter	L	L	L	H	H	H	H	M	M	H	H	H	H	H

INFLUENCE LEVEL	
H	HIGH
M	MEDIUM
L	LOW

A. Input parameters

Winding speed

Results showed that one critical factor affecting fault occurrence during coil winding was the winding speed. This aligns with the research provided by Hagedorn at al. [5], in which the quality of coils produced depends significantly on this parameter. When there are high-speed winds during coil production, results showed that errors like overlapping, or gap, can increase due to less precise wire placement control. Conversely, slow wind speeds may lead to inefficient production and hence negatively impact overall productivity [5][150]. Therefore, opting for an optimal winding speed assures that a balance between efficient production and quality output is achieved while minimising possible fault occurrences [5]. This proves the significance of winding speed in determining potential faults.

Wire tension

Tension has become an indispensable input factor influencing faults during coil winding processes due to its control over the tightness of windings [148]. With excess tension comes undue stress on wires, which can lead to breaks and deformations, while inadequate tension begets excessively loose coils resulting in sub-optimal efficiency and even unwinding events. Therefore, by balancing tension levels appropriately, one can minimise risks of faults while reaping maximal benefits from optimal performance and higher-quality outcomes [6].

Wire diameter

During the process of coil winding, one input parameter stands out as being crucial – "wire diameter". This parameter has a significant impact on fault incidence levels thanks to its effect on space usage within the coil [40]. Improper utilisation of this space can result in issues like gaps or overlaps [152]. Opting for thicker wires creates more tension during winding that may cause rupture or deformation, while thinner wires could be too loose for optimal performance and cause unwinding difficulties [26]. Henceforth, choosing an appropriate wire diameter is paramount when attempting to decrease fault frequency levels since it plays such an influential role in coil winding.

Bobbin shape

Creating faults during coil winding depends heavily upon selecting an adequate bobbin shape as an input parameter [4][6]. It determines how the wire gets wound around them and their impact on uniformity during winding. Using incorrect bobbin shapes can cause irregularities leading to faults like double windings or gaps. This is due to inconsistent windings resulting from unsuitable proportions of different parts of the wires attached together using insulating material present between them [5]. This result on different layers been wound on top of each other over designated time intervals leading to breakage/deflection. Appropriate selection becomes essential for flawless operation without any mishaps, as they significantly affect whether faults occur.

B. Output parameters

The simulation model produces two main output forms. Firstly, it displays a winding scheme representation providing the location of all turns and layers involved in the winding process. This representation shows the precise position of every turn, including faults like high electrical resistance, geometric faults and hotspots. Secondly, the model calculates the cumulative error in electrical resistance, allowing the model to determine the moment when a bobbin should be considered scrapped due to the high percentage of accumulated faults.

Electrical resistance

During the coil winding process, results show that multiple interdependent factors such as wire diameter, winding tightness and uniformity must all be considered, since they directly impact the electrical resistance of the wire. Larger wire diameters or tighter windings can exacerbate this condition, while uneven coiling can also lead to irregular resistivity, which hampers overall performance [153]. Thus, gaining insight into these interdependent variables and effectively regulating them contributes towards successful electrical resistance control throughout the coil winding operation. With regard to the variation in applied tension levels under different conditions when fluctuations occur, exceeding yield limits while applying tension could potentially deform wires or decrease their cross-sectional areas, which would inevitably raise electrical resistance rates within this area [3][5].

Figure 4.1 displays the output obtained from the DES model. This figure represents the winding scheme displaying vital information such as the high electrical resistance, location of hotspots and geometrical faults. Once the input parameters were received, the model introduced variations in the value of applied tension based on the given inputs. The DES model analyses these variations in applied tension causing tension values to fluctuate as previously discussed by Escudero-Ornelas et al. [6]. If the tension exceeds its limit, it may lead to wire deformation resulting in a reduced sectional area and an increase in electrical resistance, within that specific region.

Then, the model then calculated the change in electrical resistance for each coil turn and determined the caster angle that causes geometric defects as later explain in section 4.2.2. As shown in Figure 4.1, this illustration provided the positioning of individual turns and identified any faults present. These faults can include electrical resistance (represented with a red circle), imperfections in shape (represented with a letter as explained in section 3.1.4) or clusters of electrical issues known as hotspots (represented as a group of three or more red circles).

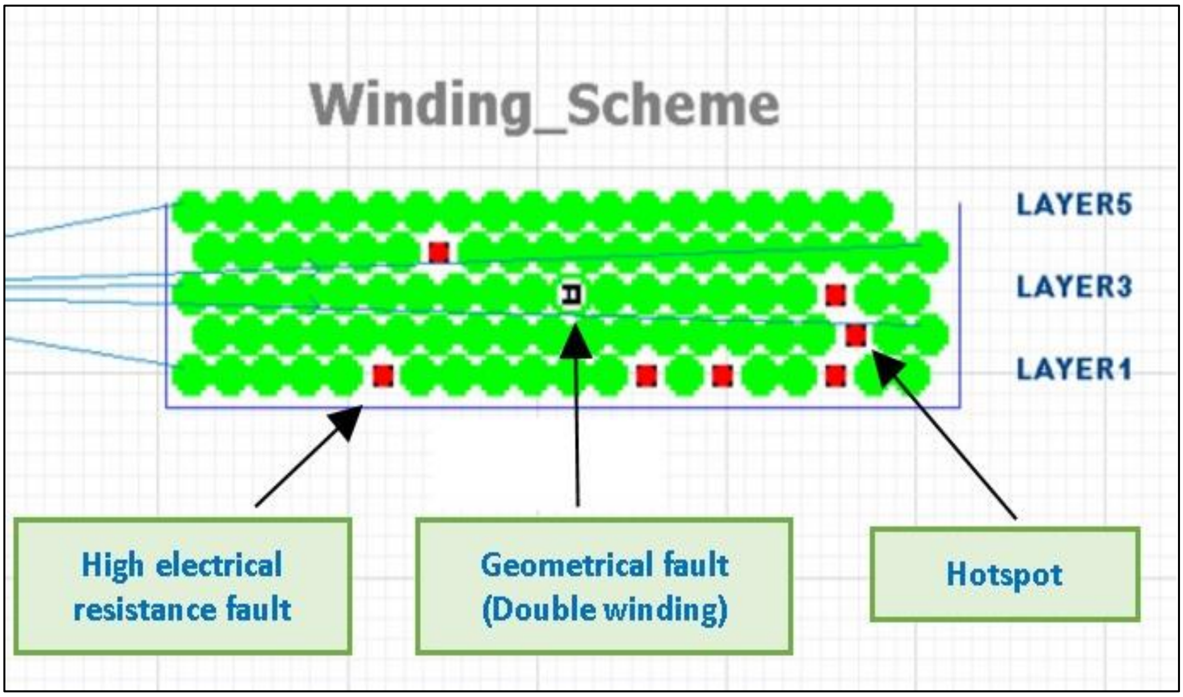


Figure 4.1. Example of the DES model representing outputs such as electrical and geometrical faults.

Another result obtained within this research was a database consisting of tables filled with critical data, which were discussed in depth in section 4.2.2. This database included specifics such as electrical resistance values of individual turns during the winding process and caster angles for each turn along with any geometrical faults present. The goal of this extensive database was to pinpoint precisely where troublesome abnormalities originate in order to make necessary adjustments towards preserving optimal production parameters. By using this same comprehensive set of data as training material for supervised learning algorithms, it is possible to elevate and improve manufacturing practices accordingly.

Location of hotspots during coil winding

Utilising the DES model yields a variable output facilitating predictions concerning potential hotspots during coil winding operations. Hotspots depict positions on copper wires with greater electrical resistance and mapping them out proves critical in avoiding setbacks in function and reliability. The methodology used by DES involves monitoring resistance levels throughout the entire length of wire being wound. By recording the changes in resistance for each turn, it was possible to identify areas with elevated electrical resistance within the coil winding. These regions were deemed as potential focal points for future inspection steps, as displayed in Figure 4.2.

However, results show that in cases where hotspots go unchecked, elevations in temperature could cause damaging insulation breakdowns or create short circuits, which would lead to perceptible damage to the stator. Therefore, predictive determinations surrounding hotspot locations through DES findings present significant insights into promoting enhanced reliability and heightened performance levels during coil winding exercises.

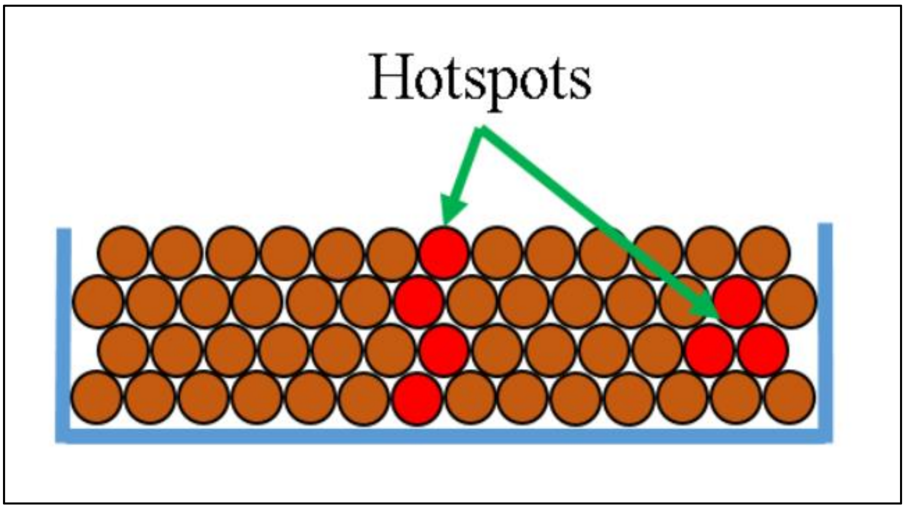


Figure 4.2. Representation of hotspots (in red) in different winding layers during an orthocycling winding.

4.2.2 Identification of interdependencies in linear winding

Based on the findings from the linear winding process a flowchart was developed as presented in Figure 4.3. This flowchart captured the ever-changing aspects of the process including the interactions between wire laying, mechanical deformation, thermal behaviour and electrical properties. Despite the difficulties presented by using materials and nonlinear effects over time, it was managed to incorporate these factors into the flowchart. This comprehensive flowchart enables data analysis for simulation purposes.

4.2.3 Displaying results from the DES model

The DES model provided valuable insights regarding faults encountered during coil winding operations. The simulation model results were displayed in the form of tables formed of eight columns per layer in the coil, as shown in Figure 4.4. These columns provided information on the layer number, the individual tension value used for each turn according to variation, the potential faults that could arise, the type of deformation per turn, the percentage of variation added to the base tension, the wire diameter, the electrical resistance value, and the amount of variation detected in the electrical resistance.

Turns	Layer 1	Fault	Deformation	Variation T	Diameter	Electrical resistanc	Variation ER
1	42.32	No other	Elastic	5.80%	1.18	0.0014461363	0.00%
2	40.06	No other	Elastic	0.14%	1.18	0.0014461363	0.00%
3	40.18	No other	Elastic	0.45%	1.18	0.0014461363	0.00%

Figure 4.4. Representation of the first three layers while modelling the coil winding process using a DES model.

- **Geometrical defects** such as double winding, gaps, crossings, among other issues stem from the mishandling of physical components affecting wire overlapping completeness, and the unbalanced tension or existence of gaps within wires.
- **Electrical failures** due to increased electrical resistance relate to parameters such as wire diameter and tension levels (among others) directly influencing a coil's electromagnetic properties.

Figure 4.4 offers further vital specifics concerning each fault – like its location within the windings and level of severity experienced. The information presented in this figure is of great worth in comprehending the root causes of issues and formulating plans to minimise them in forthcoming winding procedures for coils.

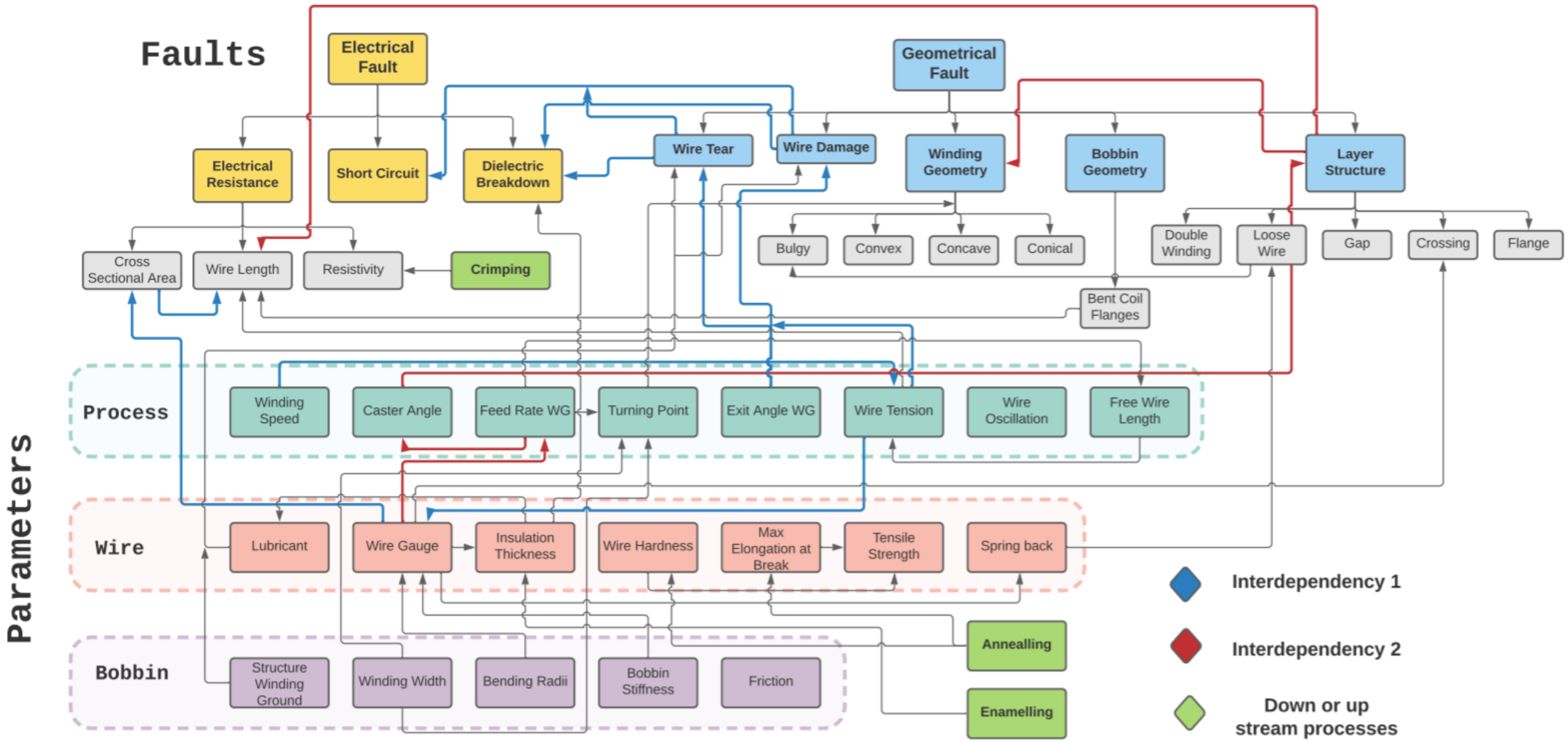


Figure 4.3. Flowchart of interdependencies in a linear coil winding process.

To determine values for each row in the aforementioned figure, several calculations using specific equations had to be undertaken. These equations were developed with an aim to reflect specific aspects paramount to the winding process while also accounting for interplay between various input parameters like wire diameter, winding speed, tension and bobbin shape among others. Due to its manifold nature and complexity involving multiple variables within its loop, such as turning times, considerations like those included in these diverse formulas become critical when collecting correct data about geometrical/electrical faults that manifest at given positions on coils, and in ascertaining the severity levels involved.

These formulas enabled the model to have an accurate measurement of such outcomes regarding fault presence across varying assemblages of wound coils whose degree or type may differ based on varied input parameters. These equations allowed the model to capture any change in input parameters and their impact on the electrical and geometrical properties of the output, which is the wound coil.

A. Calculating the number of turns during coil winding (column 1)

The initial column of Figure 4.4 implements an iterative formula as shown in the Equation 1, to determine the number of turns involved in the process of coil winding. The term "Number of Turns" indicates the number of loops made around the core, which has an impact on both the electrical and mechanical properties of the coil. The parameter "Length of wire" refers to the length of wire used in the winding process. It takes into account any variations or wastage that may occur during coil production. The "Pitch" parameter represents the distance between consecutive wire turns, indicating how closely spaced each loop is, along the length of the coil.

$$Number\ of\ Turns = \frac{Lenght\ of\ wire}{Pitch} \qquad \text{Eq. 1}$$

This count serves as a foundation for the simulation, enabling a thorough examination of possible faults and their occurrence timeframes by presenting a sequential account of the winding procedure. An iterative formula suits this purpose since it repeatedly computes the turns using input parameters like speed, providing means to track changes within the system that indicate potential faults. Furthermore, being able to associate turn counts with other variables or outputs allows for a complete understanding of interconnections among subsystems in coil winding processes.

B. Calculating the wire tension value with variation and the percentage variation (columns 2 & 5)

In order to calculate varying tension values accurately during coil winding processes, Equation 2 was used to represent the tension value in the second column of Figure 4.4. Winding is prone to faults that can be caused or exacerbated by defective tensions; thus, it is pivotal to determine them with precision. To establish the degree of variation applied to each turn in a coil's tension level, an innovative function was created and shown in the form of Equation 2.

$$T = T_{min} + (T_{max} - T_{min}) x \frac{Layer\ number}{Total\ number\ of\ layers} x\ probability \qquad \text{Eq. 2}$$

The model that takes a probability distribution into account to assign a tension value. However, this probability is influenced by the speed at which the winding occurs. When the winding speed is higher there is a chance of tension fluctuations [153], which then impacts how the tension value for each layer is calculated. This dynamic approach acknowledges that in real world scenarios winding speed can have an effect on tension levels and introduces a level of uncertainty into the tension variation process. To ensure that defects are prevented it remains crucial to have lower boundaries (referred to as T_{max} and T_{min}) in place to maintain tension within acceptable limits. By incorporating adjustments based on probability and speed related factors, into this equation it enhances the adaptability of the winding process and improves precision when it comes to controlling tension.

Then to calculate the variation percentage presented in column 5, Equation 3 was implemented.

$$Tension\ Variation\ Percentage = \frac{T - T_{min}}{T_{max} - T_{min}} x100\% \qquad \text{Eq. 3}$$

Equation 3 calculates the percentage of tension variation compared to the range between the tension (T_{min}) and maximum tension (T_{max}). It shows how far the actual tension value (T) deviates from the maximum tensions. This variation percentage gives information about the amount of tension fluctuation in a specific layer while winding. Such insights are crucial, for evaluating the quality and dependability of coil winding operations.

An example of how the tension fluctuated throughout the winding process can be seen in Figure 4.5. In this example, the DES model provided the parameters for each layer and turn

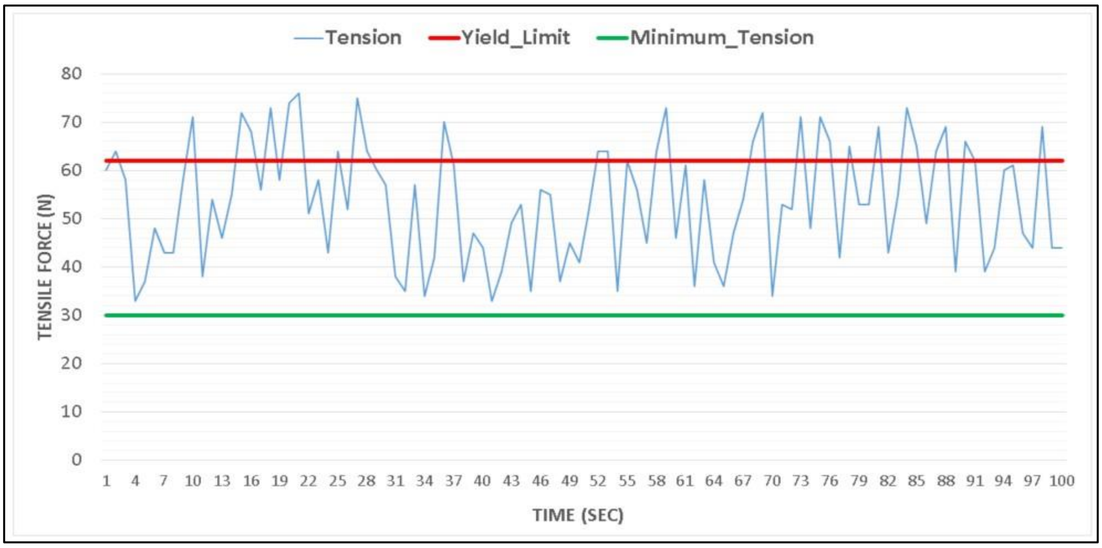


Figure 4.5. Tension chart of the DES model using a rectangular bobbin.

of wire in a rectangular bobbin at high speed (800 rpm). It highlights an upper boundary (yield limit), which could cause electrical faults if breached, and a lower boundary that results in loosely wound wire due to insufficient tension. The maximum limit for tension (also known as yield limit), was set at 61.75 Newtons as specify by existing literature[154]. This specific tension value is crucial as it marks a point in how the copper wire behaves when it is wound. Once the tension surpasses this threshold level, the copper wire shifts from being deformed elastically to being plastically deformed. By establishing the tension threshold at 61.75 Newtons, the aim is to ensure that the applied tension on the copper wire remains within the deformation range thereby reducing the risk of plastic deformation and any resulting geometric flaws or defects, during the winding process.

C. Calculating the type of geometrical fault (column 3)

By referring to Table 3.1 (section 3.1.4), a series of guidelines dictate the creation of specific forms of geometrical fault based on process parameter values and modifications. It is important to bear in mind that certain lower layer faults could result in further complications with upper or neighbouring layers, which would ultimately impact the complete winding scheme. Thus, it is imperative that any electrical or geometrical defects from earlier rounds be taken into consideration while determining those for future rounds.

To provide accurate representations of any geometric faults arising during the bobbin's surface winding process, caster angle values were calculated for every turn obtained based on both wire guide positioning relative to wires [5]. Any caster angle value detected to be out of range in the simulation model was classified as a geometric fault. These faults were identified using initials as shown in Table 3.1 (section 3.1.4) and illustrated for each turn on Figure 4.6. The presented DES model approach mapped when and what type of geometrical fault had occurred during winding. The overall results highlighted that double winding occurred more frequently among geometrical faults, unlike flange winding, which had limited appearance on bobbin edges.

According to the DES model, Equation 4 adapted from [150] was utilised for the calculation of the caster angle.

$$CA = A + B \cdot ln\ (d_b) \qquad \text{Eq. 4}$$

When determining caster angle, Equation 4 was employed which involves taking the natural logarithm (ln) and multiplying it by the bobbin's diameter (d_b), then multiplying that product by adding A and B angles occurring between the wire guide and winding location. Angle A stands between a winding location to an exact point located straight in front of a wire guide, whilst angle B occurs between the tip's end in front of the wire guide towards the winding area. After calculating the caster angle using the DES model, maximum limits for caster angles were also determined utilising Equation 5 – propounded by Dobroschke [150].

$$CA_{max} = -+\ 0.4 \cdot [A + B \cdot ln\ (d_b)] \qquad \text{Eq. 5}$$

Results have revealed significant insights into how geometrical errors are linked to caster angles when rotational speeds rise above safe levels between predefined upper and lower limits of maximum angle permitted by manufacturers. Manufacturing companies try not only to prevent this, but also lessen risks associated with errors potentially arising from excessive oscillation or misaligned machinery parts. This increasingly complex issue, given the advances made over recent years, makes machines capable of working faster than ever before while requiring high precision standards. Moreover, this demonstrates how even small variations between wires' diameters may impact weight reduction leading to changes occurring within guides' velocities themselves, hence requiring further calculations found on Equations 6.1 and 6.2.

GEOMETRICAL FAULT LIST		
Layer	Turn	GEO_FAULT
1	1	NO FAULT
1	2	NO FAULT
1	3	NO FAULT
1	4	NO FAULT
1	5	NO FAULT
1	6	NO FAULT
1	7	GAP
1	8	NO FAULT
1	9	GAP
1	10	NO FAULT
1	11	NO FAULT
1	12	NO FAULT
1	13	NO FAULT
1	14	NO FAULT
1	15	NO FAULT
1	16	NO FAULT
1	17	NO FAULT
1	18	NO FAULT
1	19	NO FAULT
1	20	NO FAULT

Figure 4.6. Lists obtain from the DES model using a rectangular bobbin: Geometrical fault type.

Equation 6.1 entails the division of the force exerted upon the wire guide by the collective mass of both copper wire and wire guide.

$$a = \frac{F}{m} \qquad \text{Eq. 6.1}$$

Equation 6.2 can be utilised to compute wire guide velocity, accounting for acceleration. Specifically, this equation requires the incorporation of the initial speed and product of acceleration, and elapsed time. Lastly, Figure 4.7 depicts changes to caster angle when using a rectangular bobbin.

$$v = v_0 + at \qquad \text{Eq. 6.2}$$

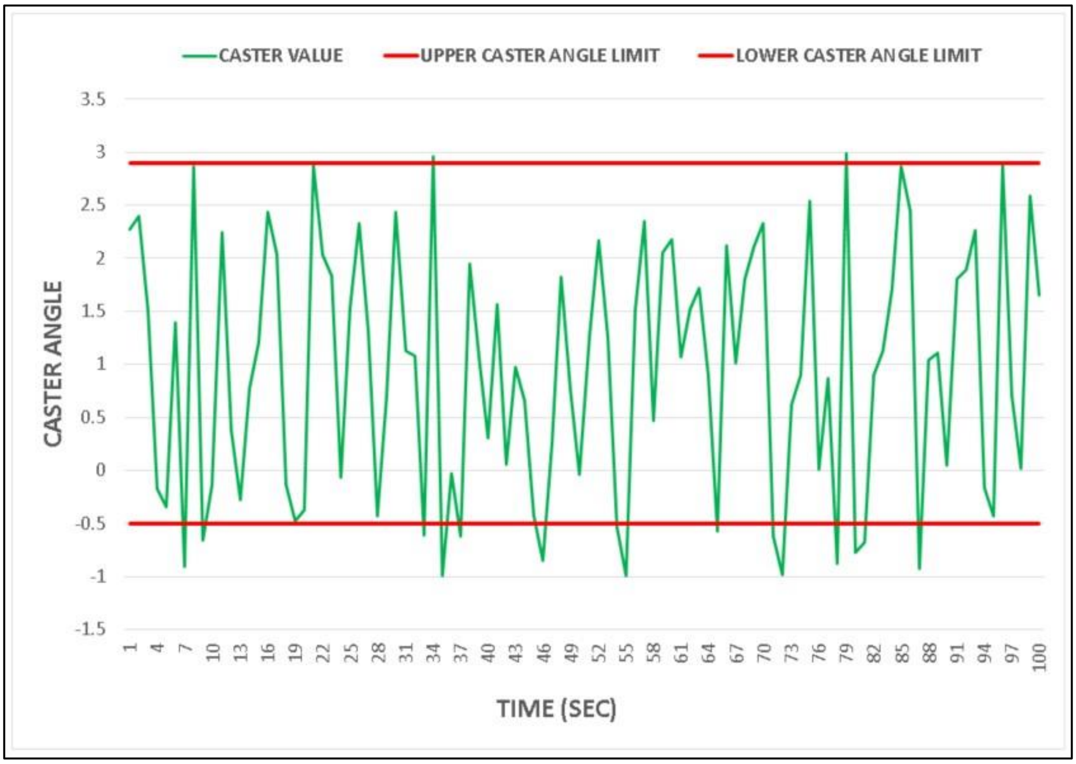


Figure 4.7. Caster angle chart of the DES model using a rectangular bobbin.

D. Calculating the type of deformation in the copper wire (column 4)

Once the percentage variation in tension was determined, it is essential for the model to recognise any potential defects caused by plastic deformation that arises when yield limits are crossed, as shown in the code presented in Figure 4.8. This applies throughout every layer and turn within these coils’ development process. Selecting faults from predetermined options depends on normal distributions: probabilities are calculated and recorded within column 3. Through analysis of the tension value after applying variation, the model accurately identified the type of deformation in each turn. To effectively present this finding, it expertly labelled each turn with either plastic or elastic deformation and displayed it in column 4.

```
base_tension = get_base_tension()
new_tension = get_new_tension()
yield_limit = get_yield_limit()
# Calculate tension variation
def calculate_tension_variation(base_tension, new_tension):
    return abs(new_tension - base_tension) / base_tension * 100
tension_variation = calculate_tension_variation(base_tension, new_tension)
# Determine deformation type
def calculate_deformation(tension, yield_limit):
    if tension > yield_limit:
        return 'Plastic'
    else:
        return 'Elastic'
deformation_type = calculate_deformation(new_tension, yield_limit)
# Calculate probability of faults
def calculate_fault_probability(deformation_type):
    if deformation_type == 'Plastic':
        probability = np.random.normal(loc=0.7, scale=0.1) # assume normal distribution
    else:
        probability = np.random.normal(loc=0.2, scale=0.1) # assume normal distribution
    return probability
fault_probability = calculate_fault_probability(deformation_type)
```

Figure 4.8. Pseudo code for calculating the type of deformation during coil winding.

E. Calculating the diameter (column 6)

In the sixth column of the table, the current wire diameters can be found, which are subject to variation due to inherent interdependencies within the system, as well as fluctuations in tension and speed during winding. Results showed that when applied tension (adapted from[154]) exceeds a threshold of 61.75 Newtons, stretching occurs leading to a permanent change in wire diameter which has significant impacts on the coil winding process outcomes.

To more accurately reflect these processes, a calculation formula was utilised incorporating original diameters, along with material properties like Young's modulus and yield strength, which allows for greater accuracy regarding how changing wires' diameters impacts upon system performance, as shown in the pseudo code in Figure 4.9.

```
original_diameter = get_original_diameter()
new_tension = get_new_tension()
yield_strength = get_yield_strength()
young_modulus = get_young_modulus()
def calculate_new_diameter (original_diameter, new_tension, young_modulus, yield_strength):
    if new_tension > 61.75:  # threshold tension
        stretch_ratio = new_tension / yield_strength
        return original_diameter * (1 - (stretch_ratio / young_modulus))
    else:
        return original_diameter
new_diameter = calculate_new_diameter(original_diameter, new_tension, young_modulus, yield_strength)
```

Figure 4.9. Pseudo code for calculating the copper wire diameter during coil winding.

Once the diameter was calculated, the model stores the values for the creation of databases for further analysis in the form of tables, as shown in Figure 4.10. Additionally, after calculating the diameter the model stores the values for creating databases to conduct analysis. These values are stored in tables as depicted in Figure 4.10. This database was designed to highlight any abnormalities in the diameter and cross section by marking them with a colour. This feature makes it easier to identify the number and location of affected diameters, on a bobbin.

DIAMETER LIST			
Layer	Turn	Diameter (mm)	Cross_Section (mm)
1	1	1.00000	0.78540
1	2	0.99977	0.78504
1	3	1.00000	0.78540
1	4	1.00000	0.78540
1	5	1.00000	0.78540
1	6	1.00000	0.78540
1	7	1.00000	0.78540
1	8	1.00000	0.78540
1	9	1.00000	0.78540
1	10	0.99974	0.78500
1	11	1.00000	0.78540
1	12	1.00000	0.78540
1	13	1.00000	0.78540
1	14	1.00000	0.78540
1	15	0.99974	0.78499
1	16	0.99975	0.78501
1	17	1.00000	0.78540
1	18	0.99974	0.78499
1	19	1.00000	0.78540
1	20	0.99973	0.78498

Figure 4.10. List (diameter variation) obtained from the DES model using a rectangular bobbin.

F. Calculating electrical resistance value and variation percentage (column 7 & 8)

To calculate this variation in electrical resistance, it is first required to calculate the wire's total electrical resistance using Equation 7,

$$R_{Cu} = \frac{\rho_{Cu}}{A_{Cu}} = \frac{4 \cdot \rho_{Cu}}{\pi \cdot d_{Cu}} \qquad \text{Eq. 7}$$

To calculate the electrical resistance in a copper wire (R_{Cu}), its resistivity value (symbolised as ρ) represented by ρ=1.72x10^-8 Ωm must be divided by the wire's cross-sectional area A_{Cu}. Equation 8 calculates the sectional area (A_{Cu}) of a copper wire.

$$A_{Cu} = \pi \, x \, (\frac{d}{2})^2 \quad \text{Eq. 8}$$

By simply inputting the wire diameter (d) into Equation 7, it is possible to calculate the cross-section area. However, Dobroschke's [150] explains that the R_{Cu} can also be calculated by using the diameter of the copper wire (d_{Cu}) instead of the A_{Cu}. Therefore, the equation has to be adjusted by multiplying the resistivity value of copper wire (ρ_{Cu}) times four and then divided by the product of multiplying π times d_{Cu}.

Dobroschke's [150] work observes how various factors affect coil conductivity, specifically noting that reduced fill factors lead to increased electrical resistance due to increased spacing between wires within the tightly wound structure. Notably however, research emphasises calculating measurements post-winding instead: Wolf [151] highlights instances where winding parameters such as the diameter and cross-sectional area approaching critical failure levels can contribute to a difference in electrical resistance. Of these parameters, the diameter wields the greatest interdependence on introduced errors and it can be analysed by using the next equation:

$$\Delta R = R1 - R0 = \frac{4L_1 \cdot \rho}{\pi \cdot {d_{nom1}}^2} - \frac{4L_0 \cdot \rho}{\pi \cdot {d_{nom0}}^2} \quad \text{Eq. 9}$$

A decrease in the diameter of a wire labelled as *d_nom1* is directly proportional to a decrease in its current-carrying capacity and, hence, an increase in electrical resistance. In multi-layering, utilising smaller diameter wires resulted from tightly compressed coils leading to shorter lengths [151]. Nonetheless, this compression also reduces cross-sectional area, thus resulting in increased electrical resistance. As a result of such, reductions that may possibly arise due to fluctuations throughout production processes or product tolerances may have significant effects on the electrical resistance, as shown in Figure 4.11. Figure 4.11 displays the variation of electrical resistance during winding, including incremental steps with each layer rolled onto the bobbin.

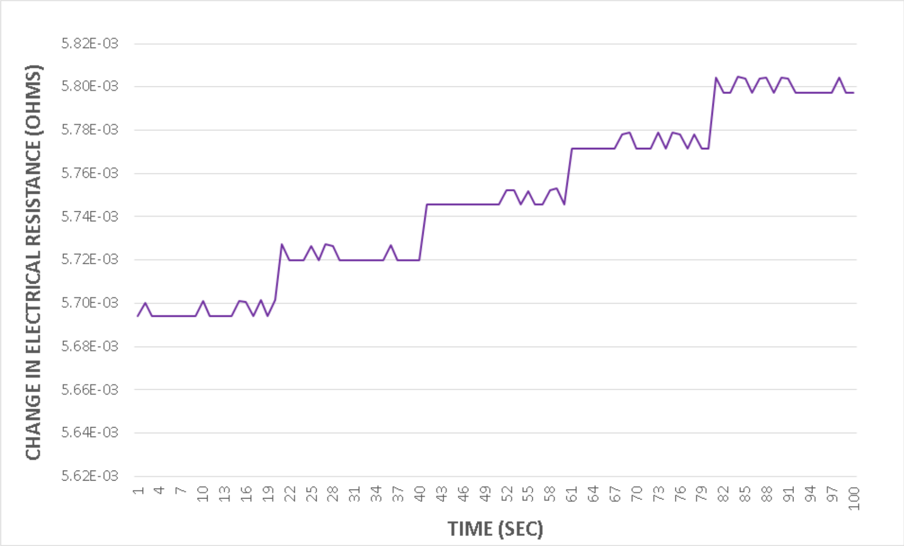


Figure 4.11. Electrical resistance chart of the DES model using a rectangular bobbin.

The work carried out by Komodromos et al. [155] offers insights into how different copper wire diameters respond to tensile force and how this affects their electrical conductivity characteristics. Experimental results showed that increasing strain levels led to changes in cross-sectional areas for all tested wires, resulting in variations in resistivity metrics across samples with small diameter sizes (0.63mm vs 1.18 mm), where respective resistance increments were measured at 23% compared with 8%. As previously echoed by Dobroschke [150] and Wolf [151], however, determining actual resistivity values during winding processes remains a challenge. The calculation of the electrical resistance value can be obtained by using the formula presented in Equation 7, but it highly depends on the layer and the bobbin shape used in the model. This equation required the resistivity, length, and cross-sectional area of the wire.

The resistivity utilised in the simulation was specify in Equation 7, yielding a value of 1.72x10^-8 Ωm. The total length of the wire was determined by Equation 10.

$$Total\ Length\ of\ Wire = P_0 \cdot N + (2 \cdot L - 2) \cdot T \cdot h \cdot N \qquad \text{Eq. 10}$$

When:

- P_0 be the initial perimeter (circumference or sum of sides) of the bobbin.
- N be the number of turns.
- L be the number of layers.
- T be the thickness of the wire.

- h be the height increment added per layer for non-circular bobbins (0 for circular).

Figure 4.12 displays an example of the first five layers of the simulation used to calculate the wire's length in the case of a circular bobbin. This calculation takes into account that each additional layer, the circumference of the bobbin increases by T (2.36 mm that represents twice the thickness of the copper wire). However, in the case of circular bobbins, there is no need to consider h so the formula becomes simpler;

$$Total\ Length\ of\ Wire = P_0 \cdot N \qquad \text{Eq. 11}$$

	Per turn mm	Per layer mm
1 Layer	94.24778	1884.956
2 Layer	101.6619	2033.239
3 Layer	109.0761	2181.522
4 Layer	116.4903	2329.805
5 Layer	131.3186	2626.371

Figure 4.12. Example of the first five layers where wire length was calculated for a circular bobbin.

After determining the length of the wire, the electrical resistance was calculated in each layer to serve as a reference for detecting any variations in the process. This procedure allowed the quantification of the variation in the electrical resistance per turn. These parameters were incorporated into the model for a second trial run, with a base tension of 40 Newtons and a winding speed of 300 rpm adapted from [148][154]. These parameters were selected as standard from previous experiments in literature [154], since they marked common values utilised during linear winding.

The simulation was validated against the model's logic and revealed that faults occur at 300 rpm due to high variation, as depicted in Figure 4.13. This figure presented the results obtained from the simulation, specifically the results from the third layer during linear winding because this layer is known to present faults that accumulated from previous layers. During this trial the simulation presented a column for geometrical faults, where if a fault was presented, it would be highlighted in red, otherwise it would be stayed as green. The next column was dedicated to detecting the type of deformation, in which if the predicted deformation was permanent (plastic), it would be highlighted in pink for better visualisation.

3	Fault	Deformation	Variation T	Diameter	Electrical resistanc	Variation ER
61.81	Double winding	Plastic	55%	1.18	0.00152114	0.17%
61.17	No other	Elastic	53%	1.18	0.00151856	0.00%
41.84	No other	Elastic	5%	1.18	0.00151856	0.00%
55.23	No other	Elastic	38%	1.18	0.00151856	0.00%
49.72	No other	Elastic	24%	1.18	0.00151856	0.00%
69.41	Double winding	Plastic	74%	1.18	0.00152502	0.43%
38.05	No other	Elastic	5%	1.18	0.00151856	0.00%
49.74	No other	Elastic	24%	1.18	0.00151856	0.00%
49.56	No other	Elastic	24%	1.18	0.00151856	0.00%
41.69	No other	Elastic	4%	1.18	0.00151856	0.00%
38.06	No other	Elastic	5%	1.18	0.00151856	0.00%
41.84	No other	Elastic	5%	1.18	0.00151856	0.00%
40.17	No other	Elastic	0%	1.18	0.00151856	0.00%
38.44	No other	Elastic	4%	1.18	0.00151856	0.00%
60.17	Multiple winding	Elastic	50%	1.18	0.00151856	0.00%
38.51	No other	Elastic	4%	1.18	0.00151856	0.00%
69.71	No other	Plastic	74%	1.18	0.00152502	0.43%
38.19	No other	Elastic	5%	1.18	0.00151856	0.00%
48.63	No other	Elastic	22%	1.18	0.00151856	0.00%
69.43	Double winding	Plastic	74%	1.18	0.00152502	0.43%

Figure 4.13. Example of a trial run where variation in the electrical resistance was detected.

The rest of the columns presented key results such as the variation on tension, diameter and electrical resistance value as previously presented in Figure 4.4. It is worth noticing that if the values obtained during the trial stayed under the stablished threshold for each of the columns, the system would not highlight any turn specific turn. Finally, the last column presented the variation in electrical resistance, where if any variation above cero was detected, the system would identify it and highlighted as red.

G. Cumulative error in electrical resistance

The simulation model was modified to calculate the cumulative increase in electrical faults in the winding system, as presented in Figure 4.14. This addition takes into account the stage at which fault development exceeds a set threshold whereafter windings are unsuitable for use. In assessing cumulative errors throughout each layer of coil turns, industry experts were consulted, and they suggested on establishing a threshold value for cumulative error in electrical resistance as 10% for this model.

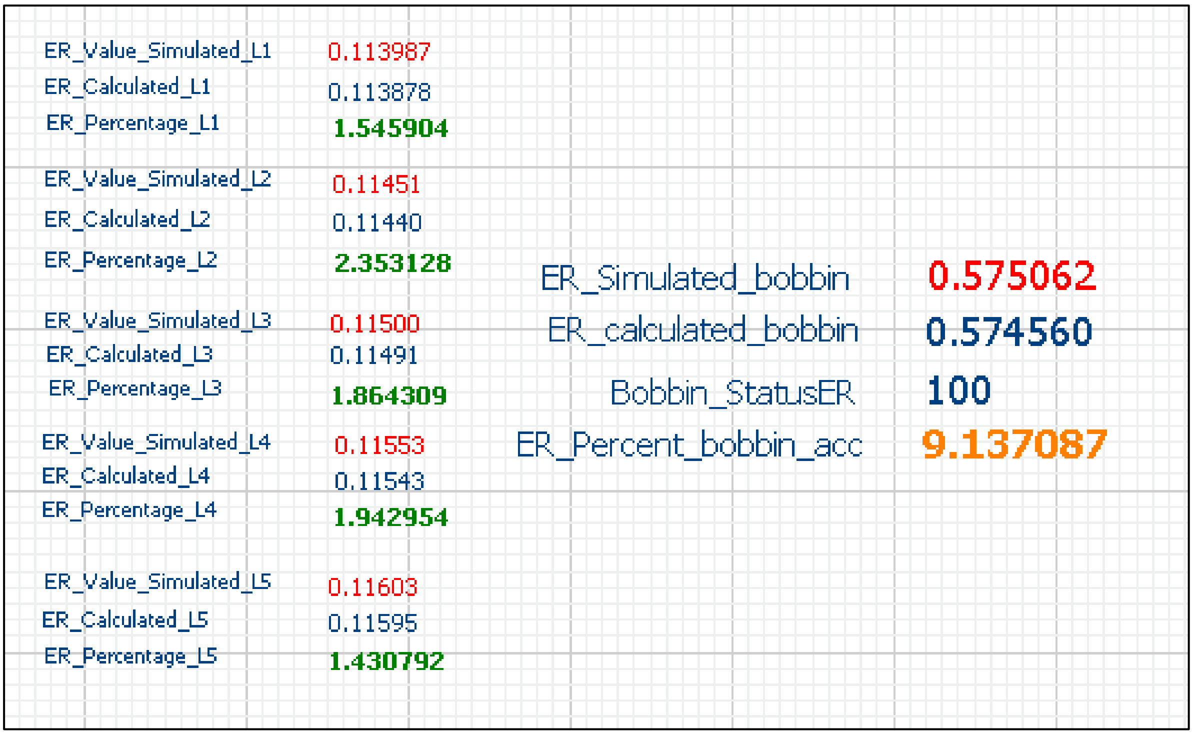


Figure 4.14. Representation of cumulative error calculation of high electrical resistance during coil winding.

When the increase in electrical resistance surpassed the set threshold, the model automatically rendered the winding unsuitable for use, was determined faulty. The cumulative error was obtained by calculating the percentage error in each turn of every layer and adding it as the winding progressed, as shown in Figure 4.15. To prevent the production of nonviable coils, the model was set to stop the process when this threshold value was reached.

```
threshold_error = 0.1  # 10% threshold
cumulative_error = 0.0  # initial cumulative error
faulty = False
def calculate_percentage_error(original_resistance, new_resistance):
    return (new_resistance - original_resistance) / original_resistance
for layer in coil_layers:
    for turn in layer:
        original_resistance = get_original_resistance(turn)
        new_resistance = get_new_resistance(turn)
        percentage_error = calculate_percentage_error(original_resistance, new_resistance)
        cumulative_error += percentage_error
     if cumulative_error > threshold_error:
            faulty = True
            break
    if faulty:
        break
if faulty:
    print("The coil winding is unsuitable for use and will be scrapped.")
else:
    print("The coil winding process is completed successfully.")
```

Figure 4.15. Pseudo code for calculating the cumulative error during coil winding

4.2.4 Interdependencies from the DES model

According to the DES model findings, it is possible to effectively detect and model interdependencies among input parameters as they relate to faults that arise during a winding process. The tension and winding speed were among the leading parameters that exhibit significant influence on the creation of these faults. Three different simulation experiments were carried out using the DES model. Each experiment focused on a different winding speed; one at a higher speed of 300 rpm, another at a medium speed of 200 rpm and a third at a lower speed of 100 rpm. The purpose of these simulations was to investigate how the different speeds affect the process of winding.

In each experiment the wire was subjected to a tension of 40 Newtons during the winding process. Variation was added to the tension based on the winding speed as discuss in Equation 2. Moreover, an established threshold for yield limit was maintain at 61.75 Newtons based on existing literature [154]. By conducting these simulation runs with varying speeds while keeping the yield limit constant, valuable insights can be gained regarding potential issues, like geometric faults and other variables that may arise during coil winding.

Experiment 1- High rotational speed

The occurrence of faults during winding can be attributed to variations in tension exceeding the yield limit per turn. At times, these variations can result in a significant uptick in tension levels by up to 70%. In the simulation experiment with the DES model Figure 4.16 displays the data collected. The experiment was conducted at a winding speed of 300 rpm. The figure illustrates how winding speed, tension parameters and geometric faults are interconnected. It provides insights, into trends, patterns and potential correlations helping us understand how different winding speeds affect the performance and reliability of the coil winding process.

Figure 4.16 offers a visual depiction of how different types of deformations variations in electrical resistance and their effects on tension values and geometric faults interact during the coil winding process. The type of deformation was highlighted according to the type of deformation for easier visualisation (green represents elastic deformation while red indicates plastic deformation). This colour coded system helps to quick identification. Moreover, the figure draw attention to points in the simulation where changes in electrical resistance were detected highlighting them in red. This visual cue helps in detecting any deviations in electrical resistance during the winding process.

An important discovery emerged from the experiment. It was observed that turns with a high variation in tension exceeding 23% caused high electrical resistance when the tension values surpassed the predetermined yield limit. As a result, certain geometric faults occurred, such as double windings and gaps in the wound coil. Furthermore, these geometric faults were

Layer 1							
Turn	Tension Value	Fault	Deformation	VarTension	Diameter	Electrical Resistance	Variation ER
1	54.20	No fault	Elastic	14.20	1.000	0.0251	0.000000
2	54.40	No fault	Elastic	14.40	1.010	0.0201	0.000300
3	66.40	Double W	Plastic	26.40	0.934	0.0230	1.260000
Layer 2							
Turn	Tension Value	Fault	Deformation	VarTension	Diameter	Electrical Resistance	Variation ER
1	46.92	No fault	Elastic	6.92	1.000	0.0202	0.000000
2	49.44	No fault	Elastic	9.44	1.010	0.0202	0.000000
3	63.40	Gap	Plastic	23.40	0.983	0.0241	1.305000
Layer 3							
Turn	Tension Value	Fault	Deformation	VarTension	Diameter	Electrical Resistance	Variation ER
1	46.85	No fault	Elastic	6.85	1.010	0.0207	0.000400
2	54.80	No fault	Elastic	14.80	0.990	0.0216	0.000400
3	65.60	Gap	Plastic	25.60	0.928	0.0245	1.390000

Figure 4.16. Results from the DES model of the winding process at 300 RPM with a base tension of 40N.

worsened by a decrease in wire diameter which further aggravated the issue. The decrease in diameter also caused an increase of over 1%, in electrical resistance.

During another trial run, now using a base tension of 60 Newtons instead, variations in tension raise up to 42% resulting in faults such as crossovers to be identified as presented in Figure 4.17. This figure presents a comparison between a simulation run at high speed with a control tension value against a simulation with a higher tension value. This produce that the wire become permanently deformed and reduce its cross-section in the process. As the formula for the electrical resistance calculation suggests, changes within the cross-section and diameter bring about consequential increases in the electrical resistance. It should be notice that during simulations, fluctuation within electrical currents was usually recorded between

0.2% up to a maximum of 2.0% – often causing rises in coil temperature and thereby negatively affecting stator insulation and performance.

3	Fault	Deformation	Variation T	Diameter	Electrical resistance	Variation ER
42.74	No other	Elastic	7%	1.18	0.00151856	0.00%

3	Fault	Deformation	Variation T	Diameter	Electrical resistance	Variation ER
85.20	Cross over	Plastic	42%	1.17	0.00154463	1.72%

Figure 4.17. Comparison between simulations trials, one with a control tension against another with a higher base tension.

Experiment 2- Medium rotational speed

Experiment 2 was conducted at medium speed, producing different results compared to the previous experiment. In this experiment the main focus was on keeping variations in tension below the base value. As a result, it was observed an increase of up to 10% in tension. This finding clearly demonstrates a significant relationship between winding speed and tension variations. It is worth noting that as the speed increases the magnitude of tension fluctuations also escalates. Figure 4.18 visually depicts this relationship by graphically representing the percentage changes in tension with respect to increasing winding speeds.

Note: The data points shown in Figure 4.18 presents the outcomes of conducting 100 runs of the DES model in order to verify its consistency. Moreover, by using an averaging method it can be ensured resilience against fluctuations and increase the reliability of the findings. Running the model 100 times strikes a balance between obtaining statistically significant results, managing computational resources efficiently, and validating the model's repeatability and robustness. An example of using this averaging method was presented by Cossar & Rezaei [156], where they explored the application of averaging estimation models in simulating Permanent Magnet AC electric motor and generator drive systems using Matlab/Simulink. It compared the performance of these models with standard switching converter approaches, finding that the average voltage models accurately predict key operational parameters while significantly reducing simulation times, making them advantageous for system-level modelling incorporating detailed mechanical and aeronautical subsystems.

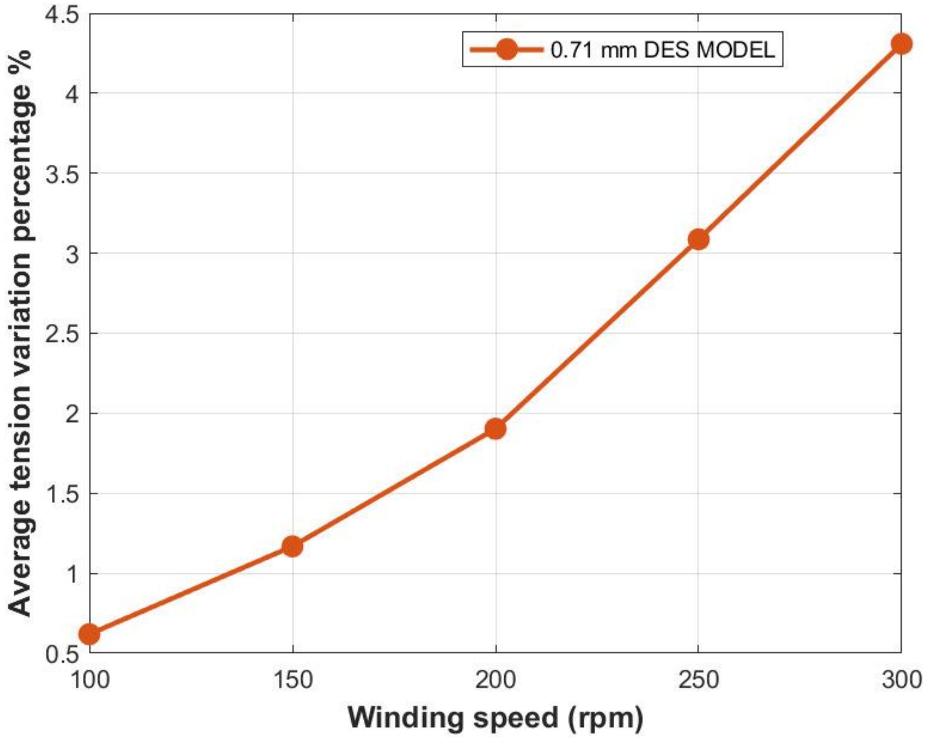


Figure 4.18. Plot of the average variation percentage in tension at various speeds.

Experiment 3- Low rotational speed

In the last experiment, the simulation was run at a low winding speed. The simulation was set with a base tension of 40 Newtons and a winding speed of 100 rpm. The results showed there were no faults detected during the winding process. This important finding is clearly shown in Figure 4.19. The consistent tension of 40 Newtons along with the low speed seemed to effectively prevent any geometric faults or changes in electrical resistance.

The reason why no faults were observed at lower winding speeds is because of the interaction between the controlled factors and the natural behaviour of the winding process. When the speed is slower there is less stress and tension on the wire during winding. By maintaining a controlled tension of 40 Newtons, it was ensure that there is not much strain on the wire, which helps prevent issues like double winding or gaps. This reduced tension also helps minimise variations in resistance, which ultimately leads to a decrease, in faults. This result highlights how important it is to control these winding parameters for the success of the process.

Layer 1							
Turn	Tension Value	Fault	Deformation	VarTension	Diameter	Electrical Resistance	Variation ER
1	42.74	No fault	Elastic	2.74	1.010	0.0197	0.000300
2	60.60	No fault	Elastic	20.60	1.010	0.0197	0.000300
3	48.74	No fault	Elastic	8.74	1.000	0.0201	0.000000
Layer 2							
Turn	Tension Value	Fault	Deformation	VarTension	Diameter	Electrical Resistance	Variation ER
1	58.00	No fault	Elastic	18.00	0.990	0.0210	0.000400
2	60.00	No fault	Elastic	20.00	0.990	0.0210	0.000400
3	61.00	No fault	Elastic	21.00	1.010	0.0202	0.000400
Layer 3							
Turn	Tension Value	Fault	Deformation	VarTension	Diameter	Electrical Resistance	Variation ER
1	60.20	No fault	Elastic	20.20	0.990	0.0215	0.000400
2	56.20	No fault	Elastic	16.20	1.000	0.0216	0.000000
3	53.80	No fault	Elastic	13.80	0.990	0.0216	0.000400

Figure 4.19. Results from the DES model of the winding process at 100 rpm with a base tension of 40N.

A. Wire tension and electrical resistance variation

According to the results from the DES model, it was found that changes in critical input parameters resulted in faults such as increased electrical resistance. The model revealed two significant associations among critical process parameters:

- The first one being between wire tension and electrical resistance,
- The second being between wire gauge, wire guide, and caster angle.

Figure 4.20 graphically demonstrates how variation in the electrical resistance of a rectangular bobbin increases the tension applied to the wire. This fluctuation reached as high as 11% when tension (represented by a green solid line) surpassed the yield limit (indicated by a red dashed line) by nearly 40 N. In addition, this graph indicated that when annealed copper wire with a diameter of 0.71 mm encountered tension beyond its yield limit (61.75N), it transformed from elastic deformation into plastic deformation mode, resulting in a smaller diameter that escalated electrical resistance significantly, creating problems for the coil's overall electrical resistance which directly impacts motor performance and reliability.

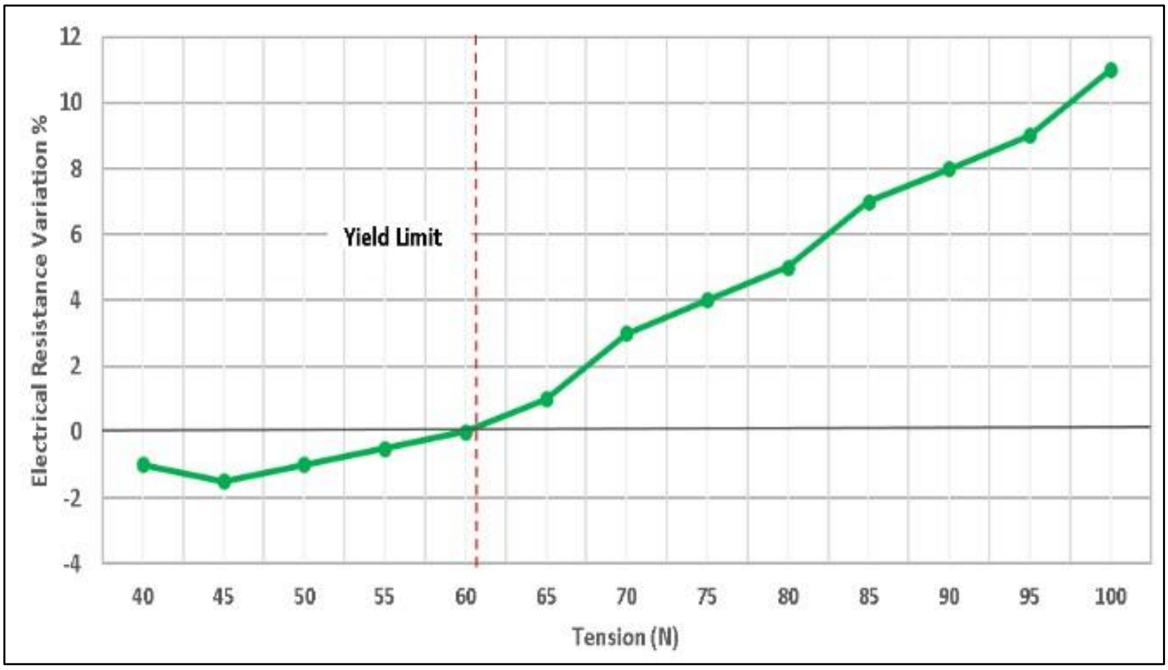


Figure 4.20. Plot showing variation in electrical resistance for a rectangular bobbin with respect to tension in the wire. The red dashed line shows the yield point of the wire.

B. Wire gauge, wire guide and caster angle

The DES model revealed how specific parameters, such as wire diameter, could considerably affect both wire guide speed and caster angle. Figure 4.21 (a) demonstrates these impacts, the blue line depicts changes in decreased or increased diameters when there are fluctuations in the wire guide speed that then influence how much the purple line decreases or increases downwards when charted from 6.2 to 5.8 degrees.

Results showed that improper tolerances during manufacturing or inappropriate levels of stress applied during winding could result in a variance in wire gauge. According to the DES model analysis, changes in wire gauge affected the speed of the wire guide as depicted by Figure 21 (a). In this figure, it illustrates that wire weight influences guide speed due to smaller diameters generating less weight resulting in faster guides than usual, while larger diameters generate extra weight causing slower movements which affect caster angles which alters the winding geometry resulting in various contours like convex or concave windings observed as a reduction in fill factors.

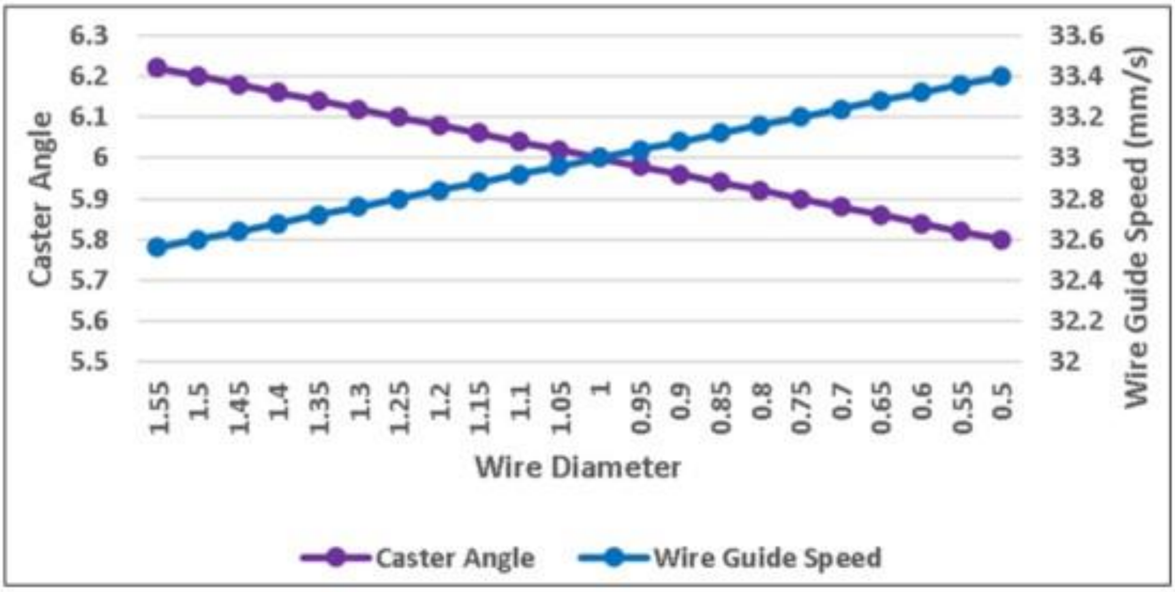


Figure 4.21. (a) Variation in winding speed and caster angle with respect to the diameter of the wire.

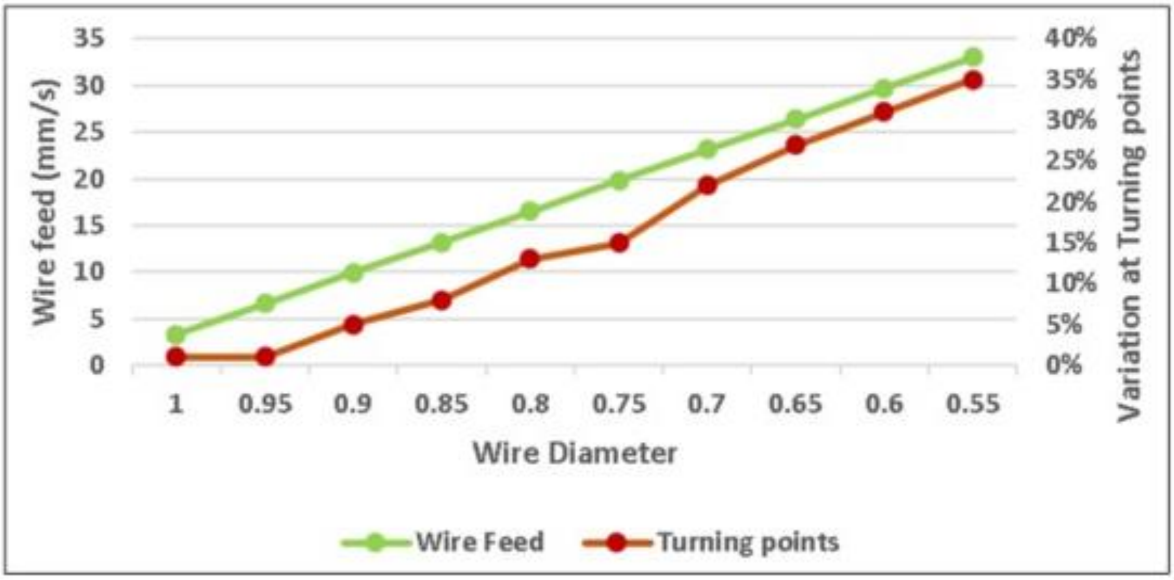


Figure 4.21. (b) Relationship between wire diameter, wire feed rate and variation of wire guide at turning points.

The graph presented in Figure 4.21 (b) displays an interesting finding regarding wire diameter reduction. Specifically, when reducing it by half, there is a consequential increase of almost 40% in the green line, which represents the feed rate of the wire, as well as over a 35% increment in the red line – indicating greater variation when stopping at turning points. As stipulated earlier, using thinner wires results in elevated speeds for both the guiding system and wires themselves, affecting said variability. The DES model was utilised to calculate variations occurring based on distance travelled after deceleration commenced.

In order to accurately calculate the wire displacement (s) from a starting point to a critical turning juncture along a given wire guide path, Equation 12 was used, where velocity (v), elapsed time (t), acceleration (a) and time elapsed squared (t^2) were used. However, quite often there exists only compounded variations within these calculations due largely to shifting conditions resulting from heightened momentum caused by an increasing wire feed.

$$s = vt + \frac{1}{2}at^2 \qquad \text{Eq. 12}$$

This anomaly initiates additional errors cumulatively experienced with every turn taken, effectively impacting proper alignment of wires whilst also distorting geometric shapes along with contributing, potentially, to what could be a poor fill factor. This generates a need for methods to calculate percentage variation between the precise stopping point required at the exact turning mark, and the actual final locations of the wire guide stopping, either before or after as per variance in the acceleration levels. In this regard, the DES model offers ideal opportunities to model correlations among various parameters of complicated processes involving deformable materials.

When creating the simulation model for geometrical faults, the caster angle was determined by examining both wire guide position and the wire's location on the bobbin's surface [5]. By using the maximum caster angle as the benchmark for boundary determination purposes, it was possible to establish both upper and lower limits within which no geometrical faults should occur. However, should rotational speeds see excessive variation and cause the safety limit for caster angles to be exceeded, then a certain type of geometrical fault may result. It is imperative to consider that an increased span between safety limits in relation to measured rotational speed will ultimately yield unnecessary geometry failure; such failures if any must always be minimised.

The rate at which the wire guide moves has a direct bearing on the caster angle relative to minimum threshold requirements expected from this action, which would produce a smooth circular motion during its rotation cycle around the coil (bobbin). If the wire's movement was not significantly reduced, gradually a decrease of the caster angle would occur resulting in gaps being produced in the coil structure. This will be observed in a significant reduction of the bobbin's fill factor from its standard 90.7% to just 65-75%. However, on the other hand, when the wire guide speed is increased beyond required upper limits, double-winding faults will be generated, and major workflow disruption could ensue.

A sudden change in wire guide speed can occur when the diameter of a wire keeps fluctuating. This can cause an increase in its feed rate but also make it impossible for it to reach the anticipated turning points (Figure 4.21 b). Known as abnormal acceleration, this anomaly arises due to mismatching between wire feed speed and winding location. For thinner wires, faster wire guide speeds lead to more significant differences while still reaching turning points.

The typical approach for obtaining a positive caster angle during winding entails situating the wire guide behind the designated location. Such an approach ensures proper tensioning of wires and enables efficient wrapping progress. Results suggest that reduced weights of wires lead to an increase in speed once passing through guides, effectively reducing the caster angle and subsequently creating geometrical faults, such as gaps, upon surpassing designated areas intended for wrapping. Conversely, if too much weight is added onto wires, causing slower progression coupled with incorrect casters, this can lead to the inward dragging of wires creating double layering concluding in unsatisfactory filling factors for resulting coil geometries, which could be either bulgy or concave.

4.3. Results from the experiments on the coil winding machine

This section presents results obtained through a series of experiments using a lab-based linear coil-winding machine. These results have been instrumental in validating the DES model and attention was paid towards exploring underlying findings and clarity around validation-critical results when compared to predictions, as guided by the DES Model.

4.3.1. Electrical Resistance faults

During the experimentation with a linear winding machine, it was aimed to assess how various process parameters, namely winding speed, wire diameter and bobbin shape impacted occurrences of faults within this system. The experimentation began by quantifying wire electrical resistance using a *FLUKE 8808A* bench digital multimeter prior to engaging in any tests as presented in Figure 4.22.

Figure 4.22. Fluke 8808A Bench Digital Multimeter used to measure the electrical resistance in the copper wire. (Adapted from Fluke)

The FLUKE *8808A* multimeter was selected due to its level of accuracy, precision and stability. The Fluke 8808A multimeter has a specified DC voltage accuracy of 0.015% allowing it to provide precise resistance measurements within a deviation of only 0.0015 Ohms, from the actual resistance value. This makes it ideal for detecting the smallest variations in electrical resistance. Its reputation as an instrument from a reputable brand, combined with its versatility and easy, to use interface ensures that it can effectively fulfil the precise measurement needs during this research.

To account for changes resulting from experimental procedures associated with this research effort, measurements were recorded before and following every experiment conducted during this investigation to analyse what happens when rotational speed varies as specified in the design protocol per test round. Based on the findings, a plot was created, as presented in detail in Figure 4.23. This shows the electrical resistance's variation magnitudes across different bobbin shapes during varying rates of rotation.

Note: The figures displaying plot charts in this results section (4.3 and 4.4) represent the averaged data points obtained from performing 33 experiments conducted on the linear winding machine. This limited number of experiments was attributed to the extensive setup requirements and the time-consuming nature of result analysis associated with running a linear winding experiment. Nonetheless, despite the relatively small number of trials, the averaged data points provide valuable insights into the performance and behaviour of the system under study. This averaging method not only enhances the reliability of the findings but also helps mitigate the impact of outliers or anomalies, thus ensuring the accuracy and validity of the results.

A. Winding speed and change in electrical resistance

Findings from the experimental data, presented in Figure 4.23, reveal that maximum elevation in electrical resistance occurred when using a rectangular bobbin at a winding speed of 800 rpm. The trend reflected that augmentation in rotational velocity amplified variations seen within electrical resistance measures. Specifically, observations indicated significantly lower-level changes when speeds were kept low. This finding accentuates a clear correlation between increasing rotational speed and heightened levels of electrical resistance during winding procedures. The variation was created because the wire feed increases and creates a momentum that does not allow the wire guide to stop at the exact turning point causing extra tension on the wire as explained by Hagedorn et al. [5]. This extra tension causes the cross-sectional area of the wire to be reduced creation a variation in the electrical resistance.

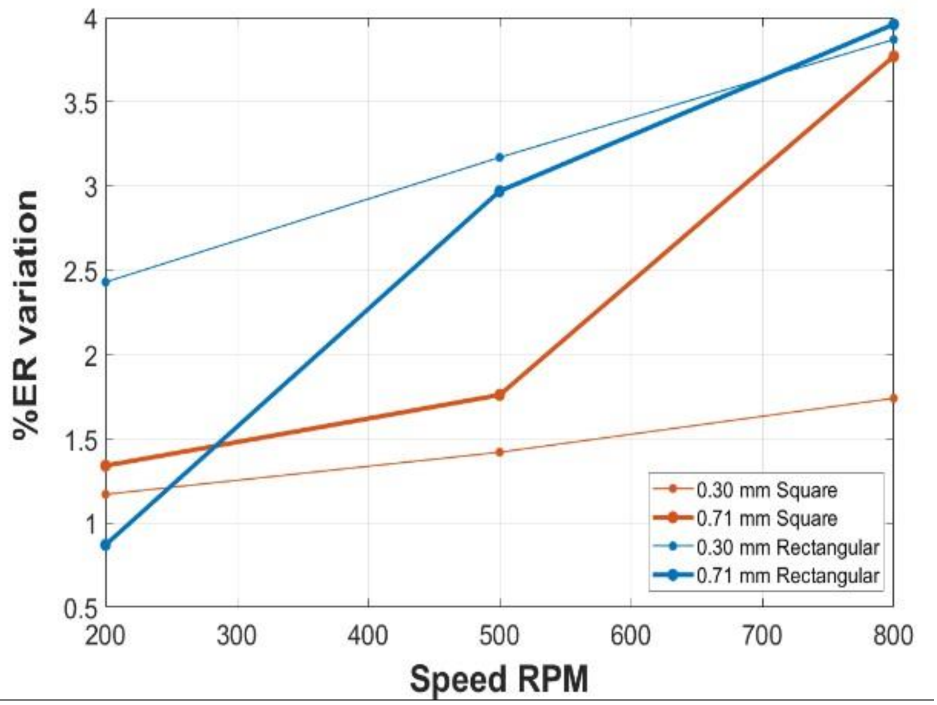


Figure 4.23. Electrical resistance variation percentage with different wire gauges and bobbin shapes.

B. Bobbin shape and change in electrical resistance

An analysis was conducted to uncover how bobbin shape affects electrical resistance changes, finding that the rectangular shape presented an average increase in electrical resistance of 4% at high speeds, whereas its counterpart – square-shaped bobbins – displayed only a slight average increase of 2.7%. The aspect ratio greatly influences these differences in bobbin shapes. The height-to-base measurements dictate whether the bobbin will be rectangular or square shaped – where a larger aspect ratio corresponds to more variation seen within resistive properties, and vice versa. Figure 4.23 showed that using bobbins with higher aspect ratios result in double or nearly double variations compared to their counterpart; rectangular results are nearly twice as high as those seen for squares. These findings suggest that careful consideration of bobbin shape may best address manufacturing needs when fabricating products reliant on electrical components.

C. Wire gauge and change in electrical resistance

The experiments investigated the complex relationship linking wire gauge to fluctuations in electrical resistance levels. It became apparent that as wire diameter increased, so did overall levels of electrical impedance – especially noticeable when comparing different gauges using square-shaped bobbins where nearly a 2.0% increment was observed between measurements for large versus smaller-sized wires, whereas when using rectangular-shaped bobbins, variations attributed to different diameters were less consequential, ranging at around only 0.2%. Therefore, results presented in Figure 4.23 showed that variations arising due to differences in both factors (i.e. wire gauge & bobbin shape) contribute to the accumulation of defects over time.

4.3.2. Geometrical faults

The approach taken to study the winding schema defects involved recording videos during experimentation so that it could be closely analysed to see how different forms of geometric flaws would manifest over time. Special care was taken to examine each individual video on a per-frame basis using an exhaustive checklist for identifying common forms of geometric errors within winding schemata. To give an example: Figure 4.24 shows multiple images taken from footage following high-speed (800 rpm) testing with square and rectangle bobbins. These images depict several types of geometric fault, including gaps, crossings, and double windings. From this collection of recorded data points, it was possible to produce a graphical representation (Figure 4.25) illustrating how changes in winding speed relate to alterations in the occurrence rate of particular geometrical faults.

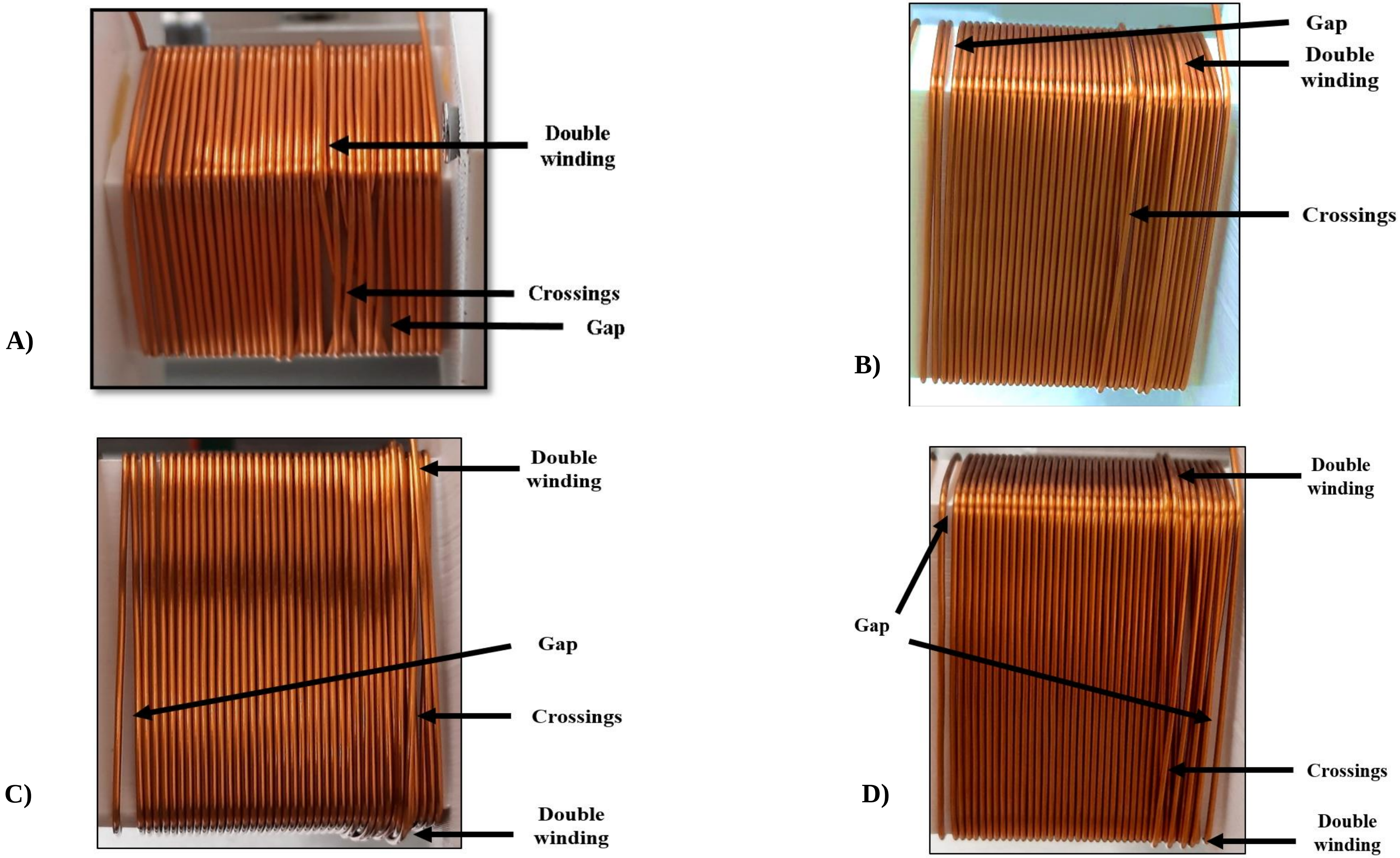


Figure 4.24. Geometrical faults during linear winding at 800 rpm using a square bobbin (A & C) and rectangular bobbin (B & D).

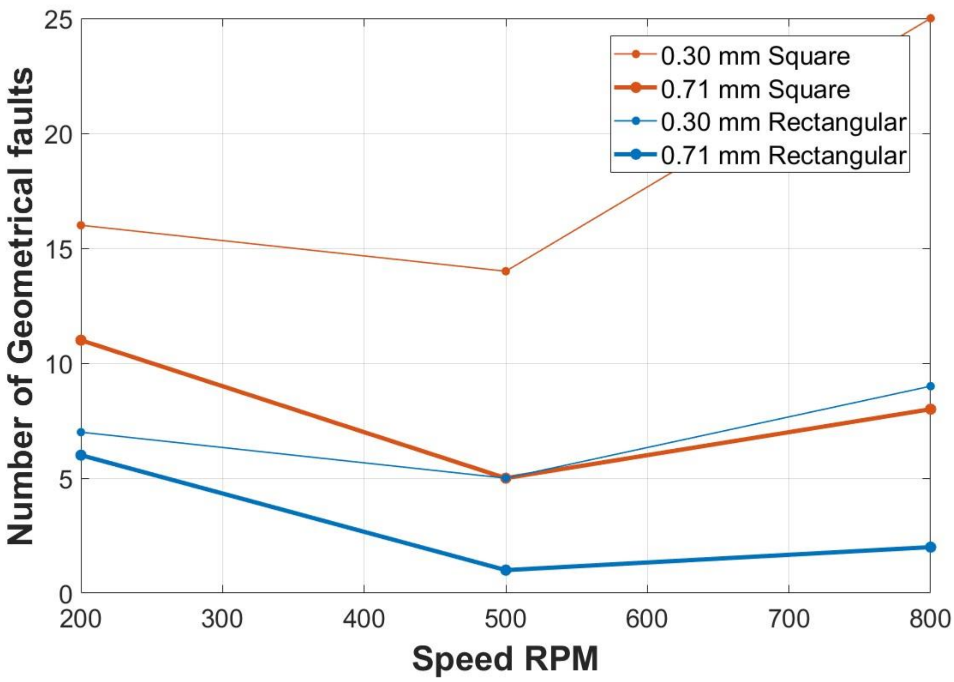


Figure 4.25. Plot with the number of geometrical faults at different winding speeds variating input parameters.

A. Winding speed and geometrical faults

Analysing the data presented within Figure 4.25 highlights some clear trends regarding their relation to geometric faulting tendencies while employing different winding speeds. The most notable being a substantial increase demonstrated among fold defects while utilising both bobbins shapes under either higher or lower rotational settings, particularly registered upon reaching either 200 or 800 rpm set points.

The occurrence of faults when changing the speed at which the wire was wound can be attributed to several underlying factors. Firstly, variations in winding speed directly affect the tension applied to the wire during the process. This increased stress on the wire can lead to fold defects due to excessive stretching or bending. Secondly, the choice of bobbin shape, the wire length between the winding point and the wire guide interacts with the winding speed influencing how layers of wire are stacked. This interaction can cause misalignments contributing to a tendency for faults at specific speeds. Additionally, as the winding process involves accelerations and decelerations it can disrupt the smooth winding of the wire and potentially result in defects like double windings or gaps. Lastly, properties inherent to the copper wire itself such as its elasticity and resistance to deformation play a role in how it reacts to stress when wound at different speeds.

Modifications in the diameter of the wire have an impact on the occurrence of geometric faults when the winding speed changes. The dynamic behaviour during speed changes in winding along with material properties like flexibility and elasticity and the need for tension adjustments all depend on variations in wire diameter. Additionally, changes in wire diameter from smaller to larger gauges can influence interactions with the bobbin including its shape and contours, which can affect how wire layers are stacked and aligned.

This changed significantly though once testing under moderate operational ranges (500 rpm); both trials exhibited lower counts in geometric anomalies noted during normal usage conditions. Conversely, this led to further difficulties being experienced within subsequent trials where speed kept rising which consequently caused similar fault occurrences seen when executing standard procedures with minimal wind speeds (mentioned above) leading to the conclusion that these findings suggest a correlational association between winding velocity and geometrical faults that arise during winding.

B. Bobbin shape and geometrical faults

Modifying the shape of the bobbin can have an impact on the occurrence of geometric faults in coil winding processes. This is because there are interconnected factors involved. When the bobbin shape is change it directly affects how the layers stack and align which can lead to misalignments. It also has an effect on how tension is distributed along the wire potentially resulting in uneven winding. The altered shape may guide the wire in ways causing overlaps and uneven winding. Additionally new contact points and friction may arise, further contributing to faults [3]. Ensuring that the bobbin shape is compatible with the characteristics of the wire is crucial for achieving winding. It is important to understand and manage all these implications because changes in bobbin shape can compound with variables like dynamic behaviour disruptions during speed changes or interactions, with other factors.

According to the data presented in Figure 4.25, choosing the right shape for the bobbin can have a significant impact on the outcome of the winding process. Notably, using a square-shaped bobbin seems to result in substantially more geometrical faults compared to using a rectangular-shaped one. Specifically, it was found that running the winding machine at lower speeds with a square-shaped bobbin would lead to over double the number of errors than those resulting from utilising its alternative counterpart. While both shapes seem comparable regarding geometric troubles during medium-speed operations, faults amplify significantly, and almost triple, when utilising thinner gauge wire with square-shaped bobbins. When working under higher speed conditions, selecting the rectangular shape delivered remarkably better results – yielding only two defects, compared to the eight presents (on average) when using a square bobbin.

C. Wire gauge and geometrical faults

Modifying the thickness of the wire used in coil winding processes can result in types of geometric issues such as double winding and gaps due to a combination of interconnected factors. When adjusting the wire thickness, it is important to make changes in tension to ensure proper winding. Thicker wire usually requires higher tension. The mechanical properties of the wire such as strength and resistance to deformation also change with thicknesses affecting how the wire responds to winding forces and potentially causing misalignments and geometric problems. Additionally, variations, in wire thickness can impact layer stacking and distribution of tension which may introduce overlaps and irregularities during the process.

The insights offered by Figure 4.25 underscore the vital role played by wire gauge in creating geometric flaws during winding processes. Specifically, this impact is notable with reduced-sized wire gauges employed for winding tasks. In analysing both square- and rectangle-shaped bobbin performances under different conditions involving diverse wirings sizes, it was established that fine-gauged wiring sizes led to more fault appearances than larger ones did. Conversely, designing wound systems using heavy-duty wires produced fewer geometric anomalies across all bobbin categories analysed hereunder, although attention should be paid to these very fine wiring details so as not to cause irreparable deficiencies too often observed within various designed items. For example, when using square bobbins, thinner wiring created 25 fault spots. However, embracing thicker wire lowered this number to only 9 faults, even at high winding speeds. It is evident that using reduced-sized wires produces profound effects on the occurrence of geometrical faults.

4.4. Comparison of results between simulation model and physical experiments

4.4.1. Electrical resistance faults

The obtained results from the DES modelling were validated through experimentation conducted within laboratory settings utilising linear coil-winding machines. These experiments assessed key process parameters through their deliberate variation for increased accuracy assurance purposes. Subsequently, the results were compared with those derived from the DES model. For analysis purposes of the electrical resistance variation upon different wires sizes, Figures 4.26 and 4.27 were developed.

Figure 4.26 highlights correlations between rotational velocities, represented by rectangular bobbins, along with electrical resistance percentages presented as straight dashes depicting a series of experiments. While Figure 4.27 examines these same variables utilising square bobbins instead, each of these figures also analyses two variants: thicker wires (represented by blue lines 0.71mm) and thinner ones (represented by red lines 0.3mm). The findings show an established correlation between winding speed and electrical resistance percentual variation for this test setup, displaying higher percentage variations with utilisation of thicker wires – especially at increased velocities where changes can ascend to 4% as observed in Figure 4.26.

Although both Figures 4.26 and 4.27 demonstrate uniform increases in percentage variations, which are consistent with winding velocity increases, results indicate that a rectangular bobbin's overall discrepancies are more significant compared to those exhibited via a square bobbin's analysis. Regarding the square bobbin, systematic variation increases were only witnessed at higher respective speeds and thicker wires ranging from 1.3% to a maximum of 3.7%.

Based on these results, it is clear that the shape of the bobbin plays a critical role in the percentage variation of electrical resistance in copper wire. This research indicates that rectangular bobbins tend to create higher variations even when winding speeds are slow, whereas square bobbins remain relatively consistent until higher speeds are reached. This is due to the aspect ratio of the bobbin shape and its influence on tension during winding. A greater aspect ratio leads to rapid fluctuations in tension throughout the process and can exceed yield limits. In contrast, bobbin shapes with a square aspect ratio maintain consistent tension throughout the process, resulting in less variation during winding. This finding is crucial for manufacturers seeking to reduce variation in electrical resistance and improve coil quality.

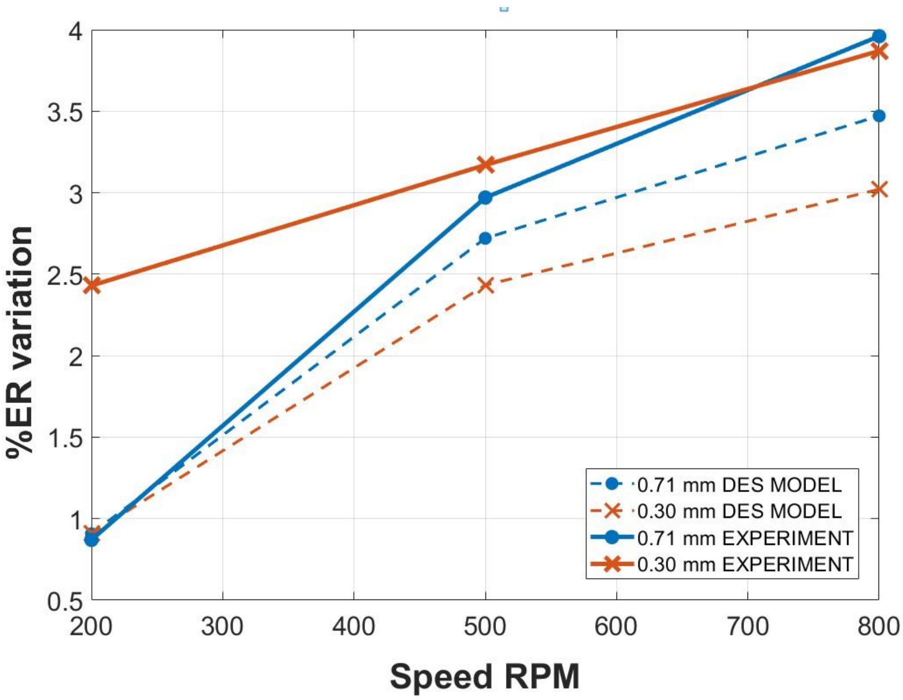


Figure 4.26. Comparison for a rectangular bobbin with two different wire gauges using a DES model and linear winding experiments to determine the percentage error in electrical resistance.

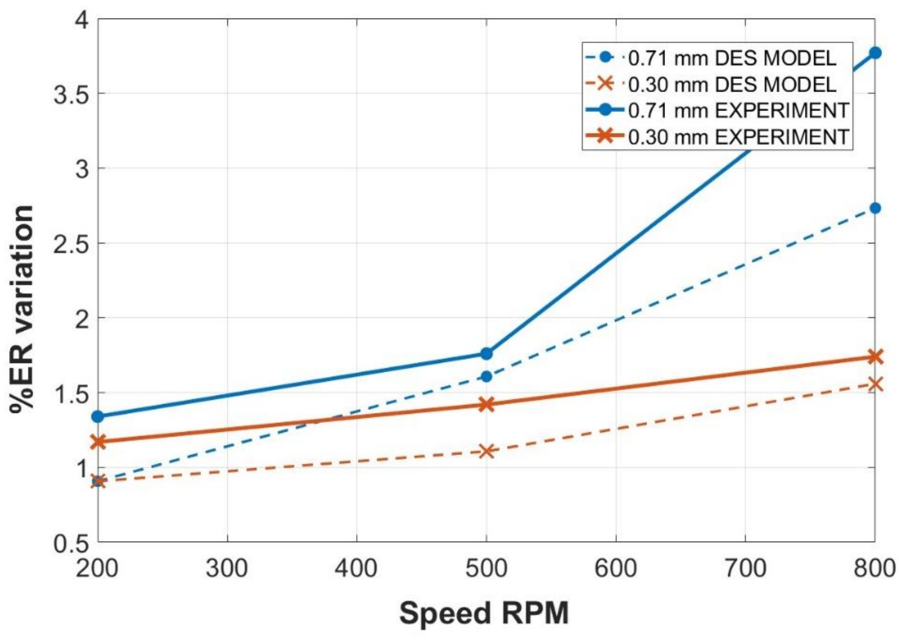


Figure 4.27. Comparison for a square bobbin with two different wire gauges using a DES model and linear winding experiments to determine the percentage error in electrical resistance.

4.4.2. Wire gauge

In addition, experiments were conducted with different wire gauges, which showed correlation between winding speed and wire diameter. The comparisons between the DES model and physical experiments revealed that larger diameter wires tend to deform more easily at high speeds leading to greater electrical resistance. Conversely, the DES model confirmed that smaller diameter wires exhibited lower levels of electrical resistance variation. However, it is worth noting that the DES model considered only three input parameters with high influence, whereas realistic operational environments have multiple factors impacting fault creation such as friction in wire guides [3]. One possible input parameter that can influence the occurrence of faults during winding is friction within the wire guide. When friction increases it applies additional tension to the wire as explain by Le-Blanc [3], which can potentially create defects in the final product.

4.4.3. Accuracy of the results from the DES model

Following the physical experiments depicted in Figures 4.26 and 4.27, an evaluation of the DES model's accuracy was conducted by examining its percentage error or difference in results. Calculating the percentage error determines how much trend differs between the DES model and experiments using a linear winding machine. By referring to Table 4.2, it can be seen how the variation in electrical resistance differs between both these factors. For rectangular bobbins that use thinner wires (0.30 mm), there was an increased percentage of error (1.56%) compared to experiments, suggesting external factors were at play such as material handling or machine wear and tear. On the other hand, when testing square bobbins, a smaller percentage of errors were observed at only 0.27%. It's fair to say that out of these two models tested so far, the square bobbin appears more accurate owing to fewer discrepancies in results found – albeit both models remain relatively reliable, with under 5% errors overall.

Table 4.2. The Percentage Error results for the rectangular and square bobbin when calculating the electrical resistance.

	Rectangular bobbin		
	200 RPM	500 RPM	800RPM
0.71 mm	0.02%	0.25%	0.49%
0.30 mm	1.56%	0.74%	0.85%

	Square bobbin		
	200 RPM	500 RPM	800RPM
0.71 mm	0.43%	0.16%	1.04%
0.30 mm	0.27%	0.31%	0.19%

Table 4.3 summarises the calculated cumulative errors for different DES model scenarios. To determine this, the percentage difference between regular electrical resistance and high electrical resistance during winding was calculated, recorded and added up throughout the entire simulation process. The results indicated that, as winding speed increases in both types of bobbin shapes (square or rectangular), there is an increase in overall cumulative error rates. However, this tended to be more noticeable with rectangular ones because of the constant wire length changes that occur during winding due to their shape, leading to higher errors than those recorded on square ones.

Table 4.3. The cumulative error results for the rectangular and square bobbin when calculating the electrical resistance in the DES model.

	Rectangular bobbin		
	200 RPM	500 RPM	800RPM
0.71 mm	0.90%	2.60%	3.47%
0.30 mm	0.89%	2.45%	3.01%

	Square bobbin		
	200 RPM	500 RPM	800RPM
0.71 mm	0.90%	1.67%	2.75%
0.30 mm	0.87%	1.22%	1.58%

4.4.4. Geometrical faults

To evaluate how accurately the DES model detects geometric faults on the first layer of a bobbin, two plots were generated (Figures 4.28 and 4.29). Both experimental data and the DES model revealed higher occurrences of geometric imperfections during high-speed runs (e.g., ramping up/down affects caster angles), but also noted considerable incidences when operating at slower speeds. In fact, thinner wires are especially problematic as their greater spring-back effect can be difficult to manage compared with thicker wires given up/down ramping issues, which exacerbate imperfections. Interestingly, a median speed indicates lower numbers of geometric faults as caster angles remain more stable. However, the square bobbin in Figure 4.29 produced a significantly greater number of faults compared to the rectangular bobbin shown in Figure 4.28.

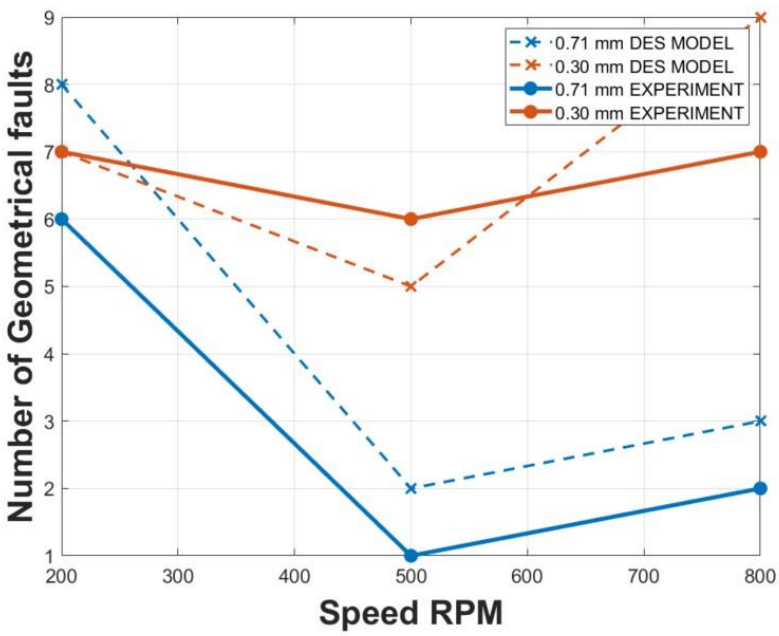


Figure 4.28. Comparison for a rectangular bobbin with two different wire gauges using a DES model and linear winding experiments to determine the number of geometrical faults in the first layer.

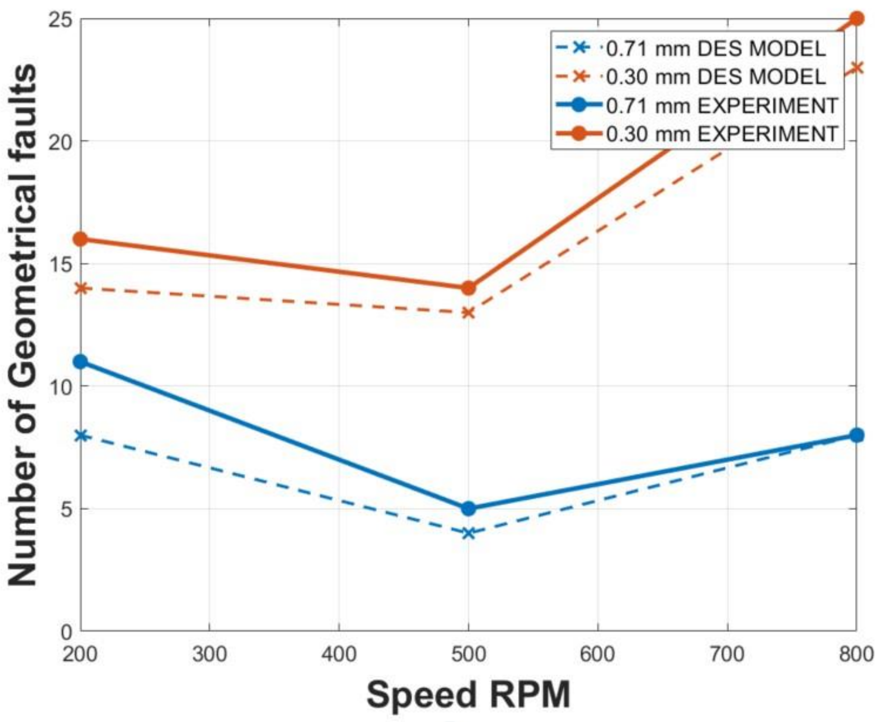


Figure 4.29. Comparison for a square bobbin with two different wire gauges using a DES model and linear winding experiments to determine the number of geometrical faults in the first layer.

Indeed, when using thinner wires at slower speeds rectangular bobbins showed only 7 imperfections, whereas the same configuration with a square bobbin caused that number to increase to 16. This merits attention since having an aspect ratio of 1:1 appears to result in more imperfections that are geometric during winding processes. Additionally, it has been observed that processing speed plays an important role too, since wire guides move too fast at high speeds and they may miss turning points – thereby generating larger changes in casting angles leading ultimately to incorrect wire placement and resulting in double windings.

Ensuring a caster angle within the established limits is reliant on both the aspect ratio of each bobbin and the speed variation. Therefore, regulating these parameters is essential for achieving proper winding. To achieve this, control features can be introduced to maintain a consistent caster angle throughout the process. One potential solution involves calculating turning points that are specific to the current winding speed, enabling the wire guide to halt at precise intervals and maintain a stable caster angle even at high speeds.

As presented in section 3.1.5, findings showed that thinner wires are prone to a spring-back effect during coil winding leading to greater geometrical faults compared to their thicker counterparts, an observation confirmed by comparing experimental results with those obtained through a DES modelling technique. It is thus advisable for manufacturers to use a uniform diameter of wire throughout all stages of coil-winding processing so as not to incur such difficulties.

Experts within simulation and electrical motor manufacturing industries have approved the implementation of DES models given their accuracy in detecting fault-causing factors while maintaining quality standards during manufacture (with no other pre-existing fault detection technology providing enough detail about location within bobbins being available yet). Through utilisation of a specified turn's electrical resistance measurements, a manufacturer attains more confidence when conducting end-of-line tests.

While validating effectiveness, the experiments only considered two different wire gauges at extreme ends of the size spectrum. Hence, it is important to conduct further tests to look at the effects resulting from variations in wire diameters on the electrical resistance observed after coil winding. With this strategy, it is possible to test the DES model using other winding techniques such as needle winding – according to experts familiar with simulation and electrical motor manufacturing processes.

4.5. Summary

This chapter presented the results obtain from a DES model that addresses interdependency in processing criteria driving error-prone outcomes during electric motor manufacturing processes. This model includes time-dependency within the coil-winding stage to simulate deformable copper wire behaviour resulting from factors specifically addressing input variables, including wire tension, winding speed, bobbin shape and diameter.

Both simulated and physical experiments on the coil-winding machine were conducted using validated critical parameters variation targeted at determining their effect on generating defects during primary steps towards electric motor manufacture, alongside expert feedback for validation purposes. The results demonstrated specific input variables such as wire tension and winding speed played essential roles throughout the various stages within the coil-winding stage required for fault detection accuracy, thus improving end-product quality expectations.

Conducted experiments have uncovered a range of notable correlations influencing electrical resistance during the coil-winding process. Specifically, winding speed and wire thickness were observed to have a direct relationship with electrical resistance variation, resulting in greater variation when using thicker wires or higher speeds. Bobbin shape is another pivotal factor to consider; when using rectangular bobbins, significantly higher variations were noted at slower switching speeds. On the other hand, square-shaped bobbins remained consistent until higher wind speeds were used. These findings indicate that while DES models are reasonably reliable for predicting outcomes during winding processes, errors can emerge. In comparing models' efficacy at different configurations, thinner wires in combination with rectangular bobbins proved particularly challenging, generating up to 1.56% maximum error rates.

Beyond these aspects, geometric faults were also noted throughout all tests conducted irrespective of wire size or speed setting (most prominently for square-shaped bobbins and thin-gauge wiring). To improve winding quality and achieve better end-products while reducing waste and inefficiencies in manufacturing processes altogether, strategies promoting control features aiming to maintain consistent caster angles need to be considered for wider implementation across the manufacturing floor as industry standards progress. Finally, this research advocates further observational testing aimed at measuring how different wire diameters ultimately influence post-process electrical resistance levels after successful coil-winding delivery has been achieved.

CHAPTER V: ENHANCING FAULT DETECTION IN COIL WINDING MANUFACTURING PROCESSES USING A HYBRID COMPUTATIONAL FRAMEWORK

5.1 Introduction

In this chapter, an analysis of the results obtained from the proposed hybrid computational framework for fault detection in the coil winding manufacturing process is presented as shown in Figure 5.1. Utilising a method called knowledge distillation for transferring knowledge presents an approach to condensing the valuable insights and expertise contained within a complex simulation model into a lighter and more efficient form. By simplifying this knowledge into a condensed model, it is possible to greatly reduce simulation time while still maintaining a level of accuracy [151]. This approach takes advantage of the ability of distilled models to capture patterns and relationships, from the original simulation optimising computational resources without sacrificing performance.

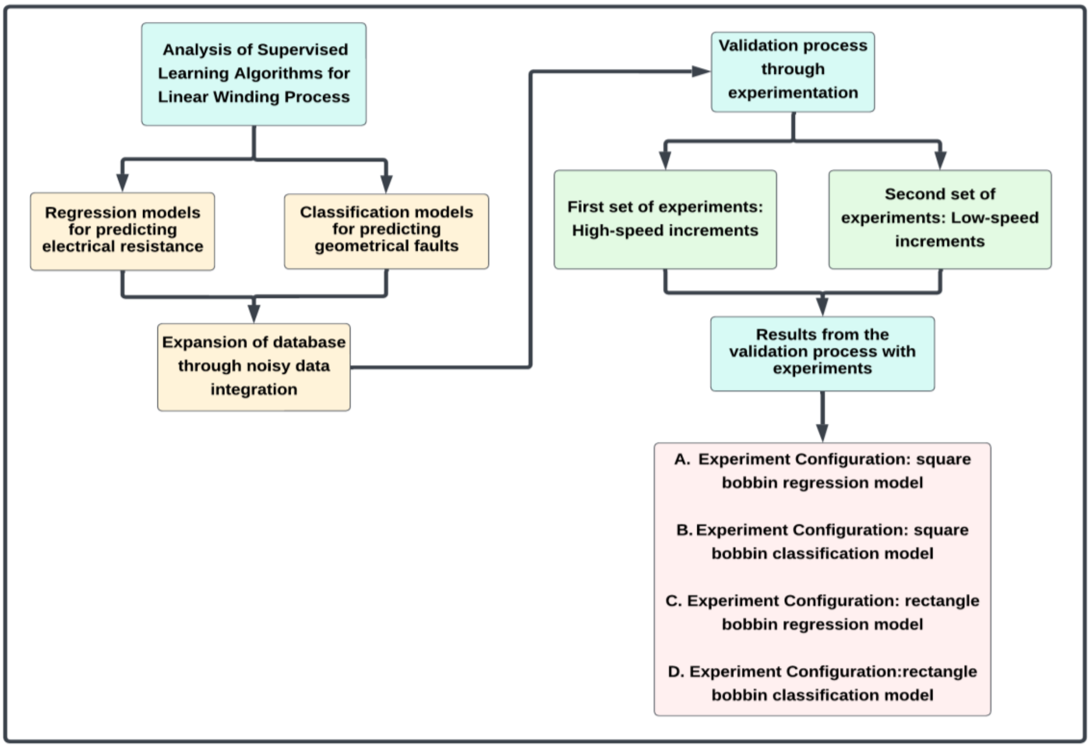


Figure 5.1. Chapter Overview: Results from the hybrid computational framework for fault detection in the coil winding manufacturing process.

The approach of KD in this research entails transferring the understanding of a complex model, like the DES model, that represents how a bobbin behaves when being linearly wound to a faster and simpler model such as the RF model, which acts as a student. The purpose of this transfer is to distill the knowledge contained in the DES model into the student model so that it can make accurate predictions, about the state of the bobbin while also simplifying computations and improving efficiency. This chapter highlighted any potential benefits related to the modified strategy for the coil manufacturing process, which included a reduction in the manufacturing time, improved stator quality, substantial improvements towards overall machine safety, and an increase in overall level of trust towards future designs.

5.2 Results and comparison of the SML models

The linear winding process presented several challenges during the simulation process as discussed by Sell-Le Blanc et al. [3] because of its intricate and constantly changing nature due to the use of deformable material. Results showed that interactions between multiple physical phenomena during this process such as the motion of laying wire combined with mechanical deformation, thermal behaviour, and electrical properties, makes it difficult to accurately predict nonlinear influences over time [148]. Additionally, other external factors like material properties or operator behaviour introduce more variability into the system making data analysis for simulation difficult [161].

Next, the focus of the chapter was to demonstrate how well the new proposed framework presented in section 3.2 could predict and enhance the simulation speed for models simulating linear coil winding processes. The goal was achieved by comparing several SML algorithms with different datasets and selecting the one with the best performance. The process began by using the software “Witness Horizon” to develop a DES model that simulated the various interdependencies during the winding stages of the process as discussed in section 3.1. This model could be used for developing preventative maintenance plans aimed at reducing vulnerability when faults inevitably arise. Although the DES model delivered noticeable improvements in efficiency over other simulation models, such as FEA, the DES model took in average two minutes to simulate a single coil on a *quad-core Intel Core i5-9300H 9th Generation* processor with 8GB RAM. As Thompson et al. [101] mentions, currently industrial settings have a demand for even shorter computational times.

Therefore, there was a need of a technique capable of been used as a student model during the KD process while improving the accuracy and speed of predictions in the DES model. After a thorough review of the literature, SML algorithms was selected as a solution for the following reasons:

- **Availability of Labelled Data:** In manufacturing settings labelled data is often easily accessible which is advantageous for learning.
- **Enhanced Prediction Accuracy:** Supervised learning models are specifically designed to provide predictions based on historical data making them well suited for improving prediction accuracy.
- **Faster Simulation Speed:** Once trained supervised learning models are computationally efficient. Can make faster predictions compared to time consuming DES simulations.
- **Sensitivity Analysis:** Supervised learning models can be utilised for sensitivity analysis enabling the understanding of how variations in input parameters influence outcomes.
- **Model Generalisation:** These models can learn patterns from training data and adapt to evolving manufacturing processes.

Other approaches such as unsupervised learning, rule-based systems or reinforcement learning do not offer the same advantages in terms of prediction accuracy and simulation speed.

- **Unsupervised Learning:** Unsupervised methods focus more on data exploration and grouping than providing accurate predictions, which makes them less suitable for predictive modelling in manufacturing.
- **Rule Based Systems:** While rule-based systems are automated, they may not be well suited for ever changing manufacturing processes. They often require manual adjustments and maintenance.
- **Reinforcement Learning:** While powerful reinforcement learning may not be practical for manufacturing processes due to its time-consuming trial and error approach and may not directly address the need, for simulation speed.

Therefore, multiple SML algorithms such as DT, RF, SVM, KNN, NB, and Neural Networks were compared to select the most accurate and efficient algorithm in section 5.2.1. To assess the precision and accuracy of these learning algorithms and compare their performance, visual tools such as scatter plots and confusion matrices were utilised. Scatter plots has been used as visual representations when evaluating the connection between predicted and real values, in regression or classification scenarios [37]. These charts provided insights into the models ability to differentiate between classes (fault types) and how their performance varies across decision boundaries. Confusion matrices were also used to provide a detailed breakdown of the models predictions in comparison to the actual labels (geometric faults) during the classification process. These matrices present information on positives true negatives, false positives and false negatives for each class. By analysing these matrices, it was possible to evaluate the accuracy of the models. This analysis helped identify strengths and weaknesses for each algorithm.

Hyperparameter tuning within an SML algorithm like a neural network was also explored to understand whether it would yield better results than the other algorithms. During the hyperparameter tuning process, various parameters of a neural network such as learning rate, activation functions, number of layers and neurons per layer were adjusted while the objective of improving predictive accuracy of the network remains. This culminated in using a finely-tuned neural network for comparison against other algorithms.

When it comes to comparing various SML algorithms utilised in linear winding processes, Figure 5.2 highlights six primary process parameters that functioned as inputs for evaluation purposes: winding speed, wire gauge, bobbin shape, layer, yield limit, and caster angle. The first parameter, winding speed, represents the rotational speed of the shaft while winding. The second, wire gauge, refers to the diameter of the copper wire. Bobbin shape is another variable, limited to two shapes: square and rectangular. Layer refers to a specific coil-winding layer consisting of 20 turns each and a complete bobbin comprising five layers in total. Yield limit was another crucial parameter analysed that described the point where wire transitioned from elastic to plastic deformation with 0 or 1 representing two respective states. Caster angle was an angle that defined the orientation between the winding location at the bobbin and the wire guide.

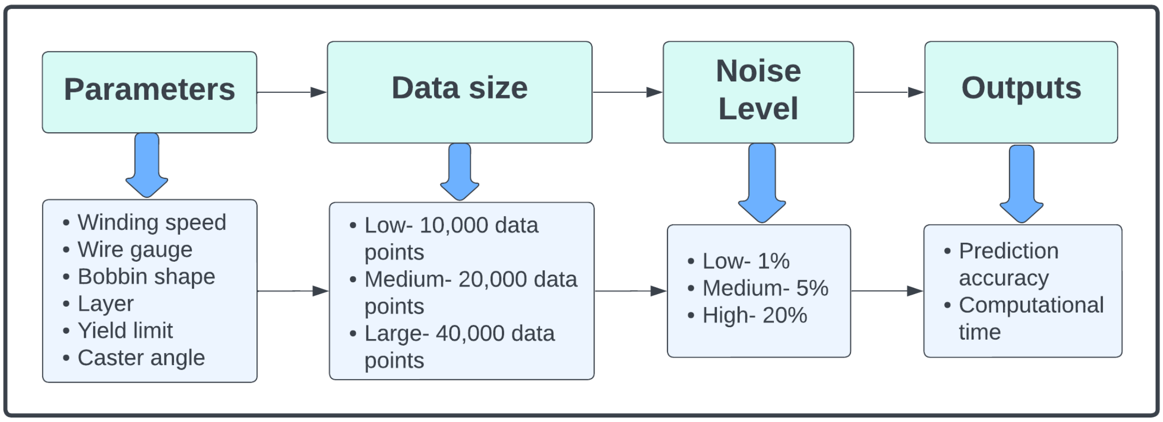


Figure 5.2. Factors introduced to the SML algorithms for comparison.

This research utilised two types of models to analyse the data, a regression and a classification model. While the regression model forecasted changes in electrical resistance by each coil winding turn's percentage variation, the classification model, on the other hand, successfully identified geometric faults per turn. To determine how well each model performed predictions, both models were evaluated using established techniques.

Predictive accuracy was deployed successfully during the evaluations for both models, along with limited simulation periods and varied dataset sizes (Figure 5.2). The comparisons between the SML algorithm advantages and disadvantages were discussed using three crucial parameters initially (winding speed, wire gauge, and bobbin shape), rather than six. This was done to compare the different algorithms based on their computational complexities while increasing practical applicability through minimising overfitting risks as suggested by Greasley & Edwards [82].

The framework involved utilising three distinct datasets (consisting of differing data sizes) containing various levels (ranging from 1% to 20%) of added white Gaussian noise through random perturbations inherent within each simulation model's output structure. Adding said noise levels into the model’s simulation would produce expected measurement errors or uncertainties associated with realistic industrial manufacturing scenarios necessary for testing the corresponding model's robustness effectively under varying data input conditions [6].

5.2.1 Analysis of Supervised Learning Algorithms for Linear Winding Process

In this analysis, it was examine how different supervised learning algorithms perform when it comes to predicting electrical resistance during the winding process. Accuracy charts have been plotted which showcase how well these algorithms predict winding speed (which ranges from 100 to 350 rpm) and electrical resistance (which ranges from 100, to 900 milliohms). The original values are represented by the blue markers while the red markers indicate the predictions made by the algorithm. For this evaluation, a dataset comprising 40,000 data points was utilised and no noise was introduce during testing.

A. Analysis of regression models for predicting electrical resistance during linear winding

The DT algorithm has shown promising abilities when it comes to the linear winding process. The MSE of 0.156 indicates a reasonably accurate prediction. By looking at the accuracy plot (Figure 5.3), it is possible to see that the algorithms predictions (shown in red) closely match the resistance values (shown in blue) at different winding speeds. This suggests that the DT algorithm has the potential to accurately predict resistance during linear winding a factor, in the manufacturing process of EM.

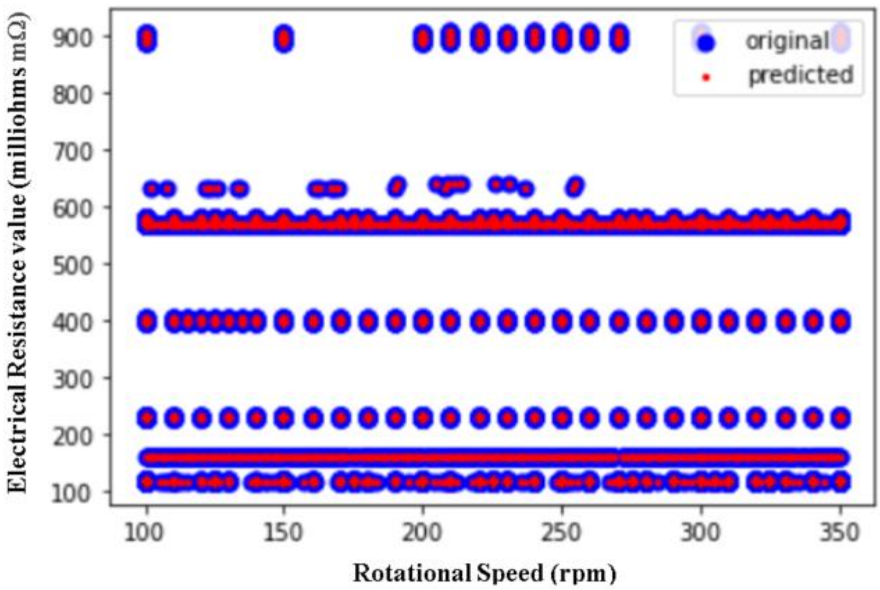


Figure 5.3. Regression model performance of the DT model showing the predicted electrical resistance (in red) compared to the actual values (in blue), with a MSE of 0.156.

The RF algorithm, which is a technique, for ensemble learning showed impressive accuracy when it came to predicting electrical resistance in the linear winding process. It achieved a level of precision with a MSE of 0.142 as shown in Figure 5.4. Its effectiveness comes from using ensemble learning, which combines the outputs of multiple trees to reduce overfitting and improve accuracy. Moreover, RF is known for its ability to handle linear relationships and accurately assesses the importance of features. These factors contribute to its predictive performance, in the manufacturing domain.

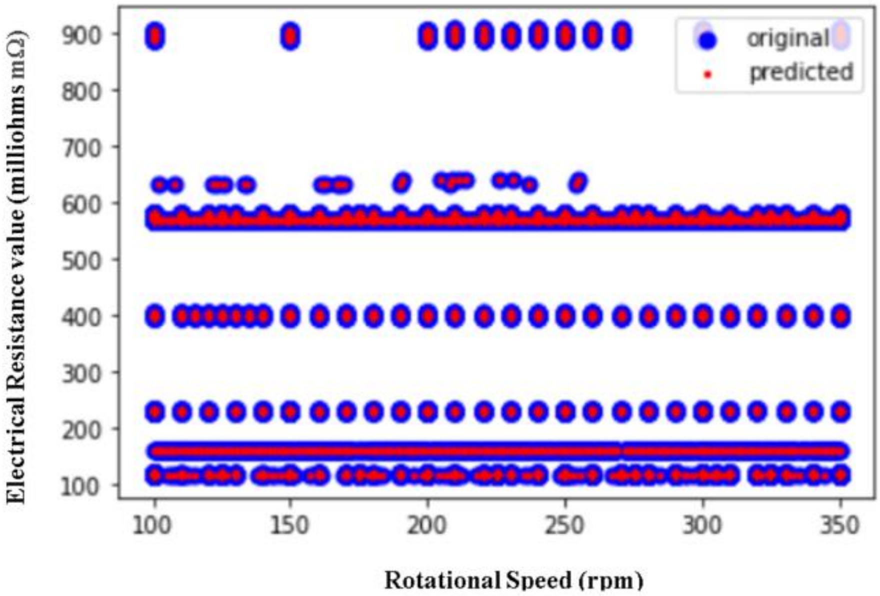


Figure 5.4. Regression model performance of the Random Forest model showing the predicted electrical resistance (in red) compared to the actual values (in blue), with a MSE of 0.142.

In this case the SVM algorithm, known for its flexibility and effectiveness showed a MSE of 40529 as shown in Figure 5.5. This indicates a difference, between the predicted electrical resistance and the actual values. There could be multiple reasons behind this less than ideal performance. Firstly, the accuracy of SVM is greatly influenced by the choice of hyperparameters. If these parameters are not properly tuned it can have an impact on the results. Secondly, if the relationship between winding speed and electrical resistance is highly non-linear, SVM might struggle to model it. Another important factor is the pre-processing of data, including scaling and normalisation. This step is crucial for SVM to perform at its best because it is sensitive, to how features are scaled. Lastly, given the complexity of both, SVM models and the dataset itself there is a possibility that overfitting occurred. This highlights the importance of controlling model complexity to avoid such issues.

Importantly the analysed algorithm showed an enhancement in their predictive accuracy when it came to electrical resistance particularly within the 550 to 600 milliohm range. This specific interval seemed to be crucial as it exhibited a level of precision and better alignment with the actual values predicted by the algorithms. The reason behind this improvement can be attributed to the algorithms ability to effectively capture and understand the patterns and dynamics inherent in the winding process, within this particular resistance range.

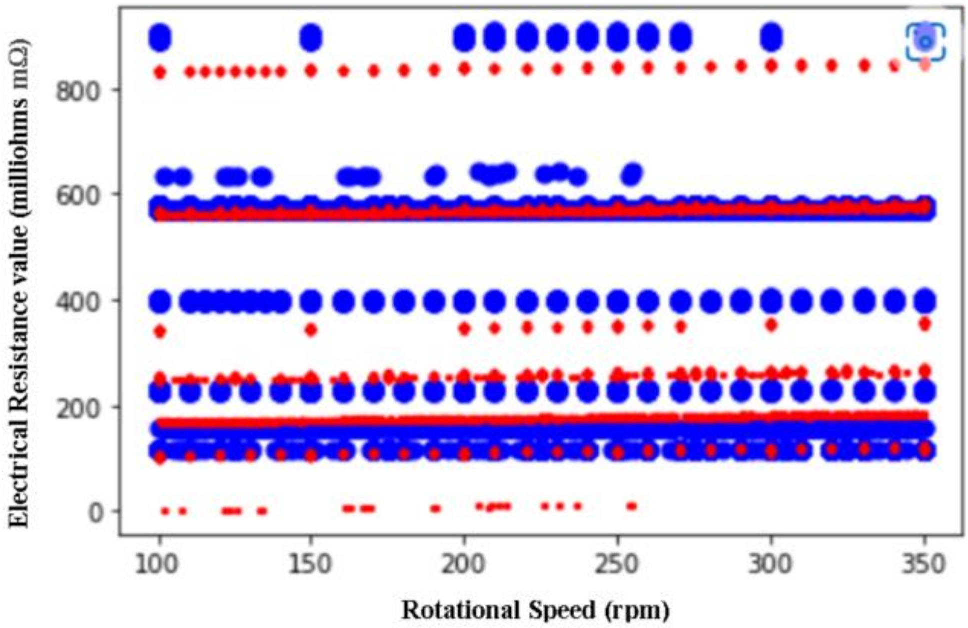


Figure 5.5. Regression model performance of the SVM model showing the predicted electrical resistance (in red) compared to the actual values (in blue), with a MSE of 40529.

The KNN algorithm did not perform well as expected with a MSE of 39052 as shown in Figure 5.6. It particularly struggled in predicting electrical resistance values that were above 600 or below 150 milliohms. Most of its predictions fell within the range of 150 to 600 milliohms suggesting that it was more accurate in that specific zone. However, when it came to values outside this range the algorithm faced difficulties due to its reliance on neighbours for predictions. This made it sensitive to the distribution and density of data points. Therefore, the algorithms performance was affected by data representation and irregularity in data distribution beyond the mentioned range. To enhance its accuracy across all resistance values carefully should be given to the pre-process data and potentially explore weighted distances, for neighbour contributions.

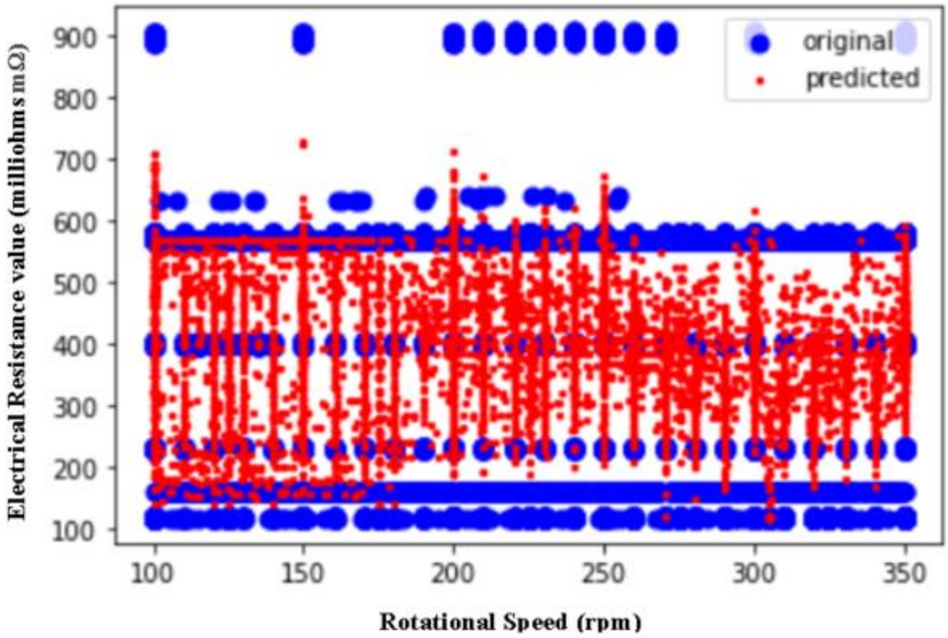


Figure 5.6. Regression model performance of the KNN model showing the predicted electrical resistance (in red) compared to the actual values (in blue), with a MSE of 39052.

The performance of the NB algorithm was not optimal as it had a high MSE of 32938 as shown in Figure 5.7. Interestingly the algorithm faced challenges in predicting a wide range of electrical resistance values. It often focused its predictions on points like 200, 300, 500 and 650 milliohms. Among these, the algorithm frequently predicted values around 500 milliohms. This tendency to localize predictions indicates that the algorithm struggled to capture the complexities and variations within the continuum of resistance. The localized nature of its predictions may be attributed to assumptions about feature independence inherent to the NB algorithm. To improve its adaptability and accuracy across a range of electrical resistance values possible enhancements could include advanced feature engineering addressing assumptions, about feature independence and exploring ensemble techniques.

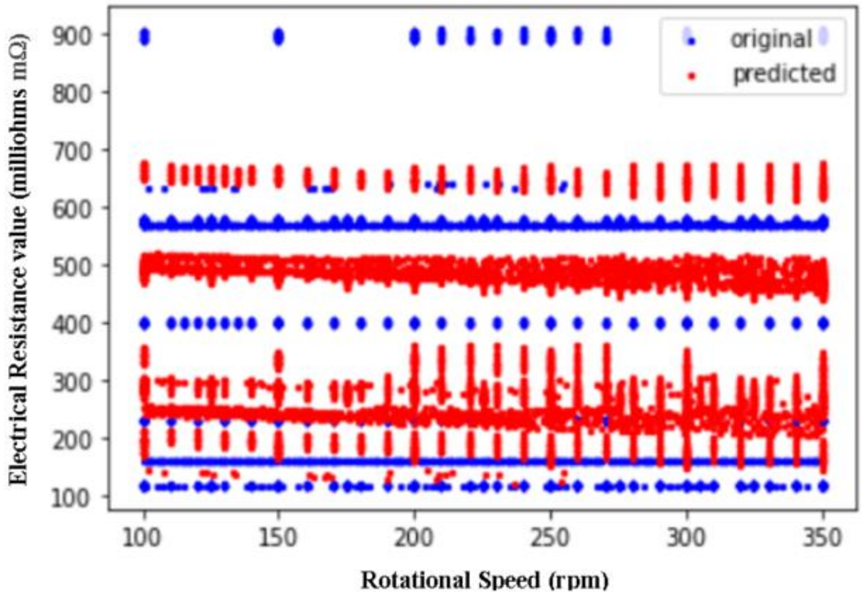


Figure 5.7. Regression model performance of the NB model showing the predicted electrical resistance (in red) compared to the actual values (in blue), with a MSE of 32938.

The tune ANN showed promising performance with a MSE of 148 as shown in Figure 5.8, were most of the predictions were accurate and aligned well with the actual electrical resistance values. However, there was an anomaly in the predictions between 100 and 250 rpm, specifically at an electrical resistance of 650 milliohms. During this range, the model had some mispredictions that deviated from the values. These discrepancies might indicate that the ANN model is sensitive to combinations of speed and electrical resistance, which warrants further investigation into potential causes like insufficient training data in that range network architecture.

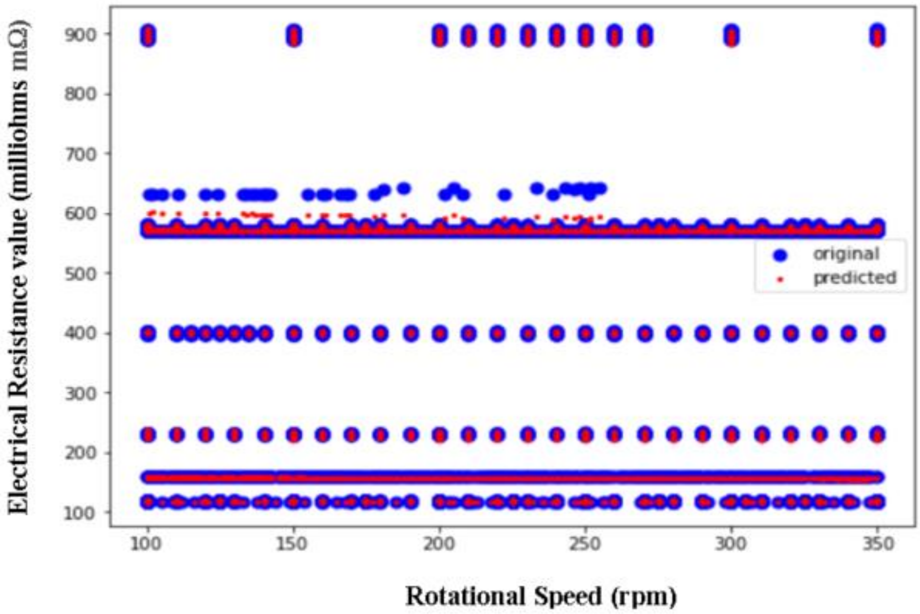


Figure 5.8. Regression model performance of the tune ANN model showing the predicted electrical resistance (in red) compared to the actual values (in blue), with a MSE of 148.

In this evaluation of different supervised learning algorithms, each algorithm demonstrated its own unique strengths and weaknesses when it came to predicting electrical resistance during the linear winding process. The DT algorithm although it had a MSE of 0.156 showed only moderate predictive ability. However, the RF model outperformed it with a MSE of 0.142 indicating its proficiency in capturing underlying patterns in the data.

The SVM algorithm showed an MSE of 40529 suggesting non-accurate predictions for electrical resistance. On the hand both the KNN and NB algorithms had even higher MSEs (39052 and 329338 respectively) indicating significant challenges in making accurate predictions. Notably, NB exhibited a bias towards specific resistance values, which limited its ability to provide diverse predictions.

Lastly, the tune ANN displayed promising potential with an MSE of 148. Although there were some mispredictions at data points, particularly around 650 milliohms within a specific range of speeds the ANN showcased overall accuracy. In conclusion, the RF algorithm emerged as the effective, in predicting electrical resistance followed closely by the DT and the tune ANN models.

B. Analysis of classification models for predicting geometrical faults during linear winding

In this section, the goal is to assess how six different supervised learning algorithms perform on the winding model focusing on classification. To evaluate their performance confusion matrices were used to analyse how well each algorithm classifies data points into specific categories. A confusion matrix can be used to understand the algorithms accuracy, in identifying true positives true negatives, false positives and false negatives providing an overview of their classification accuracy.

When evaluating the accuracy of classifications using confusion matrices geometric states that may occur during the linear winding process were represent. Each state signifies a condition or pattern that the model aims to classify. Here is a breakdown of the states shown on the axes:

1. **No Fault:** This is when there are no irregularities or faults in the process, which is considered an ideal state.
2. **Double Winding:** It refers to when the wire is wound in a double loop instead of a single one resulting in a fault.
3. **Gaps:** This indicates gaps or spaces in the winding deviating from the desired uniformity.
4. **Crossing:** This happens when wires cross or overlap, creating irregularities in the pattern.
5. **Flange Winding:** It describes winding at the edges or flanges of the bobbin.
6. **Loose Winding:** It represents winding that is too loose or slack deviating from the desired tightness.

By utilising these states within a confusion matrix, it is possible to evaluate how accurately each algorithm classifies instances into these specific fault categories. This provides insights, into how well the classification models perform.

The DT algorithm demonstrated an overall accuracy of 90.86% as shown in Figure 5.9, indicating its ability to correctly classify the majority of instances. However, it is important to investigate the misclassifications in the confusion matrix for an understanding of its performance. It seems that the algorithm sometimes misclassifies faulty winding as 'Double Winding' (110 cases). This could be due to the complexity involved in the process. In situations, slight variations in the winding pattern may resemble a double loop leading to misclassification. The algorithm might struggle to distinguish these subtle differences.

Moreover, there are instances where gaps are misclassified as 'Loose Winding' (399 cases). This could be because both types of faults exhibit irregularities that deviate from uniformity making it challenging for the algorithm to differentiate between them especially when the variations are subtle. Similarly, there is a tendency for 'Crossing' faults to be misclassified as 'Double Winding' (363 cases) possibly because the algorithm finds it difficult to discern the nuanced differences between these fault types. 'Crossing' involves wires overlapping or crossing paths, which can resemble a pattern of 'Double Winding' in cases and cause confusion, for the model.

	NF	D	G	C	F	L
NF	[[7371	0	0	0	0	0]
D	[110	0	0	363	0	0]
G	[0	0	657	0	0	0]
C	[0	0	0	457	0	0]
F	[0	0	0	42	601	0]
L	[0	0	399	0	0	0]]

Figure 5.9. Classification performance of the DT model, with an accuracy of 90.86%, highlighting misclassifications across different geometrical states.

The RF algorithm obtained an accuracy rate of 98.83% as shown in Figure 5.10, which indicates its strong ability to correctly classify instances. While there are some misclassifications they are relatively minimal. When the algorithm misclassifies 109 instances as 'Double Winding' that were actually non faulty, it suggests a challenge in distinguishing normal winding patterns from those that resemble 'Double Winding.' This misclassification could occur when occasional variations in the winding process mimic the pattern of a loop causing confusion, for the model. However, it is more concerning when the algorithm misclassifies 11 actual 'Double Winding' instances as non-faulty. This implies that some genuine 'Double Winding' faults are not being accurately identified. It is possible that the algorithm fails to capture all the patterns that define 'Double Winding,' leading to these false negatives.

Despite these misclassifications, the RF algorithm still demonstrates great accuracy. Its capability to handle DT and combine their results allows for highly accurate classification of different geometrical states. However, further optimisation and fine tuning may be necessary to reduce the occurrences of misclassifying 'Double Winding' cases as non-faulty and improve the precision and reliability of the algorithm.

	NF	D	G	C	F	L
NF	7360	11	0	0	0	0
D	109	364	0	0	0	0
G	0	0	657	0	0	0
C	0	0	0	457	0	0
F	0	0	0	0	643	0
L	0	0	0	0	0	399

Figure 5.10. Classification performance of the Random forest model showcasing an accuracy of 98.83%, with minor misclassifications between geometrical states.

The SVM algorithm achieved an accuracy rate of 98.48% as shown in Figure 5.11, indicating its proficiency in accurately classifying geometrical states. A notable concern is the misclassification of 110 instances as non-faulty when they were actually 'Double Winding.' This suggests that the SVM algorithm may struggle to distinguish between winding patterns and those resembling a 'Double Winding' pattern. It seems to be sensitive to variations in the process that occasionally mimic the 'Double Winding' pattern resulting in these false negatives. Another issue arises from the misclassification of 42 instances of 'Double Winding' as 'Flange Winding.' This indicates a similarity in patterns, between these two types that poses a challenge for the algorithm to differentiate accurately. Fine-tuning may be necessary to distinguish these distinct geometrical states.

	NF	D	G	C	F	L
NF	7371	0	0	0	0	0
D	110	363	0	0	0	0
G	0	0	657	0	0	0
C	0	0	0	457	0	0
F	0	42	0	0	601	0
L	0	0	0	0	0	399

Figure 5.11. Classification outcomes of the SVM model with an accuracy of 98.48%, capturing slight misclassifications, particularly related to double winding.

The accuracy of the KNN algorithm is impressive at 92.93% as shown in Figure 5.12. However, it does have an issue where it sometimes misclassifies certain types of faults as non-faulty except for the 'Loose Winding' fault. This drawback is concerning because misclassifying faults can have consequences in manufacturing processes. To be more specific when the algorithm misclassifies 'Double Winding,' 'Gap,' 'Crossing' and 'Flange Winding' as faulty instances it could potentially lead to overlooking important problems during the linear winding process. Gap had the highest rate of misclassification, where the KNN algorithm incorrectly classified up, to 249 instances. To address this concern, further investigation and adjustments, to the algorithms parameters may be necessary. This will help improve its sensitivity to fault patterns and ensure identification of various geometrical states.

	NF	D	G	C	F	L
NF	7296	40	35	0	0	0
D	131	338	4	0	0	0
G	249	0	408	0	0	0
C	82	2	0	364	9	0
F	132	19	0	4	488	0
L	0	0	0	0	0	399

Figure 5.12. Classification results of the KNN model demonstrating an accuracy of 92.93%, displaying varying misclassifications, notably in recognizing loose winding.

In the NB classification with a accuracy of 98.22% as shown in Figure 5.13, there is a pattern worth mentioning when it comes to misclassifications between 'Double Winding' and 'Flange Winding'. Specifically, there were 42 instances where 'Double Winding' was mistakenly labelled as 'Flange Winding', which suggests some similarities in their features. Additionally, 'Flange Winding' was incorrectly identified as 'Crossing' 22 times indicating an overlap or similarity, in their characteristics. This pattern highlights the importance of refining our features and fine tuning the algorithm to accurately differentiate between these complex geometric states.

	NF	D	G	C	F	L
NF	7371	0	0	0	0	0
D	110	363	0	0	0	0
G	0	0	657	0	0	0
C	0	4	0	431	22	0
F	0	42	0	0	601	0
L	0	0	0	0	0	399

Figure 5.13. Classification performance of the NB model with an accuracy of 98.22%, demonstrating some misclassifications, notably associated with double winding and flange winding.

The classification model ANN had an accuracy rate of 98.35% when it comes to classifying different geometric states during the winding process as shown in Figure 5.14. However, upon examination of misclassifications valuable insights were obtained specifically in which 'Double Winding' appears to be a point of confusion. It has been misclassified as 'Flange Winding' 126 times. This suggests that there may be some similarities in the patterns of features between these two states and it could be due to the complexities involved in wire placement and variations in tension that occur in both cases.

Moreover, it is interesting to note that 'Crossing' has been misclassified once as 'Flange Winding.' This raises questions about how distinguishable these two states are based on their features. There may be characteristics shared between 'Crossing' and 'Flange Winding,' which could lead to this particular misclassification. It poses a challenge in defining features that clearly separate these states possibly requiring a more refined set of features or adjustments to the algorithm.

Furthermore, the fact that Crossing' has been misclassified as "Flange Winding' four times and 'Double Winding' seven times suggests a potential overlap in their feature space. These geometric states might exhibit similarities making it difficult for the algorithm to establish a clear boundary, between them. Improving feature selection by considering these nuanced differences could enhance the performance of the model.

	NF	D	G	C	F	L
NF	[[7346	0	0	0	0	0]
D	[126	359	0	0	0	0]
G	[0	0	659	0	0	0]
C	[1	0	0	481	0	0]
F	[17	7	0	4	635	0]
L	[0	0	0	0	0	365]]

Figure 5.14. Classification outcomes of the tune ANN model with an accuracy of 98.35%, highlighting misclassifications and trends in categorising different geometrical states.

In summary, RF and SVM showed accuracies of 98.83% and 98.48% respectively making them stand out. These models excelled in distinguishing geometric states. RF displayed stability while SVM showcased separation boundaries. On the hand DT, KNN, NB and ANN achieved accuracies above 90% indicating their suitability for this task. However, they did have some misclassifications, particularly when categorizing 'Double Winding' and 'Flange Winding,' which suggests that there are overlapping feature patterns.

The recurring trend of misclassifying 'Double Winding' as 'Flange Winding' across models (and vice versa in some cases) highlights the importance of having clearer feature definitions, between these states. Furthermore, distinguishing between 'Crossing' and 'Flange Winding' also proved challenging at times indicating an area where feature refinement is needed.

5.3 Expansion of database through noisy data integration

Expanding a database, by incorporating data using Gaussian noise has implications in the field of machine learning and data analysis. One essential benefit is improving the robustness and generalisation of the model. By introducing Gaussian noise into the dataset during training the model becomes more adept at handling variations and uncertainties present in real world data. This enhanced robustness ensures that the model can effectively adapt to noisy data it may encounter when used practically making it more reliable.

Additionally, integrating data into the dataset promotes a diverse representation of information. Injecting noise expands the range of patterns and variations captured in the dataset. This increased diversity helps models identify features and patterns amid noise making them more versatile and adaptable to various scenarios they may encounter during application.

Another significant advantage of incorporating data is its role in preventing overfitting. Overfitting occurs when a model overly optimises for the training dataset potentially leading to performance on data. By including data, randomness and complexity are introduced into the dataset discouraging models from relying heavily on specific patterns that may be unique, to the training data itself. This helps in creating a model that can generalise better and is not overly dependent, on the details of the training data.

Furthermore, including noisy data makes the dataset more similar to real world conditions making the models training more realistic and practical. Real world data often contains noise caused by factors like measurement errors, environmental conditions or human mistakes. By incorporating data, the model learns to identify patterns, amidst real world noise, which accurately represents its intended application environment. Lastly, integrating noisy data leads to an expanded dataset that acts as a form of data augmentation. This larger dataset allows for training potentially enhancing the models learning and overall performance.

The preference, for using Gaussian noise as a technique to enhance datasets through data augmentation is rooted in its properties. Gaussian noise, characterized by a bell-shaped probability distribution known as the distribution offers a practical approach. This distribution is well defined making it easy to work with widely recognized in the fields of statistics and probability theory [161].

Moreover the application of Gaussian noise is supported by the Central Limit Theorem [7]. This theorem states that when a large number of variables are summed together regardless of their original distributions, they tend to follow a Gaussian distribution. Therefore, Gaussian noise does not only possess elegance but also mirrors the aggregation of various random influences commonly observed in natural processes and measurements. The widespread occurrence of Gaussian noise, in processes makes it a suitable option for simulating uncertainties encountered in real world situations. This has led to its use in modelling and simulations.

Although other types of noise such as uniform noise, Poisson noise or Laplace noise have their applications and advantages [109], Gaussian noise stands out due to its versatility and broad range of uses. It can represent a spectrum of uncertainties from fluctuations to significant deviations. This aligns well with inference, hypothesis testing and meaningful analysis of results. Consequently, Gaussian noise is an appropriate choice for data augmentation as it enables models to handle uncertainties that arise across different domains.

5.3.1 Steps to extend a data base using Gaussian noise

Using Gaussian noise to enhance the dataset is a technique for introducing variability and resilience. Unlike other methods, like linear transformations or simple random noise addition, Gaussian noise offers a more realistic and flexible way to simulate various real-world scenarios [109]. This randomness follows a distribution enabling the generation of data points that closely mimic natural fluctuations observed in many real-world phenomena. As a result, it enriches the dataset by making it more adaptable and diverse.

Figure 5.15 presents the steps involved in extending a database using Gaussian noise:

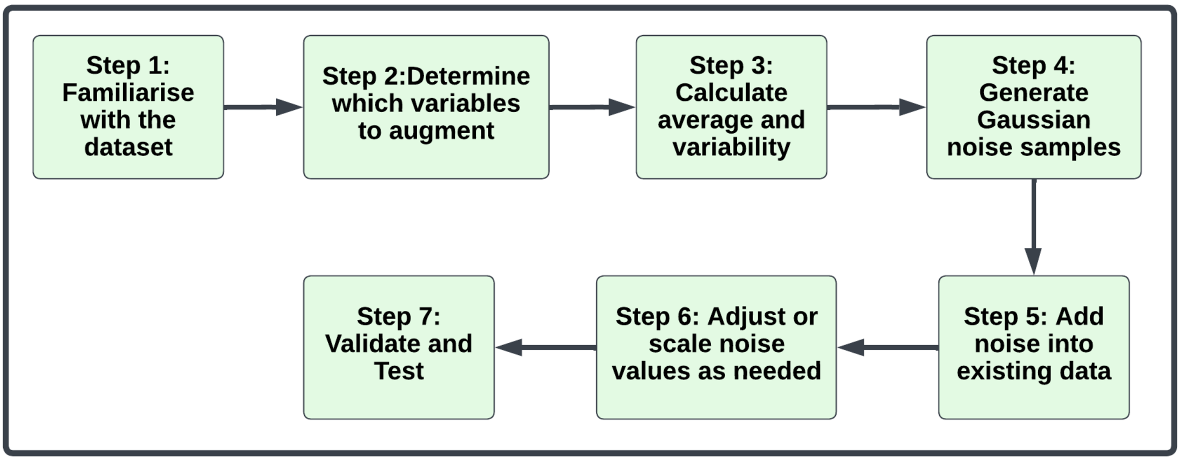


Figure 5.15. Steps to extend a data base using Gaussian noise (adapted from [109]).

In the first step, it is important to familiarise yourself with the dataset that is relevant to the winding process. This means examining features like speed, tension, bobbin shape, wire gauge and other relevant factors. Moving on to the second step, identify which specific variables associated with the process need to be enhanced or modified. These variables could include speed, tension or wire gauge.

Moving on to the third step, the standard deviation for each selected variable based on the data from the dataset needs to be calculated. These statistical measures play a crucial role, in generating Gaussian noise that accurately reflects the characteristics of the dataset. Then in step four, generate Gaussian noise samples using these calculated average and standard deviation values. It is essential to ensure that this generated noise truly captures the variability and distribution observed in the existing dataset.

Now, in step five it involves integrating this generated Gaussian noise into their variables within the dataset from the linear winding process. This integration effectively expands the dataset by adding 10,000 extra data points. Step six requires adjusting or scaling these noise values so that they align appropriately with the context of the process. For example if certain variables such as wire gauge (0.30 to 1.10 mm) have defined ranges it's important to make sure that these adjusted noise values fall within those ranges.

Finally, step seven focuses on validation and testing. Validate the dataset to ensure that the added noise aligns with the intended distribution and accurately represents the characteristics of the winding process. Evaluate how this expanded dataset affects model performance, by testing it within the RF model. These steps collectively outline how to extend a dataset using Gaussian noise and apply it to the winding process data set.

5.4 Validation process through experimentation

Experiments were conducted utilising a linear winding machine whereby validating regression and classification models was achieved by comparing predicted values against actual measurements obtained from the winding machine. The objective was to determine the extent of accuracy within each of the models while attempting to handle real-world data inputs effectively. Furthermore, it was demonstrated how well these models performed in providing accurate outputs when utilised in authentic production environments. It is worth noticing that this research was only able to verify the model's results in linear winding processes exclusively, limiting its abilities for generalisability outside this scope. However, other winding processes, such as needle winding, may include different applications and features that are subject to various challenges unique to themselves, making predictions of their outcomes an arduous task wherein new experimental techniques are required.

To validate the results obtained from the chosen SML algorithms, a series of empirical experiments using a linear coil-winding machine (200 mm Coil Winder MK4) were conducted. These laboratory tests were structured according to the DoE principles [47] as presented in Table 5.1 and involved performing a total of 33 trials – divided into two sets – utilising a wire gauge measuring 1 mm (the most frequently used in industry). Throughout these experiments various input parameters were varied, such as alterations in bobbin shape as well as rotational winding speed settings, while also examining their impacts on performance metrics within coil winding.

Table 5.1. Experimental Design for Linear Winding Process: Variation in Speed, Copper Wire Size, Layers per Bobbin, and Bobbin Shape.

Experiment Set	Experiment Number	Speed (rpm)	Copper Wire Size (mm)	Layers per Bobbin	Bobbin Shape
1	1	200	1	1	Square
1	2	400	1	1	Rectangle
1	3	600	1	2	Square
1	4	800	1	1	Rectangle
1	5	1000	1	2	Square
1	6	1200	1	1	Rectangle
1	7	1400	1	2	Square
1	8	1600	1	1	Rectangle
2	1	200	1	1	Square
2	2	250	1	1	Rectangle
2	3	300	1	1	Square
2	4	350	1	1	Rectangle
2	5	400	1	1	Square
2	6	450	1	1	Rectangle
2	7	500	1	1	Square
2	8	550	1	1	Rectangle
2	9	600	1	1	Square
2	10	650	1	1	Rectangle
2	11	700	1	1	Square

First set of experiments: High-speed increments

The first experimental set was made up of 22 test runs that incorporated significant speed variation through ramp-up intervals, these speed increments were measured at 200 rpm per interval. During this set of experiments, the copper wire size was kept constant, at 1 millimetre. However, the focus was on analysing how an incorrect wire laying when a defect was created in the first layer affected multiple number of layers per bobbin. Therefore, during this set, experiments using 1 to 2 layers per bobbin were conducted to observe and analyse any inaccuracies, in the wire laying process and their implications. Lastly, in these experiments, two different bobbin shapes were tested, which included square and rectangle bobbins.

Second set of experiments: Low-speed increments

The second set of experiments consisted of 11 trials. These trials aimed to examine variations in speed with ramp up intervals at intensities (50 rpm per interval). Unlike the first set of experiments, for the second the number of layers per bobbin was kept consistent at only one layer. This allowed the analysis of how speed variation, on its own influenced the process.

5.4.1 Results from the validation through experimentation

Post-experiment evaluations evidenced remarkable correlations between predicted results obtained through the SML algorithms and the actual performance scores. This demonstrated the high level of accuracy anticipated for the proposed algorithm with the regression and classification models across numerous types of winding configurations available. The results highlight how effective an SML approach can be at predicting faults within coil winding processes.

Tables 5.2 & 5.3 present the SML comparison results wherein every individual table corresponds to a certain model type, either regression or classification model. The tables offered concise insights into the efficiency of every algorithm concerning accuracy, computation time, and other important metrics. In fact, these tables presented comparisons between several SML algorithms used across databases of different sizes and were catered towards various models (regression and classification). Each table contained six columns that highlighted values obtained, corresponding to separate input parameters, like normal MSE or computational time required to run the algorithm expressed in seconds, together with associated accuracies and models having fewer inputs/noise levels. The rows within each table evaluate an algorithm's performance based on the selected input parameter.

The assessment of the machine learning algorithm’s performances on test datasets without any modifications was referred to as the "Normal" column in this research. The effectiveness and quality of a regression model can be closely monitored through keeping track of its MSE value displayed in the normal column. To determine whether a regression model has performed well or not depends on whether it achieves low MSE values which ensure that predicted outcomes match closely with actual readings obtained from test data. Similarly, for classification models, accurate predictions would result in higher percentages showcased by its accuracy rate presented in its corresponding normal column against real-life classifications obtained from testing data.

Results affirmed that for multiple database sizes (small/medium/large), RF tend to perform better than competing algorithms when it comes to regression models, as shared in Table 5.2. Evaluating the model, with multiple data sizes can provide insights into whether the model tends to overfit or underfit in various scenarios thereby guiding the need, for appropriate adjustments. In terms of classification analysis (see Table 5.3), RF provided great outcomes with near-perfect accuracy stood out significantly among DT & ANN models in distinct databases.

Incorporating Gaussian noise into a model is crucial as it helps replicate the unpredictability of real-world scenarios and introduces diversity. This in turn allows for an evaluation of the models capabilities and its ability to handle uncertain and noisy data. Remarkably enough, adding noise into datasets did not impacted significantly on the RF extraordinary proficiency over its fellows despite expected variations. The reason why RF's are resilient to noise could be attributed to its structure, which combines predictions from multiple DT. This approach helps reduce the influence of data points ensuring that RF continue to perform exceptionally well even when there is additional noise present.

Regarding the database sizes:

- Small: 10,000 data points
- Medium: 20,000 data points
- Large: 40,000 data points

As for the Gaussian Noise levels:

- Low: 1%
- Medium: 5%
- High: 20%

The Gaussian noise levels selected were determined through a comprehensive approach combining insights from literature review (reference), previous research experiences, and feedback from industrial experts. This multi-faceted strategy ensured that the chosen noise levels were both theoretically grounded and practically applicable, aligning with the research's objectives and the real-world scenario of the dataset.

Through analysis, it was determined that SML algorithms were more accurate when more process parameters were included, as there is a positive correlation between their accuracy and parameter inclusivity in models. When all six parameters were utilised, heightened accuracy was achieved, signifying how vital utilising a comprehensive suite of input variables can be in constructing model accuracies. Moreover, it was revealed that algorithmic computational times relied on parameter numbers; fewer inputs resulted in faster processing times. Irrespective of this, some algorithms like SVM and NB were not significantly impacted by increasing parameter numbers with normalised processing time-frames.

NB and SVM are reliable algorithms for classification [37][82]. They are not easily influenced by an increase in input parameters or irrelevant features. SVM is particularly adept at handling outliers and can effectively establish decision boundaries even in high dimensional spaces [123]. Contrary, NB operates on a Bayesian probabilistic framework that performs well in higher dimensions by leveraging its assumption of independence, between features [82]. Lastly, a decrease in accuracy was observed with high noise levels for SML implementations, according to our results. The accuracy of these algorithms decreased when noise was introduced to the database because noise brings in irrelevant information that can confuse the classification process. NB assumes that features are independent and noise can disrupt this assumption resulting in dependable probability estimates [137]. SVM strives to identify decision boundaries and noise can cause misclassifications making it more challenging to accurately separate data points [107].

The decision-making difficulty arises from choosing between multiple effective methods based on comparability regarding factors such as MSE, which measures model accuracy concerning time consumption, computation-wise, among others considered for our evaluation [110]. The results reveal that among SML algorithms, RF demonstrated superior prediction accuracy and computational efficiency compared to ANN and DT during the experiment, as outlined in Table 5.4.

RF was the best performing algorithm out of all those assessed. While other models varied between promisingly successful predictions rates, their datasets did not match the precision level presented by the preferred method (RF). It is recommended that during the selection process, algorithms should be selected based on their intended use of either regression or classification. Results have shown that RF remains a viable option in predicting faults (regression or classification) during coil winding.

Table 5.2. Comparison of SML algorithms used to predict the electrical resistance variation using a regression model.

Regression model						
Small size data base						
Algorithm	**Normal (MSE)**	**Time (sec)**	**Less Inputs (MSE)**	**Low Noise (MSE)**	**Medium Noise (MSE)**	**High Noise (MSE)**
Decision tree	1.06E-05	0.012	9.977	0.001	33853.008	74487.611
Random forests	**4.96E-05**	**0.527**	**9.661**	**0.000**	**17391.274**	**41278.502**
SVM	69293.371	6.032	69293.434	69292.281	69296.280	69299.664
KNN	56192.413	0.068	36241.777	68983.506	70967.778	70079.733
Naive Bayes	56659.396	0.010	57151.719	56675.043	57029.997	58147.182
ANN	53727.155	5.139	40562.635	178.889	21941.214	44037.859
Tuned ANN	57.025	36.142	78.693	4462.809	29123.410	50425.850
Medium size data base						
Algorithm	**Normal (MSE)**	**Time (sec)**	**Less Inputs (MSE)**	**Low Noise (MSE)**	**Medium Noise (MSE)**	**High Noise (MSE)**
Decision tree	8.96E-06	0.019	9.35911	0.00025	34258.705	65433.753
Random forests	**1.39E-05**	**0.969**	**8.95601**	**0.00016**	**17923.527**	**36512.877**
SVM	64775.10	23.409	64713.816	64777.689	64794.597	64794.012
KNN	46436.38	0.128	31887.110	62514.667	63157.183	65623.351
Naive Bayes	53084.92	0.058	53111.955	53135.864	53578.540	54218.376
ANN	48503.08	11.336	36807.826	23544.680	30870.775	38387.342
Tuned ANN	329.07	68.621	126.330	689.822	20275.535	41250.020
Large size data base						
Algorithm	**Normal (MSE)**	**Time (sec)**	**Less Inputs (MSE)**	**Low Noise (MSE)**	**Medium Noise (MSE)**	**High Noise (MSE)**
Decision tree	0.156	0.035	9.359	0.380	16808.191	41612.006
Random forests	**0.142**	**2.277**	**8.956**	**0.229**	**9062.494**	**21736.310**
SVM	40529.314	88.554	64713.816	53168.203	53167.622	53173.368
KNN	39052.865	0.249	31887.110	50853.274	51769.254	52430.471
Naive Bayes	32938.993	0.065	53111.955	32961.317	33617.950	35368.012
ANN	33397.427	15.540	36807.826	518.626	13715.903	21829.835
Tuned ANN	148.138	87.928	126.330	35.270	17638.035	26226.156

Table 5.3. Comparison of SML algorithms used to predict the type of geometrical fault using a classification model.

Classification model						
Small size data base						
Algorithm	**Normal (Accuracy %)**	**Time (sec)**	**Less Inputs (Accuracy %)**	**Low Noise (Accuracy %)**	**Medium Noise (Accuracy %)**	**High Noise (Accuracy %)**
Decision tree	0.6956	0.009	0.4612	0.6956	0.6956	0.6956
Random forests	**0.9996**	**0.269**	**0.7380**	**0.9996**	**0.9996**	**0.9996**
SVM	0.9996	0.786	0.6592	0.9996	0.9996	0.9996
KNN	0.9704	0.181	0.7176	0.8788	0.8100	0.7748
Naive Bayes	0.9996	0.028	0.5604	0.9996	0.9996	0.9996
ANN	0.9984	7.416	0.372	1.0000	0.9996	0.9992
Tuned ANN	1.0000	21.088	0.5496	1.0000	1.0000	1.0000
Medium size data base						
Algorithm	**Normal (Accuracy %)**	**Time (sec)**	**Less Inputs (Accuracy %)**	**Low Noise (Accuracy %)**	**Medium Noise (Accuracy %)**	**High Noise (Accuracy %)**
Decision tree	0.8384	0.011	0.6823	0.8384	0.8384	0.8384
Random forests	**0.9998**	**0.541**	**0.8570**	**0.9996**	**0.9990**	**0.9983**
SVM	0.9978	52.417	0.7271	0.9983	0.9981	0.9969
KNN	0.9741	0.394	0.8508	0.9266	0.8965	0.8642
Naive Bayes	0.9894	0.034	0.6825	0.9895	0.9895	0.9895
ANN	0.9985	10.633	0.6764	0.9992	0.9971	0.9967
Tuned ANN	0.9989	39.273	0.7386	0.9985	0.9969	0.9973
Large size data base						
Algorithm	**Normal (Accuracy %)**	**Time (sec)**	**Less Inputs (Accuracy %)**	**Low Noise (Accuracy %)**	**Medium Noise (Accuracy %)**	**High Noise (Accuracy %)**
Decision tree	0.9086	0.019	0.7658	0.9086	0.9086	0.9086
Random forests	**0.9883**	**1.633**	**0.8243**	**0.9890**	**0.9888**	**0.9883**
SVM	0.9848	319.185	0.7484	0.9848	0.9848	0.9848
KNN	0.9293	0.749	0.8450	0.8918	0.8735	0.8464
Naive Bayes	0.9822	0.027	0.7751	0.9822	0.9822	0.9822
ANN	0.9835	48.704	0.6727	0.9868	0.9843	0.9837
Tuned ANN	0.9875	74.548	0.7651	0.9870	0.9865	0.9866

Table 5.4. Results of the comparison between SML algorithms.

	Regression	**Classification**
1st	Random Forest	Random Forest
2nd	Decision Tree	Artificial Neural Network
3rd	Artificial Neural Network	Decision Tree

5.5 Results from the validation process with experiments on a coil winding machine

The results in section 5.4 suggests that an effective approach to predicting coil-winding faults is by utilising the RF algorithm. Results demonstrated outstanding performance by this method in both regression and classification models. To validate this claim, a linear coil winding machine was employed, which showed the accuracy rates of the model when variations were introduced in the form of four experiment configurations, as presented in Table 5.5. For instance, findings indicated that the square bobbin classification model was exceptional with an accuracy rate of 99.33%, while its counterpart, a rectangular bobbin, showed lower performance at 94.17%. The reasons behind this difference is explained in the following sections. Nonetheless, while RF continues to be a feasible option in predicting coil winding faults, further investigation is necessary for identifying ideal algorithms and parameters fitting unique winding configurations.

Table 5.5. Experimental results comparing the accuracy of a train RF algorithm against a linear winding machine.

Experiment configuration		**Accuracy**
1	Square Bobbin regression model	94.85%
2	Square Bobbin classification model	99.33%
3	Rectangle Bobbin regression model	94.92%
4	Rectangle Bobbin classification model	94.17%

A. First Experiment Configuration: square bobbin regression model

The square bobbin experiment highlights electrical resistance analysis through regression models with an impressive average accuracy rate of 94.85%. However, during initial experiments, when examining the first layer of bobbins within this model, there was a decrease in accuracy due to a higher percentage of faults present within this particular layer. The explanation of why this occurred could be linked back to a lack of support for wire motion since no prior wires helped guide its positioning (unlike those of the upper layers), as shown in Figure 5.16.

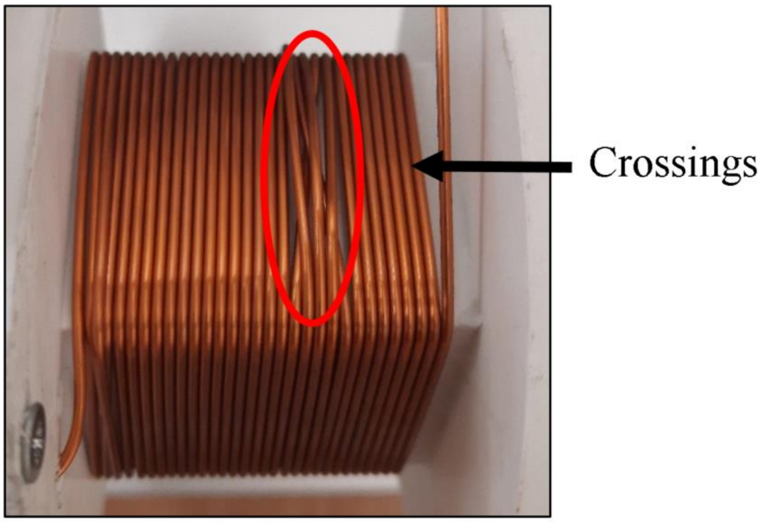


Figure 5.16. Geometrical faults such as crossings detected in the first layer of the square bobbin configuration.

Faults often arise on the first layer of winding because there is no existing support to guide the wires movement during this stage. When the winding process begins, the wire is placed directly onto the bobbin without any layers to help position it. Unlike, in upper layers, where the wires receive support and alignment from wound layers, the first layer lacks this foundational support. As a result, the wire on the first layer is more susceptible to instability and misalignment, which can cause problems like overlaps, gaps or uneven winding. These initial issues can spread through upper layers worsening as the winding process continues. The absence of wires to guide positioning makes the first layer particularly prone to faults, emphasizing how crucial it is to have control and monitoring during this phase of winding.

Despite these challenges faced early on, subsequent modelling work improved significantly, as previous layers provided important guidance and information that contributed towards greater precision. Results from the second set of experiments, which featured much smaller speed increments compared to earlier iterations, presented an exceptional average rate of 98% accuracy. When consideration was given to further enhancing the already elevated test experiences through regressive modelling techniques employed within these experiments going forward, KPIs such as additional training time should be considered if the desired objectives are missing from specific test requirements or evaluation criteria.

B. Second Experiment Configuration: square bobbin classification model

The results from the classification model were exceptional during the initial set of experiments, with an outstanding accuracy score of 99.33%. A subsequent run yielded even better results as it managed to achieve a perfect score of 100%. This means that the model excelled at identifying geometric faults with pinpoint accuracy along with determining their nature. It can conclusively be said that this model performed exceptionally well in forecasting defects and their respective types during coil winding. Furthermore, it demonstrated greater proficiency during what can be considered as more uniform conditions in its second round of testing.

C. Third Experiment Configuration: rectangle bobbin regression model

To evaluate the regression and classification models' precision levels, two configurations with different ramp speed variation using a rectangular bobbin shape were tested. In the initial experiment set-up, results showed that the regression model had a precision rate of 94.92%. However, during the testing of this configuration, the second layer exhibited a larger number of faults than its first one, resulting in decreased precision for its second iteration, as presented in Figure 5.17. This downgrade stemmed from an inequality in tension across various turns of coil winding caused by variations such as fluctuations in velocity [6]. This variance led to more stress being exerted on the copper wire, which ultimately results in electrical defects as explain by Mayr et al. [159]. Conversely, higher precision rates were achieved by winding only one layer during the second testing phase while ensuring low speed disturbances.

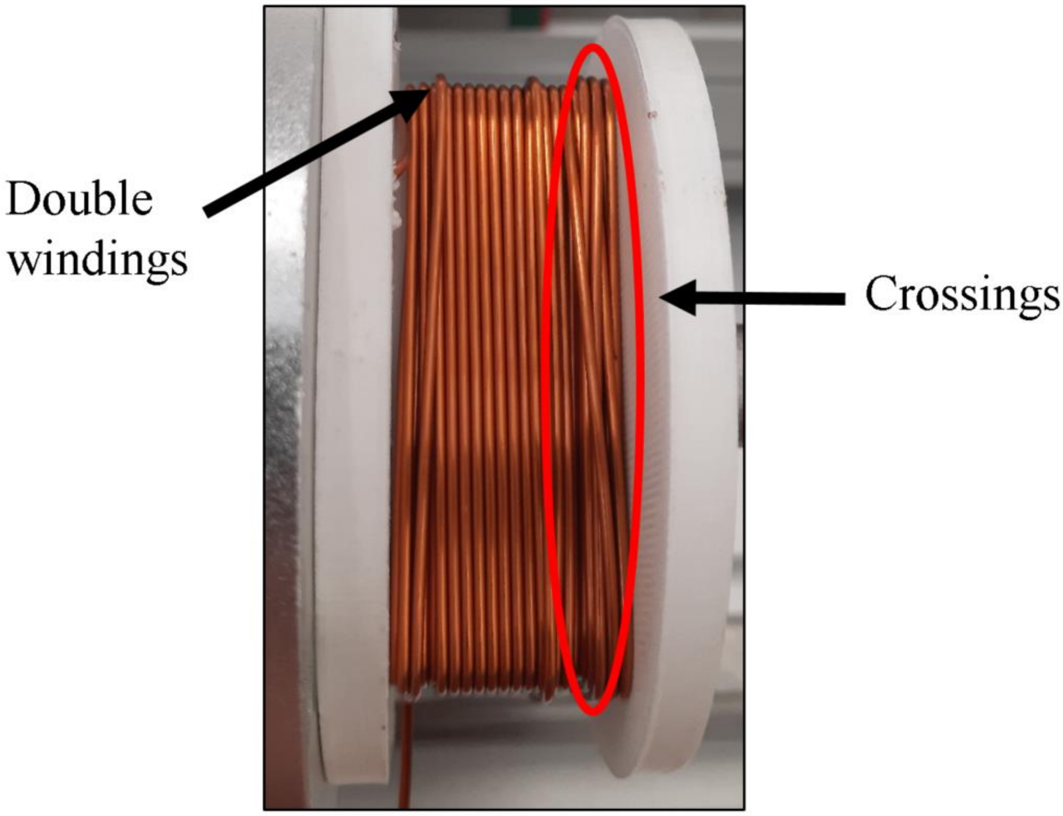


Figure 5.17. Geometrical faults such as crossings and double windings detected in the second layer of the rectangular bobbin configuration.

D. Fourth Experiment Configuration: rectangle bobbin classification model

Based on the results, it was determined that the classification model demonstrated an average accuracy of 94.17%. During the initial round of tests, the model displayed a mean accuracy of 96%, which decreased during the second set of experiments due to increased fault occurrences. The factors behind these faults mostly include variations in rotational speed, which lead to inconsistencies and voids in the winding, as well as inaccuracies within the winding machinery when reaching the turning points, caused by speed variations such as ramp-ups. In a follow-up series of tests, it was found that the average accuracy further decreased to 91%, highlighting that low-speed variation can lead to poor coil winding tension and resulted in misclassified geometrical faults (while electrical faults remained unaffected). These results underscore that the model's performance would vary depending on bobbin shape and winding speed, emphasising that extensive experimentation and analysis are needed for improving accuracy, as well as for identifying the optimal parameters for various configurations.

Discrepancy between Simulation and Physical Experiments

In this section the results obtained from the simulation model to those acquired through experiments conducted on the linear winding machine were compared. This comparison was crucial in verifying the accuracy and reliability of the simulation framework when it comes to replicating the linear winding process. While the initial findings showed promising alignment between the simulation and experimental results, there are some differences that require investigation (Section 5.5). These disparities in performance metrics may be attributed to the simplified nature of the simulation model and its limited parameterisation. To address this, it is suggested to expand the model parameters to include parameters such as friction which was discussed by Hoffman et. al. [32].

Incorporating "friction" as a parameter in future work (as discussed in Section 4.4.2 and elaborated upon in Section 7.3.1) holds great potential, for improving simulation accuracy by accounting for frictional forces on the wire within the winding process. By implementing these enhancements, the goal is to achieve a comprehensive and accurate representation of winding process leading to a deeper understanding of the interdependencies and optimised manufacturing performance.

5.6 Summary

In this chapter the results from enhancing a DES framework that models interdependencies for the early detection of faults in an electrical process where deformable material is involved, were presented. The main objective was to reduce computational time and quality costs. A hybrid model using the KD approach was developed where a SML algorithm was trained using the DES model as a teacher model. This helped maintain accuracy whilst reducing simulation time. Multiple SML algorithms were evaluated, such as RF, which possess the ability to handle complex data while thoroughly identifying numerous interdependencies among production parameters, contributing immensely across a multitude of product quality features.

During this research, a linear winding machine was used to validate the framework and compare its accuracy. It was observed that the RF algorithm significantly reduces simulation time from two minutes to less than a second. The potential applications of this model are extensive, including decreasing EoL test times, for example during winding resistance tests. Moving forward, future research can explore how scalable this approach could be for more intricate systems, such as needle winding, and for different industrial settings.

Discussing further the results obtained in this chapter, the shape of the bobbin and the speed of winding resulted in having a significant impact on how accurate regression and classification models were at predicting changes in electrical resistance and identifying geometrical faults during coil winding. The regression model's accuracy was impacted notably by the layer of winding, indicating a need for better initial layer guidance. However, although the classification model generally showed strong accuracy, it was also vulnerable to bobbin shape and winding speed variability. To ensure that a more precise fault classification was feasible, it is necessary to gather additional data. This research demonstrated that RF models have the potential for modelling different winding set-ups while detecting and classifying faults, but there is a necessity for more experimentation to further enhance their efficiency. The proposed method can save time spent on testing, as well as reducing maintenance expenses, while improving electric motor reliability through algorithms that adapt as more information becomes available.

CHAPTER VI: EXPLORING INTERDEPENDENCIES: A MULTI-OBJECTIVE OPTIMISATION APPROACH TO ENHANCE LINEAR WINDING PROCESSES

6.1 Introduction

This chapter intends to provide a discussion on the results obtained from the potential impact that a multi-objective optimisation approach has on a linear winding process. This approach aimed to balance and optimised multiple objectives simultaneously, initially two goals were selected for the multi objective optimisation approach: reducing costs and minimising faults. Practical examples illustrating this approach in action have been analysed to evaluate its effectiveness in achieving desired objectives. While these objectives are crucial, they are only the first of a list of objectives that can be incorporated into the optimisation framework. As this research progresses more objectives such as energy efficiency, increasing production throughput, minimizing material usage, and mitigating environmental impact can be introduced to further enhance the optimisation process.

One key aspect that was explored was the interaction between different objectives within the system. It is important to recognise that these objectives were not independent, but rather interconnected. Making adjustments to one variable often resulted in changes in others creating a complex network of cause-and-effect relationships known as interdependencies [6]. Understanding these interdependencies was crucial for the success of the multi-objective optimisation approach. This chapter evaluated the correlation between the multiple objectives and interdependencies as a means of better understanding the impact of cross-relationships between various objectives. This analysis enabled the shedding of light on the underlying dynamics of the multi-objective approach, providing insights into how best to configure and adjust processes for maximum effectiveness and efficiency.

6.2 Problem definition

This research optimisation process aimed to achieve two primary goals: reducing production costs and minimising the number of faults. It can be challenging to find the balance, between increasing production speeds in manufacturing to reduce costs and ensuring product quality [160]. When the speed is increased, it adds extra tension on the wires, which can lead to permanent deformation and produce a misplacement in the surface bobbin, resulting in a number of faults [113]. This emphasises the trade-off between speed and product quality, in winding processes. To achieve both cost reduction and minimise faults a strategic approach was needed, that took into account and addresses these interconnected factors.

The objective functions played a crucial role in guiding this research for optimal solutions. By evaluating these functions, it was possible to determine how well a potential solution aligned with the goals. As discussed by Huber et al. [109] it is important to strike a balance between these objectives, as improvements in one area could potentially have negative consequences in another.

6.3 Selection of the multi-objective optimisation algorithm

The decision to use the NSGA-II over other highly regarded multi-objective optimisation algorithms like the SPEA2 or MOEA/D was primarily due to its well-established success and the unique features that align particularly well with this specific research problem, as presented in Table 6.1. This algorithm effectively tackles problems encompassing multiple objectives and constraints making it excellently suited for this complex optimisation task [128][144]. Its fast, non-dominated sorting approach and consideration of crowding distance contribute significantly to its efficiency in identifying Pareto-optimal solutions promptly [134]. Additionally, NSGA-II maintains an excellent balance between exploration and exploitation leading to a diverse yet convergent Pareto front.

When this specific problem's characteristics were considered, NSGA-II emerged as the most appropriate algorithm for this research. Its consistent performance, ability to handle multiple objectives and constraints effectively, alongside its flexibility with various variable types make it an obvious choice [128][161]. It is important to mention that the selection of the algorithm always relies on the specifics of the problem at hand and there is not a one-size-fits-all solution. To make a well-informed decision, it is necessary to take into account both the limitations and advantages of all algorithms.

Table 6.1. Comparison table of multi-objective algorithms with its advantages and disadvantages [109][132][160].

Algorithm	Advantages	Disadvantages
NSGA-II	Maintains a good balance between convergence and diversity, leading to a well-distributed Pareto front.	Can be computationally expensive for high-dimensional problems due to its nondominated sorting and crowding distance calculations.
	Effective in handling various types of multi-objective optimisation problems.	Might struggle to handle problems with many objectives efficiently.
	Utilises elitism to preserve good solutions across generations.	Requires careful parameter tuning to achieve optimal performance.
SPEA2	Simple to implement and widely used in the research community.	Can be less effective for problems with a large number of objectives.
	Integrates a density-based fitness assignment approach, promoting a diverse set of solutions.	Might struggle with high-dimensional problems due to the size of the archive.
	Allows for the use of external archives to store non-dominated solutions from previous generations, aiding in maintaining diversity.	Requires additional parameter tuning for optimal results.
	Handles constrained optimisation problems effectively.	
MOEA/D	Proven to be efficient for problems with irregular Pareto fronts.	Selecting suitable decomposition methods and weight vectors can be challenging and require domain-specific knowledge.
	Decomposes the multi-objective problem into scalar subproblems, leading to better handling of high-dimensional problems.	Scalability issues can arise as the problem size and complexity increase.
	Can achieve a good balance between convergence and diversity.	The performance heavily depends on the quality of decomposition methods and weight vectors chosen.
	Allows for parallel evaluations of subproblems, making it more efficient for computationally expensive objectives.	Additional algorithm tuning is often necessary for optimal results.
	Performs well on large-scale and complex multi-objective problems.	

6.3.1. Influence of Population Size and Number of Generations on the runtime of the NSGA-II Algorithm

In real-time or near-real-time contexts, the runtime of the NSGA-II algorithm holds immense significance. To measure the impact of diverse settings on the algorithm's time efficiency, several tests were conducted by manipulating population sizes and numbers of generations. Figure 6.1 below, displays the outcomes obtained:

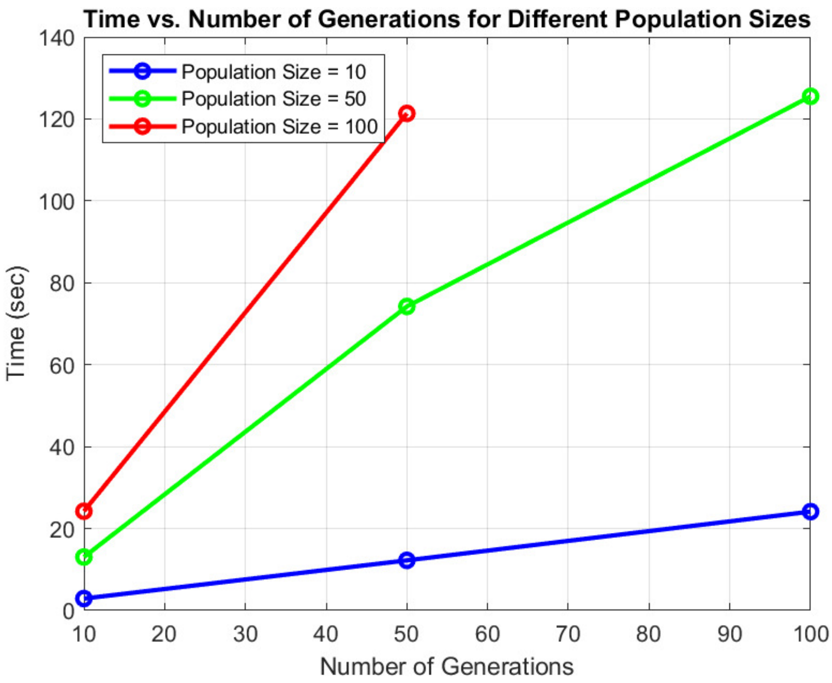


Figure 6.1. Line chart of the influence that population size and number of generations has on the runtime of the NSGA-II algorithm.

The chart clearly presents a notable trend: an upsurge in runtime accompanies an increase in both population size and number of generations. For instance, when the population size was held constant at 10, while doubling the number of generations from 50 to 100, a near doubling in runtime (approximately from 12 to 24 seconds) was observed. Similarly, by fixing the number of generations at 10, while raising the population size to 50, the runtime escalates from around 3 to 13 seconds. This was fully anticipated since a larger population necessitates evaluating more potential solutions within each generation [113]. Interestingly, enforcing both these factors ultimately leads to an escalation in computational expenditure presented in the form of a longer running period.

On a final note, it is vital to highlight that, even though augmenting population size and number of generations can boost solution quality via a more comprehensive exploration of solution space, this improvement comes at the cost of temporal efficiency [135]. As such, the implementation of the NSGA-II algorithm mandates astute balancing between solutions quality and computational efficiency in tune with the system's unique stipulations and circumstances.

6.3.2. Plotting the solution space

A parallel coordinate plot was used to represent the solution space and assess how well the NSGA-II algorithm performs in achieving its objectives of minimising cost and reducing geometrical faults in the linear winding process. Parallel coordinate plots are a valuable tool for visualising high-dimensional data – particularly in multi-objective optimisation problems like this one. In this type of plot, each dimension of the data was represented by a vertical axis and all these axes run parallel to each other. Each individual solution or population member was depicted as a line on the plot passing through all the axes, as presented in Figure 6.2. To conduct this simulation the following input parameter ranges were considered:

- Speed (200 to 350 RPM)
- Tension (50 to 95 Newtons)
- Wire gauge (0.9 to 1.1 millimetres)
- Number of layers (1 to 5 layers)
- Bobbin shape (1= rectangle or 2= square)
- Caster angle (2 to -2 degrees)
- Yield limit (0 for below the limit and 1 for, above it).

In the parallel coordinate plot, each line represents a combination of input parameters allowing the observation of how the NSGA-II algorithm explores and optimises these values. The colour-coded bar at the end of the plot indicates the winding speed of each solution. The brightness of the lines ranging from dark blue to bright yellow indicates how fast is the speed (winding speed) of the solution reach by the algorithm. Brighter colours represent solutions that achieves both objectives at faster manufacturing speeds while darker blue indicates slower speeds but still achieving the minimisation of cost and faults.

The main objective of this analysis is to determine the set of input parameters that meet all constraints while efficiently minimising costs and reducing faults. This plot offers understanding of how the NSGA-II algorithm explores the solution space aiding researchers in comprehending its behaviour and its capacity to identify parameter combinations, for enhancing the linear winding process. Every solution represented on the plot enables the possibility to detect patterns, clusters, and potential outliers in the data while examining the range and distribution of solutions within the multi-dimensional solution space.

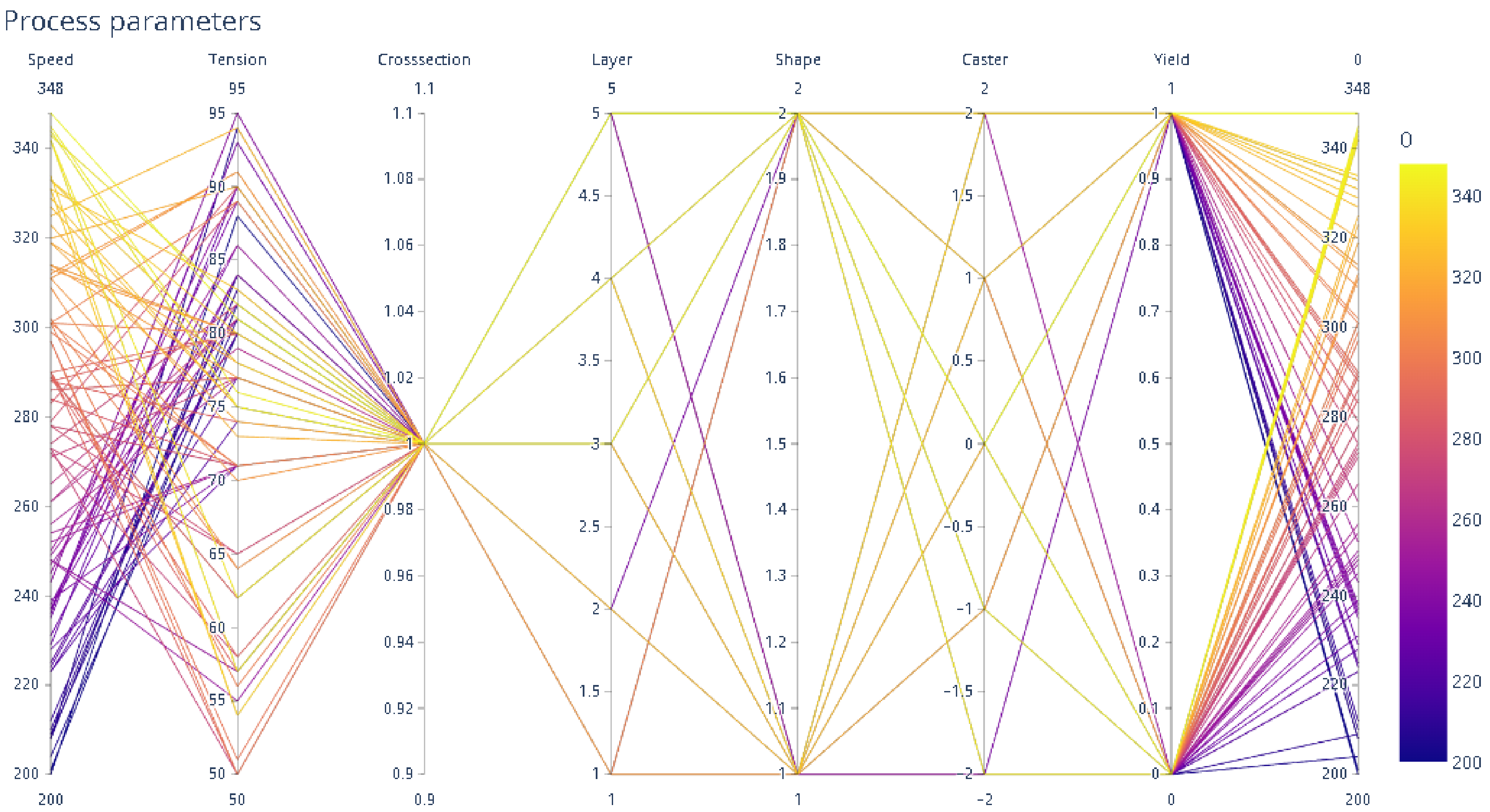


Figure 6.2. Parallel coordinate plot to represent the solution space using the NSGA-II algorithm with a Population: 100, N_Gen:10.

6.4 Evaluation phase

During the evaluation phase, two fitness functions were utilised, each with its own unique strengths and challenges.

6.4.1. First fitness function (Number of geometrical faults)

The first fitness function deployed was derived from the hybrid model (RF regression model) [152] and presented in Equation 13. The RF regression model was utilised to predict the number of geometrical faults in the winding process of electrical machines. The RF model, denoted as $RF(x1, x\,2, x\,3, x\,4)$ where $x1, x\,2, x\,3, x\,4$ represent the winding speed, wire gauge, bobbin shape, and caster angle, respectively, and y represents the number of geometrical faults, is expressed mathematically as:

$$RF(x1, x\,2, x\,3, x\,4) = \frac{1}{\mathrm{n}} \Sigma_{i=1}^{n} T_i(x1, x\,2, x\,3, x\,4) \qquad \text{Eq.13}$$

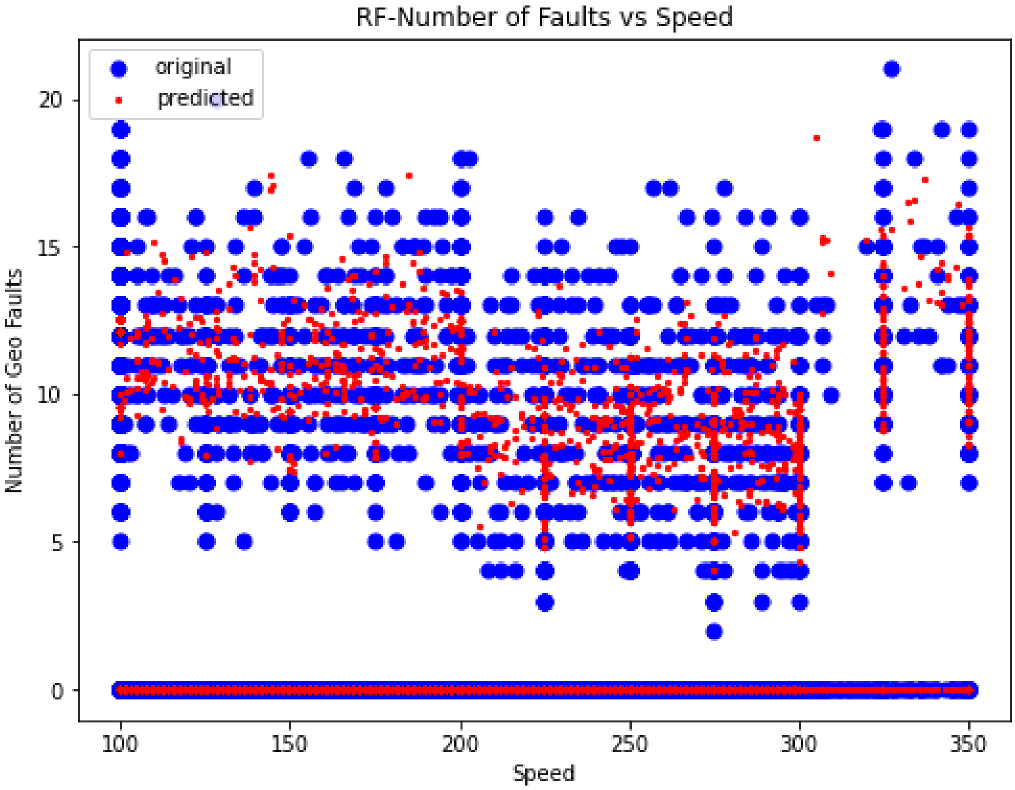
Here, n denotes the total number of decision trees in the RF model, and $T_i(x1, x\,2, x\,3, x\,4)$ represents the prediction made by the i^{th} decision tree based on the input features $(x1, x\,2, x\,3, x\,4)$. This mathematical formulation captures the RF model's ability to estimate the number of geometrical faults, offering insights into the quality of the winding process.

The RF regression model employed in this research was configured with careful consideration of several key parameters to optimise its performance for predicting the number of geometrical faults during linear winding.

- **n_estimators:** A total of 100 decision trees were chosen to balance between predictive robustness and computational efficiency.
- **max_depth:** Set to 20 to capture complex data relationships without overfitting.
- **min_samples_split**: Ensured each node had at least 5 samples before making a split, promoting stable tree building.
- **min_samples_leaf:** Required each leaf node to have at least 2 samples, preventing the model from being overly specific to the training data.
- **max_features:** Set to 'auto', equivalent to using the square root of the total number of features (4 in this case), balancing model complexity and predictive power.
- **bootstrap:** Enabled bootstrap sampling to maintain tree diversity and prevent overfitting.

This model was trained to predict the number of geometric faults and demonstrated a strong performance, achieving an accuracy of 93%, as shown in Figure 6.3. This figure suggests that the Hybrid model was highly capable of predicting fault occurrence [152]. However, it did have its limitations, for example, its struggle to accurately predict the double-windings faults, often misclassifying them as non-fault occurrences. It is important to note that double windings can significantly affect the quality of the end product [5].

To address this issue, it was recommended to keep expanding the dataset used to train the RF model by adding more examples of double windings. As Reed & Lofstrand explain in their research [5], this could help improve the RF model's ability to predict these faults.




```
Elapse time: 0.3141598701477051
MSE: 1.6404309072319785
MAE: 0.5211647698532964
Score: 0.9302315365344691
```

Figure 6.3. Scatter plot of Hybrid model for predicting number of geometrical faults.

6.4.2. Second fitness function (Cost function)

The second fitness function used in the NSGA-II algorithm was a cost function. This function served as a key performance indicator for the system and incorporated several crucial aspects of production [124]. The original DES and Hybrid models lacked the ability to accurately measure and compare outcomes in terms of cost, which was limited without a suitable cost function [6]. During this research, throughout the optimisation phase a cost function was created for the DES model and then transferred to the Hybrid model with an accuracy of 99%, as presented in Figure 6.4. The introduction of the cost function has had a profound impact on the analysis and results sections. By minimising the cost function during the optimisation process, it was possible to simultaneously optimise these important aspects of the production process.

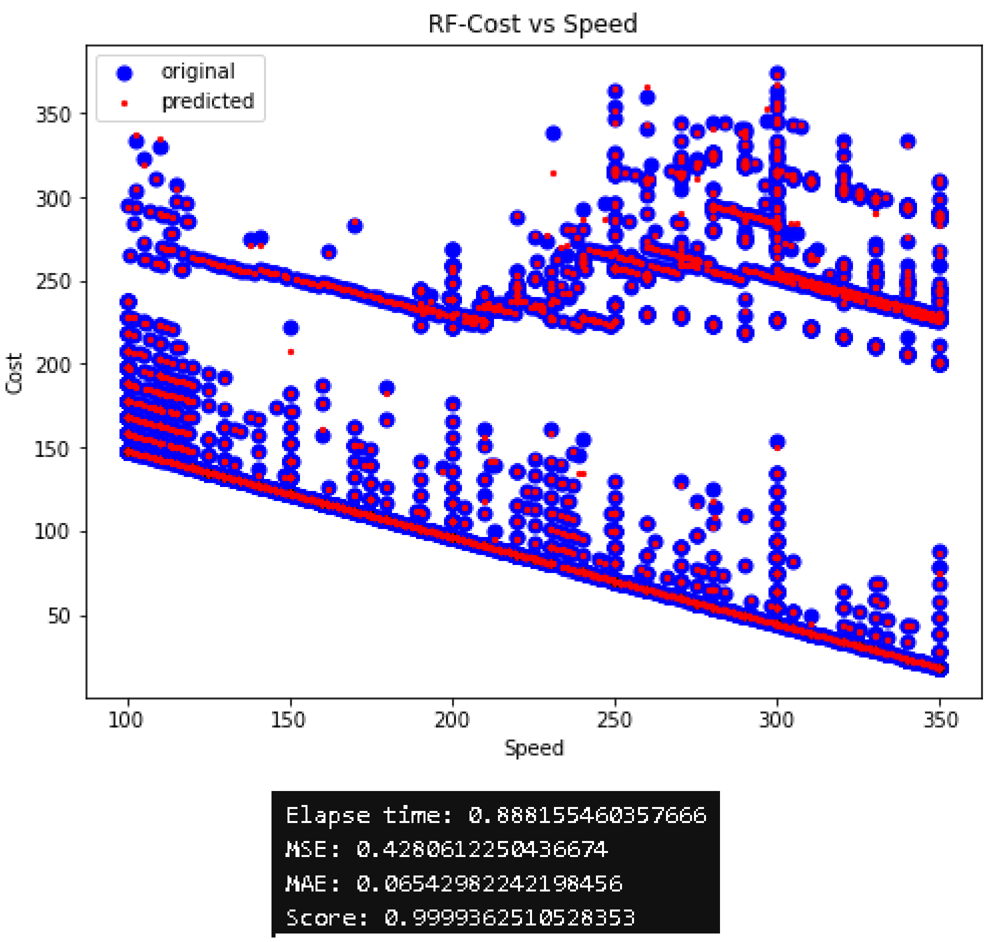


Figure 6.4. Scatter plot representing the accuracy of the cost function in the hybrid model.

This function has been presented in Table 6.2, providing a quantifiable measure of the production costs associated with different operational strategies and system configurations. As a result, it is now possible to effectively identify and evaluate opportunities to save costs.

Table 6.2. Parameters included in the cost function with their description.

Parameters	Description
S as Speed	Obtained directly from the DES model
ER as Electrical Resistance variation (percentage)	Obtained directly from the DES model
Geo as Number of Geometric faults	Obtained directly from the DES model
E as Energy cost	E = f(S): The energy cost depends on speed, which would vary based on the specific system details that have not been specified. This means that as the system operates faster it requires more energy.
R as Rework cost	R = f(ER) = (ER - 10%)*cost_per_unit_if_ER_>10%: Rework cost was calculated based on the extra percentage of ER over 10%.
W as Waste cost	W = f(Geo) = (Geo - 10)*cost_per_unit_if_Geo_>10: Waste cost was calculated based on the extra number of geometric faults over 10.
TR as Throughput Rate	TR = f(S): Throughput Rate is a function of speed, and if S>300, TR generates revenue.
OC as Operational Cost	OC = f(S): The operational costs are inversely proportional to speed, therefore as the system operates faster operational costs decrease.
C as Total Cost function	C = E + R + W + OC - TR: The overall cost encompasses the combined expenses of energy, rework, waste, and operational aspects minus the throughput rate.

Note: Please note that the formula assumes that both ER and Geo are above their respective thresholds. If they happen to be below these thresholds, it is advisable to refrain from calculating any additional costs.

The cost function was implemented for one hour of production, aiming to ensure accuracy in calculating throughput. Throughput measures how quickly a system produces output and is vital for evaluating the performance of production systems over time. To accurately calculate throughput, the simulation waits until one hour of production has elapsed ensuring that there is sufficient data available. Waiting allows initial setup effects or ramp-up issues within this introductory period to settle down so that they do not distort long-term performance measurements inappropriately.

The creation of a cost function is crucial in gauging the financial performance of this system. This cost function acts as a KPI and provides an objective measure of how effectively the system is operating from a financial standpoint [124]. Numerous elements were considered when developing this cost function, including: input speed, electrical resistance variation, number of geometric faults, energy consumption, rework efforts, waste production, and throughput rate. Implementing this strategic timing creates meaningful context for analysing measured costs while providing valuable information about the production system's performance, thus informing decisions and optimisation processes.

The cost function presented here offers a comprehensive perspective on the cost effectiveness of the system. Consequently, it aids in pinpointing areas that can be enhanced to achieve better cost efficiency. By simulating various scenarios under the DES model and using the cost function, it can be determined which approach yields the lowest production costs. Both the original DES model and the Hybrid model have been updated as a result of this new development. These models were incorporated with the new cost function providing a more comprehensive view of the system that considers not only operational efficiency and fault occurrence frequency but also associated production costs.

This update represents a significant improvement in the model's ability to make data-driven decisions about how best to optimise linear winding processes. These newly updated models allow the exploration of various scenarios and strategies enabling the identification of the optimal balance between cost, efficiency, and quality. Furthermore, these updated models also provide a more robust tool for understanding how different objectives and variables within the system interrelate.

6.5 Pareto Front

The adoption of a Pareto-based approach was used to identify the most favourable solutions for this problem. In the context of multi-objective optimisation problems, it is common to encounter situations where it is not feasible to achieve optimal values for all objectives simultaneously [109]. Instead, a collection of optimal solutions known as the Pareto front are found. A noteworthy aspect of this front was that any enhancement in one objective would invariably result in the deterioration of at least one other objective [125]. With this approach a diverse range of high-quality solutions each offering distinct trade-offs between the objectives were ascertained. This comprehensive perspective explores multiple potential solutions more effectively.

The process of objective optimisation resulted in a Pareto front, as shown in Figure 6.5, that illustrates the trade-offs between two conflicting objectives: the number of geometrical faults per layer (X-axis), and the production costs in British pounds (Y-axis). The Pareto front showcased a set of solutions that are not dominated by any solution, meaning that there is no way to improve one objective without compromising the other. For the X-axis, which represents the number of faults per layer, the range spans from 0 to 14. Lower values indicate fewer faults, which is more favourable during optimisation.

On the Y-axis, which represents production costs, the range goes from 0 to 22. Lower values indicate reduced production costs – an important factor for manufacturing. It is important to note that the cost values used in this Pareto front were obtained from existing literature and should be regarded only as reference points [5][81][162]. These values help assess cost effectiveness and facilitate comparison among solutions.

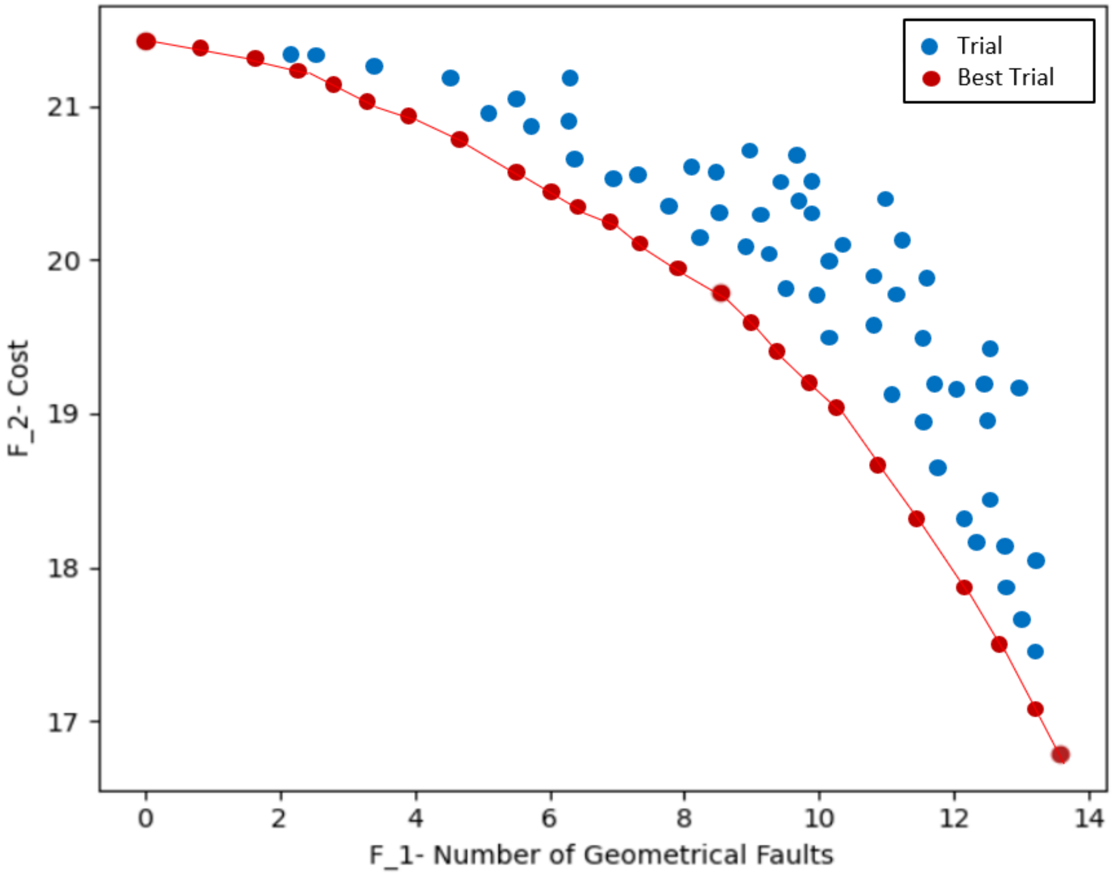


Figure 6.5. Pareto front provided by the NSGA-II algorithm with 2 objective functions.

6.6 Decision-making

Among the solutions on the Pareto front, according to the NSGA-II algorithm recommendation, there is one solution, with 8 geometrical faults, and a production cost of 20 British pounds. This particular solution stands out because it strikes a balance between the two objectives within the optimisation problem. The suggested solution was achieved by using the following input parameters: a speed of 234 rpm, a wire gauge of 0.708 mm and a squared bobbin. These input parameters play a role in determining the outcome and have been carefully chosen by the NSGA-II algorithm to find the best compromise between minimising faults and controlling production costs. In summary, both the obtained Pareto front and the recommended solution showcased how effective the multi-objective optimisation process can be. This empowers decision-makers to make choices based on their preferences and priorities, taking into account both faults and production costs while considering the specified input parameters.

6.7 Results from the correlation analysis involving interdependencies

After successfully validating both the DES model as well as its Hybrid counterpart, it was time to implement the newly-acquired optimal parameter settings obtained using a multi-objective algorithmic approach. These fine-tuned parameters represented an ideal combination leading to lower overall production costs while minimising fault occurrence frequency. Subsequently, both models were executed utilising this set of optimised parameters and the subsequent outputs were then analysed. An essential part of the said analysis involved the development of new correlation matrices for both the DES as well as the hybrid model.

During the analysis of the linear winding process, a detailed correlation analysis on the standard parameters of the process was conducted. This was done in order to comprehend how these parameters affected each other. It is important to note that the operational efficiency and cost effectiveness of the linear winding process depend on a complex interplay of multiple variables. Therefore, this analysis was critical in understanding the intricate relationships between them.

6.7.1. Steps to create a correlation matrix

To begin with, an adapted correlation matrix based on existing literature [3] and specifically adjusted for the linear winding case was created, as presented in Table 6.3. The focus of this matrix was on critical parameters such as winding speed, wire gauge, shape or aspect ratio, caster angle, and tension. In section 6.7.2, a more in deep explanation of the elements employed to create the correlation matrix are presented. This section offers insights, into the derivation, weights, interaction level and interdependency score of the correlation matrix, which aided in development an understanding of the analytical process and the relationships between variables. The five selected input parameters (winding speed, wire gauge, bobbin shape, caster angle and tension) were identified as having the most impact on the process and had the potential to be altered during the process to influence results.

The correlation matrix presented here serves as a method of measuring the interaction and interdependence between different input parameters and various types of faults (ER fault, double winding, gaps, crossover, flange and loose winding).

Table 6.3. Adapted correlation matrix for the linear winding process involving interdependencies [3].

By Sell-Le Blanc				Faults												
				ER fault	Double winding	Gap	Crossover	Flange	Loose							
				Weights												
			Deviation (0-5)	6	5	5	5	5	6							Interdependence value
Inputs	X0	Winding Speed	1	3	3	3	3	3	3	18	15	15	15	15	18	**96**
	X1	Wire gauge	2	3	3	3	3	3	3	36	30	30	30	30	36	**192**
	X3	Shape (Aspect Ratio)	3	3	3	3	3	3	1	54	45	45	45	45	18	**252**
	X4	Caster Angle	2	1	3	3	3	3	3	12	30	30	30	30	36	**168**
	X5	Tension	5	3	3	3	3	3	3	90	75	75	75	75	90	**480**
														Total I.V.		**1188**

6.7.2. Procedure for calculating the interdependency value

The method used to calculate the interdependency value was derived from the research conducted by Sell Leblanc [3]. By utilising and customising Sell- LeBlanc's established method, this research took advantage of a validated and proven approach to measure interdependencies. This adaptation ensured a contextually appropriate analysis of interdependencies, within the parameters set for this research allowing for consistent and comparable assessment.

1. **Deviation:** Each input parameter (e.g., winding speed, wire gauge) was assigned a deviation score ranging from 0 to 5 based on its perceived impact on the system. This score is recorded in the first column of the table.
2. **Weights:** Similarly, each type of fault was assigned a weight based on its significance or impact on the system (1–6). These weights are listed in the rows below each fault name. The weight values in the system represent the relative importance or impact of each type of fault. These weights range from 0 to 6 with higher weights indicating greater significance. It is crucial to assign these weights accurately as incorrect assignments may lead to overlooking critical faults or overemphasising minor issues. Failure to determine these weights correctly can have detrimental effects on the results.

   To ensure accurate weight assignment a combination of techniques was employed. The first technique involves conducting a literature review of existing studies, research, and reports on similar systems or processes [3][5][147][148][154]. By analysing this information, common faults and their relative impacts can be understood, providing guidance for assigning weight values based on previous findings. Another valuable technique was seeking the advice of industry experts. Drawing on their years of knowledge and experience in the field, experts can offer insights into the relative importance of different faults. They assess each fault based on its severity, frequency of occurrence and cost of rectification.

Historical data about the system also played a significant role in determining weight assignments. Analysing past incidences of each fault and associated costs (both direct and indirect) provided valuable information for making informed decisions. The derived weight values from these sources were then used in correlation analysis to calculate interdependency values. This analysis quantifies how system variables and faults interact and influence one another. By following these techniques and accurately determining weight assignments, a comprehensive understanding of fault impact can be achieved within the system analysis process.

3. **Interdependency interaction level:** In evaluating the interdependence between parameters, an approach similar to that of a traffic light system was adopted. The objective was to provide a clear interpretation of the correlation values and their significance. For this purpose, the Pearson correlation method was utilised as it quantifies the degree of relation between two variables. In this method, values range from -1 to +1 inclusive; a value close to +1 denotes perfect positive correlation while -1 indicates perfect negative correlation. Correspondingly, a 0 value signifies no relationship between variables. To categorise these correlation values into meaningful sections for both positive and negative correlations, a correlation-range matrix was provided, as shown in Table 6.4.

Each input fault interaction was assessed and given a score of 1, 2 or 3 based on their level of interaction or interdependence:

Table 6.4. Correlation-range matrix for interdependency interaction during linear winding.

Correlation Range				
	0	1	2	3
Positive	0	0 to 0.33	0.34 to 0.66	0.67 to 1
None	0	0	0	0
Negative	0	0 to -0.33	-0.34 to -0.66	-0.67 to -1

- A score of 1 was assigned to correlation values falling within 0 and 0.33 (positive or negative) to indicate weak or low correlation
- A score of 2 was assigned to values ranging from 0.34 through 0.66 (positive or negative) implying moderate correlation
- A score worth 3 marks was assigned to measurements ranging from approximately 0.67 through 1 (positive or negative), suggesting a strong correlation.

This 'traffic light' approach efficiently simplifies interpretation enabling a quick identification of characteristics such as strength, direction, and level of interdependence involved in model building. The utilisation of this technique proves to be highly advantageous, especially when dealing with extensive sets of data or intricate models. It aids in easily comprehending the correlation between variables, thus making it an essential tool.

4. **Individual interdependency score:** To calculate the individual interdependency score for each input parameter fault interaction, the deviation score of the input parameter has to be multiplied by the interaction score and then multiplied by the weight assigned to that particular fault. These scores were used to calculate individual interdependency values for each pair of input fault interactions. For example, the interdependency between winding speed and the ER fault can be calculated as follows: multiply 1 (deviation) by 3 (interaction score) resulting in an intermediate value of 3. This intermediate value is then multiplied by the weight assigned to the ER fault (which is equal to 6) resulting in a final interdependency value of 18.
5. **Total Interdependency value:** By summing up all these individual interdependency scores the total interdependency value can be obtained. The total interdependency value (1188) represents the sum of the interdependency values for all input parameters. This value presents a holistic assessment of the system's interdependency, where higher values denote increased intricacy in how parameters and faults interact.

6.7.3. Creation of correlation matrices

A. Original models (DES & Hybrid model)

A second correlation matrix was developed based on the results obtained from the DES model, as shown in Table 6.5. The DES model was enriched with a newly-introduced cost function (section 6.4.2) and proved to be a powerful tool for evaluating how alterations to various parameters influenced each other, as well as the overall cost effectiveness and efficiency of the process.

Table 6.5. Correlation matrix created from the results obtained from the original DES model [6].

DES MODEL				Faults												
				ER fault	Double winding	Gap	Crossover	Flange	Loose							
				Weights												
			Deviation (0-5)	6	5	6	5	5	4							Interdependence value
Inputs	X0	Winding Speed	3	3	3	3	3	3	3	54	45	54	45	45	36	282
	X1	Wire gauge	2	3	2	2	2	2	2	36	20	24	20	20	16	102
	X3	Shape (Aspect Ratio)	4	2	3	3	3	3	3	48	60	72	60	60	48	243
	X4	Caster Angle	3	1	3	3	3	3	2	18	45	54	45	45	24	164
	X5	Tension	5	3	3	3	3	3	3	90	75	90	75	75	60	333
														Total I.V.		1124

Subsequently, a third correlation matrix was generated using data derived from the updated hybrid model (RF), as represented in Table 6.6. This RF model was specifically designed to incorporate strengths from the DES model and cater more specifically to the complexities of the linear winding process. It provided another unique perspective on parameter relationships.

Table 6.6. Correlation matrix created from the results obtained from the original RF model [152].

RF MODEL				Faults												
				ER fault	Double winding	Gap	Crossover	Flange	Loose							
				Weights												
			Deviation (0-5)	6	5	6	5	5	4							Interdependence value
Inputs	X0	Winding Speed	3	3	3	3	3	3	3	54	45	54	45	45	36	282
	X1	Wire gauge	2	3	2	3	2	2	2	36	20	36	20	20	16	114
	X3	Shape (Aspect Ratio)	4	2	3	3	3	3	3	48	60	72	60	60	48	243
	X4	Caster Angle	3	1	3	3	3	3	3	18	45	54	45	45	36	165
	X5	Tension	5	3	3	3	3	3	3	90	75	90	75	75	60	333
														Total I.V.		1137

B. Optimised models (NSGA-II DES & NSGA-II RF)

After applying the NSGA-II algorithm to the original models to obtain a set of optimised input parameters, two new correlation matrices were constructed, as presented in Tables 6.7 & 6.8. The first matrix (Table 6.7) was based on the data gathered from the DES model using the optimal input parameters while the other matrix was created using data obtained from the RF model.

These updated matrices play a crucial role in understanding how the interactions between variables change after optimisation. The purpose of these matrices was to assess the correlations between the optimised input parameters and the resulting faults in the system. They were able to calculate new interdependency values, which can be compared directly to the initial values before optimisation. By analysing these results, it can be determined whether the relationships between variables have become more or less intertwined after optimisation. This analysis provides valuable insights into how effective the NSGA-II algorithm was at minimising system complexity.

Table 6.7. Correlation matrix created from the results obtained from the optimised DES model.

NSGA-II MODEL (DES)				Faults												
				ER fault	Double winding	Gap	Crossover	Flange	Loose							
				Weights												
			Deviation (0-5)	6	5	6	5	5	4							Interdependence value
Inputs	X0	Winding Speed	3	3	2	2	2	2	1	54	30	36	30	30	12	193
	X1	Wire gauge	2	3	2	3	2	2	2	36	20	36	20	20	16	114
	X3	Shape (Aspect Ratio)	4	2	3	3	3	3	3	48	60	72	60	60	48	243
	X4	Caster Angle	3	1	3	2	3	2	2	18	45	36	45	30	24	146
	X5	Tension	5	3	3	3	3	3	3	90	75	90	75	75	60	333
															Total I.V.	1029

Table 6.8. Correlation matrix created from the results obtained from the optimised RF model.

NSGA-II MODEL (RF)				Faults												
				ER fault	Double winding	Gap	Crossover	Flange	Loose							
				Weights												
			Deviation (0-5)	6	5	6	5	5	4							Interdependence value
Inputs	X0	Winding Speed	3	3	2	2	2	3	1	54	30	36	30	45	12	208
	X1	Wire gauge	2	3	2	3	2	2	2	36	20	36	20	20	16	114
	X3	Shape (Aspect Ratio)	4	2	3	3	3	3	3	48	60	72	60	60	48	243
	X4	Caster Angle	3	1	3	2	3	2	2	18	45	36	45	30	24	146
	X5	Tension	5	3	3	3	3	3	3	90	75	90	75	75	60	333
															Total I.V.	1044

6.7.4. Analysis and comparison of correlation matrices results

DES model – NSGA-II (DES): The correlation matrices for the DES model (Table 6.5) and the NSGA-II model DES (Table 6.7) exhibited discrepancies in the correlation value, which can be attributed to the impact of the optimisation process on the system. This analysis aims to explore the alterations in correlations values between the original and optimised models for each input and fault type while also providing a rationale for these alterations.

- The correlation value of winding speed (X0) decreases for most faults, specifically "double winding", "gap", "crossover" and "flange". This suggests that the NSGA-II algorithm has successfully optimised this parameter, resulting in a reduction in its influence on fault occurrence. As a result, the interdependency value decreases to 193.

- Wire gauge (X1) shows an increase in the correlation value for "crossover", indicating a slightly higher impact on this particular fault under optimised conditions. This leads to an increase in the interdependency value to 114.
- The shape or aspect ratio (X3) and tension (X5) maintain their weights and interdependency values, indicating that their influence and interdependencies remain constant despite optimisation.
- On the other hand, caster angle (X4) experiences a decrease in the correlation value for "crossover" and "flange", leading to a decrease in its interdependency value to 146.

These changes in the correlation value reflect alterations in the system's behaviour due to the application of the multi-objective NSGA-II algorithm. The algorithm modifies parameter interactions with the goal of minimising faults and costs, resulting in adjustments to the strengths of these interdependencies. These variances demonstrate that the algorithm has effectively reduced certain dependencies making it easier to manage and optimise the system.

Hybrid model - NSGA-II (RF): The correlation matrices of the RF model (Table 6.6) and the NSGA-II RF model (Table 6.8) differ in terms of the correlation values assigned to variables and faults. These differences indicate changes in interdependencies resulting from the optimisation process.

- The winding speed (X0) shows a decrease in the correlation values for "gap" "crossover" and "flange" indicating that the optimisation has reduced its influence on these faults. Consequently, its interdependency value decreases to 208.
- The wire gauge (X1) retains its correlation values and interdependency value of 114, suggesting that its influence on the faults has not changed significantly.
- Similarly, the shape or aspect ratio (X3) also maintains its correlation values and interdependency value of 243, indicating a consistent level of influence.
- On the other hand, the caster angle (X4) experiences decreased correlation values for "crossover" and "flange" leading to a decrease in its overall interdependency value to 146.
- However, tension (X5) maintains its correlation values and interdependency value of 333, implying that it remains a significant factor in causing these faults.

The changes in correlation values observed in this study can be attributed to the impact of the NSGA-II optimisation algorithm on the system's parameters. The main objective of this algorithm was to minimise the occurrence of faults and costs, thereby resulting in modifications in the relationships between variables. Notably, there have been instances where these interdependencies have been reduced, leading to a simplification in both the management and optimisation of the system.

Comparing these correlation matrices provides the opportunity to validate the interdependency values obtained from each model. A comparative analysis presented in Table 6.9, identifies consistencies and differences between matrices providing robust evidence that supports the understanding of these critical interdependencies. These newly-created matrices provided an opportunity to study how variables interacted with one another concerning their new parameter settings. It also identified any alterations in interdependency values specifically arising from incorporating these optimised parameters. Thus, a comparison of them against previous correlation matrices became necessary. Consequently, it was determined whether interdependencies had increased or decreased or remained unaffected by these newly-implemented optimal parameters. Analysing such correlations offered valuable insights into how optimal parameters affected associations among variables in the system.

Table 6.9 offers a comparison of the outcomes achieved through various models utilised in this research. Specifically, the DES model, the RF model, and the optimal parameters obtained from the multi-objective algorithm (NSGA-II) applied to both DES and RF models.

Table 6.9. Comparison between correlation matrices.

	Model	Interdependency value	Cost	Number of Faults
1	DES	1124	0.00%	15
2	RF	1137	3.65%	16
3	NSGA-II (DES)	1029	-27.95%	0
4	NSGA-II (RF)	1044	-23.73%	2

A. Total interdependency value

One of the main findings presented in Table 6.10 was the significant decrease in the interdependency value when comparing the original models (DES and RF) to the optimised models (NSGA-II applied to DES and RF). The interdependency value represented how closely linked the variables in the system were. A higher interdependency value implies complex relationships between variables, where a change in one variable can greatly affect others. This

Table 6.10. Comparison table of the total interdependency value between models.

Model	Interdependency value	Results
DES	1124	The DES model exhibited a high interdependency value of 1124, indicating a complex network of interactions among the system parameters. Understanding these relationships was crucial for optimisation efforts to avoid unintended consequences. The high interdependency value provided a comprehensive view of the system, assisted decision-making, identified crucial parameters, and served as a benchmark for optimisation strategies.
RF	1137	The RF model showed a minor elevation in the interdependency value compared to DES (1124 to 1137). This increase was attributed to the incorporation of a knowledge-based approach, which uncovered intricate relationships between variables not considered in simpler DES models. Although the interdependency value increased slightly, it represented an improved understanding of processes and more diverse aspects being considered, leading to valuable trade-offs if desirable outcomes were achieved.
NSGA-II (DES)	1029	Applying NSGA-II (DES) resulted in a decreased interdependency value of 1029. The algorithm's multiple-objective optimisation approach aimed at balancing trade-offs and achieving equilibrium, leading to reduced system complexity. The optimised parameters obtained from NSGA-II (DES) resulted in less intricate interactions among variables and improved the system's manageability and optimisation.
NSGA-II (RF)	1044	NSGA-II (RF) exhibited a further decrease in the interdependency value to 1044. The multi-objective optimisation approach significantly reduced the complexity of interactions between variables in the RF model, resulting in improved manageability and optimisation. Despite slightly higher interdependency values compared to NSGA-II (DES), the computational speed and efficiency of the Random Forest model made it a favorable choice for solving the multi-objective linear winding problem.

complexity can make it difficult to optimise and manage the system due to the intricate interplay and potential trade-offs between different variables.

The sensitivity analysis results shed light on how optimisation approaches affect the interdependency value of the models. Both the NSGA-II (DES) and NSGA-II (RF) algorithms successfully decreased the interdependency value when compared to the DES and RF models. This reduction implies system manageability, simplification of interactions, and improved optimisation capabilities. Furthermore, the NSGA-II (RF) model has an advantage in terms of speed and efficiency making it especially suitable for real time applications or situations that require decision-making. While both optimised models (RF and DES) showed improvements over the original models, the superior computational speed of NSGA-II (RF) made it the most favourable choice among all considered models.

Overall, this sensitivity analysis provides insights into how optimisation techniques impact system complexity and interdependency value. The decrease in interdependency value indicates system performance and optimisation – potentially supporting the effective decision-making and management of linear winding processes.

B. Cost value

The analysis of the cost changes associated with the different models and their optimisation parameters was a critical aspect that required careful consideration. The cost metric, which served as an essential indicator of both process efficiency and economic viability was thoroughly examined in relation to the correlation matrices, as presented in Table 6.11. Within each correlation matrix, the cost value was treated as an outcome variable when considering the optimised input parameters.

This approach explored the relationship between each parameter and its impact on overall cost within the linear winding process. Whether comparing the DES model to the hybrid model, or examining the optimised versions through the NSGA-II algorithm, changes in cost were carefully studied. This comparative analysis provided essential insights into how effectively each model and its corresponding parameters managed costs while also potentially improving process quality. By comparing these values across different correlation matrices it was possible to determine which models were most effective and thus identify optimal parameter settings in terms of cost efficiency.

As a result, this cost comparison provides insights into the cost effectiveness of models and optimisation approaches. The notable cost reductions achieved by NSGA-II (DES) and NSGA-II (RF) demonstrate the effectiveness of multi-objective optimisation in minimising overall costs in the linear winding process, making them excellent choices for practical implementation.

C. Number of faults

The application of the NSGA-II optimisation algorithm has been proven to be highly effective in reducing the number of faults in both DES and RF models. The analysis results, as presented in Table 6.12, highlight how different approaches to modelling and optimisation affect the occurrence of faults in the winding process.

This highlights the significance and efficiency of utilising this optimisation process in complex systems, as it allows for better management of parameter interdependencies leading to

Table 6.11. Comparison table of the cost value between models.

Model	Cost Variation (%)	Results
DES	**0**	The DES model served as the baseline with a cost variation of 0.00%. It provided a standard for comparison, against which the cost changes of other models were measured. Although the cost value was set at 0.00%, it does not imply no costs were associated with the DES model; rather, it facilitated meaningful comparisons with other models.
RF	**3.65**	The RF model showed a cost variation of +3.65% compared to the baseline DES model. Running the RF model required more resources, as it utilized an ensemble of decision trees and involved more complex data preprocessing and handling. The higher computational costs and slightly higher number of faults contributed to the increase in overall costs.
NSGA-II (DES)	**-27.95**	Applying the NSGA-II algorithm to the DES model resulted in a significant cost reduction of -27.95% compared to the baseline DES model. The multi-objective optimisation approach of NSGA-II achieved an optimal balance among system parameters, leading to fewer fault occurrences and associated corrective expenses. This cost reduction demonstrates the effectiveness of the optimisation approach in minimising overall costs.
NSGA-II (RF)	**-23.73**	The NSGA-II optimised RF model achieved a cost reduction of -23.73% compared to the baseline DES model. Although slightly less than the cost reduction achieved by NSGA-II (DES), it still represented a significant decrease in costs. The increase in cost compared to NSGA-II (DES) might be attributed to the slightly higher fault occurrence and computational complexity associated with the RF model.

notable improvements. Even though the NSGA-II (RF) model has a lower incidence of faults, its faster computational speed may make it more desirable in certain scenarios.

Overall, this analysis offers insights into how optimisation approaches impact fault occurrences in the winding process. The optimised models (NSGA-II DES and NSGA-II RF) stand out for their improvement in the number of fault incidences, indicating their suitability for implementation and potential to enhance overall reliability and performance of the winding process.

Table 6.12. Comparison table of the number of faults between models.

Model	Number of Faults	Results
DES	**15**	The DES model identified a total of 15 faults, primarily attributed to higher winding speeds and the use of bobbin shape variants. While higher speeds can enhance productivity, they also increase mechanical stress and complexities in wire placement. Bobbins with sharp angles or irregularities further complicate the winding process, leading to a noticeable increase in fault occurrence.
RF	**16**	The Hybrid model based on RF exhibited a slightly higher number of faults (16) compared to the DES model. This increase may be attributed to the implementation of the knowledge-based approach, which introduced additional complexity to the model, contributing to a higher fault count.
NSGA-II (DES)	**0**	The NSGA-II (DES) optimised model performed flawlessly without any faults, a remarkable achievement considering the original DES model had 15 faults. The multi-objective optimisation process effectively handled system interdependencies and identified the most suitable parameters, resulting in a significant decrease in the number of faults.
NSGA-II (RF)	**2**	The NSGA-II (RF) optimised model demonstrated a substantial decrease in faults compared to the original RF model, with only two faults identified. While not flawless like NSGA-II (DES), this refined RF model still shows remarkable improvement, emphasizing the effectiveness of the multi-objective optimisation approach in reducing fault occurrences.

6.7.5. Effectiveness of NSGA-II Multi-Objective Optimisation in Reducing System Interdependencies

The original DES model had an interdependency value of 1124, slightly lower than that of the original RF model, which had a value of 1137. These high values, in comparison to the optimised models (NSGAII), indicate that when in their original states the system parameters have complex interactions that can make optimisation challenging without unintended consequences. However, when the multi-objective algorithm (NSGA-II) was applied, both the DES and RF models showed significant decreases in their interdependency values – DES decreasing to 1029 and RF decreasing to 1044, suggesting that these optimised parameters resulted in less complex interactions between variables.

This reduction in interdependencies was promising, as it indicates that managing and optimising the system became easier with these new parameters. By decreasing interdependencies, it can be better-predict how changes in one variable will affect others, allowing for more effective and targeted optimisation strategies. In this research, this decrease coincided with notable reductions in production cost and number of faults, demonstrating the effectiveness of the multi-objective optimisation approach. This observation provides robust evidence that carefully managing system interdependencies is a critical factor in improving efficiency and cost effectiveness in linear winding processes.

Results showed that by applying the NSGA-II multi-objective algorithm to both the DES and RF models, remarkable improvements were achieved in terms of reduced interdependency values, costs, and fault occurrences. This clearly demonstrated that adopting a multi-objective approach was highly effective in optimising the linear winding process by significantly minimising production costs and virtually eradicating faults.

6.8 Summary

This section presented the results from a framework that was developed for multi-objective optimisation in an electrical manufacturing process focusing on linear winding. The main goal of this framework was to reduce costs and minimise faults simultaneously during the linear coil winding process in electrical machine manufacturing, while considering the interdependencies between these objectives. By implementing this framework, it was possible to improve cost effectiveness and decrease fault rates in winding operations. A key aspect of achieving these optimisation goals was understanding the connections between objectives, particularly the relationship between production costs and geometrical faults. To gain this understanding a correlation analysis was conducted that provided insights into how these objectives interacted with each other. The selection of variables such as rotational speed and wire gauge played a vital role in achieving a balanced equilibrium and overall operational efficiency. This delicate balance was achieved through the analysis and application of optimisation techniques such as the NSGA-II algorithm.

Among the solutions generated by the NSGA-II algorithm, one particular solution stood as particularly noteworthy. This solution effectively balanced 8 geometrical faults per layer while keeping production costs at its lowest (£20) by adjusting input parameters, like speed, wire gauge and bobbin shape. Implementing the optimised parameters obtained through the algorithmic approach in both the DES and Hybrid models led to reduced production costs and a minimisation of the occurrence frequency of faults. To understand how standard process parameters influenced each other, a correlation analysis was conducted, providing insights into the interplay of multiple variables in linear winding. Additionally, creating correlation matrices from the optimised models made it possible to assess how input parameters were related to resulting faults. This analysis revealed a decrease in interdependency value when comparing the models – the optimised ones indicating reduced system complexity and improved optimisation capabilities.

The sensitivity analysis results highlighted how optimisation approaches impacted interdependency values within these models. Both the NSGA-II (DES) and NSGA-II (RF) models successfully reduced the interdependency value, enhancing the effectiveness of system management and optimisation. The NSGA-II (RF) model, in particular, demonstrated high speed response, making it well suited for real-time applications or time-sensitive decision-making scenarios. Upon analysing the cost comparison, it became evident that the optimised models were cost effective. Notably both NSGA-II (DES) and NSGA-II (RF) achieved reductions, underscoring how multi-objective optimisation can minimise costs in the linear winding process.

Research findings revealed that the original DES and RF models exhibited interactions that posed challenges to optimisation. However, implementing the NSGA-II algorithm resulted in decreases in interdependency values indicating improved efficiency and targeted strategies for optimisation. Concurrently, there was a decrease in production costs and the occurrences of faults, further validating the effectiveness of the multi-objective optimisation approach. These findings give decision-makers the ability to make choices that take into account both flaws and production expenses, all while following input criteria.

CHAPTER VII: DISCUSSION AND CONCLUSION

7.1 Research findings and contributions

The research results were summarised in the following sections, which were organised based on research objectives and chapters. This aided understanding of how the findings align with the objectives of the research and with the corresponding chapters.

7.1.1 Identification and application of techniques for detecting interdependencies that lead to defects downstream in electrical machines.

Chapters III & IV focussed on achieving the first objective: '*Identify and apply techniques that determine the key process characteristics in an EM during an error-prone manufacturing process, detecting interdependencies that lead to defects downstream'*.

This research focused on a gap (section 2.6) in the current literature [11] by identifying and implementing techniques to uncover important process characteristics and connections that contribute to defects in a vulnerable manufacturing process. Unlike other research attempts [2][83], what sets this research apart was its identification of process characteristics and establishment of causal links providing a novel approach on how defects are anticipated and resolved. This research deepens the understanding of the interrelationships between process variables and defects, enabling a proactive prevention of defects.

To accomplish the first objective, it was required to understand aspects of the manufacturing process for EMs by identifying connections between different factors and the creation of defects [5][11]. The first step involved conducting a review of existing literature as presented in [4] to build a diverse knowledge base that combined techniques for condition monitoring, fault detection, and modelling of EM and interdependencies. By using techniques such as precedence graphs and graph network diagrams in a systematic characterisation process, it was determined which specific process variables had a significant impact on the quality of EMs. Four process variables stood out as having a vital impact: the rotational speed, the tension applied to the copper wire, the size of the wire used, and the shape of the bobbin. These factors all play a role in shaping the complex dynamics of the manufacturing process and ultimately determine the overall quality and dependability of the EM.

This research is a step forward in understanding complex manufacturing procedures specifically in the EM production. Its main achievement lies in presenting a robust framework aimed at improving the comprehension of these processes. This framework reveals previous connections between process variables and defects, shedding light on cause-and-effect relationships that were not explored before [3][123]. This scientific contribution should expand the area of process interdependencies and fault detection by providing a framework for identifying crucial process characteristics and evaluating their impact on product quality. By identifying key characteristics of the manufacturing process, and understanding how they interact with each other, it can effectively reduce defects and improve the reliability and performance of their products.

This provided the opportunity (objective 2) to later-employed modelling techniques to uncover complex relationships between these variables and downstream defects. This initial step established the foundation for later stages focused on predicting defects, optimising processes and implementing practical improvements. Ultimately, these efforts were aimed at enhancing both the quality and reliability of EM manufacturing significantly.

7.1.2 Creation and implementation of a DES model for modelling interdependencies.

Chapter IV “Modelling framework for interdependencies” focussed on achieving the second objective: ‘*Develop a framework by using modelling techniques to understand how a combination of process variables influences the creation of defects*’.

When regarding the literature [3][148], there is no research focused on modelling techniques that accurately capture the complex relationships among various parameters in the manufacturing process of EMs. While existing studies offer an overview of EM manufacturing [2][9], there is still a lack of exploration into specific modelling methods that can comprehensively understand and analyse the interdependencies between process variables. This research gap highlighted the potential for innovative insights and advancements that could improve the quality and performance of EM manufacturing. Addressing this gap held promise for streamlining processes, preventing defects, and making valuable contributions to the broader fields of manufacturing and process control.

To achieve the aim of the second objective, it was necessary to address the existing gap of modelling techniques that could accurately capture the relationships between various parameters in the manufacturing process of EMs. These techniques would need to provide real-time predictions about the likelihood of electrical and geometrical defects occurring. While previous efforts had been made in modelling how rigid materials behaved (and interconnected) during manufacturing [32][86][163], they often focussed on specific manufacturing steps rather than taking a holistic approach to analyse the entire sequential process and uncover comprehensive relationships [164]. The objective was to bridge this gap by creating a predictive modelling approach that improved the understanding of how parameters interacted and impacted upon defect occurrence throughout the EM manufacturing journey.

To overcome this limitation a solution was proposed by creating an artificial dataset using simulation techniques. An environment that accurately replicated actual manufacturing processes was carefully designed, drawing on knowledge of manufacturing science and engineering principles obtained from previous literature [3][5]. Although this simulation model required calibration and validation, the simulated dataset would help fill the information gap and allow investigation into the factors and relationships that contribute to defects.

As a contribution, a new framework was developed to study the relationships in manufacturing processes involving materials that would be considered deformable. This framework used a DES model to analyse the process of making noncircular orthocyclic coils in a linear way. The created DES model had an advantage over other models– it could detect faults and pinpoint areas where electrical resistance was high, which were often referred to as "hotspots". To make sure this DES model was accurate and reliable it underwent experimental testing using a specialised linear coil winding machine. While the DES approach was great for capturing interconnections and identifying important issues, there were also potential downsides. These included the need for setup and parameterisation for an accurate simulation as well as representing dynamic real-world conditions fully.

While simulations are valuable for studying manufacturing processes [83][165], they have limitations when it comes to accurately replicating actual conditions. Prajapat et al. [165] discusses that these limitations stem from assumptions and simplifications made in the simulation models, which may not fully capture the complexities and variations found in manufacturing environments. To tackle this issue, as previously discuss, this research emphasises the importance of conducting experiments to validate the results. This step bridges the gap between simulations and real world manufacturing settings by enabling how to assess effectively and accurately the proposed framework. This approach would help in verifying whether the insights and predictions generated through simulations hold true when implemented in an actual manufacturing environment. However, the benefits of greater understanding, and predictive capability, make this DES model an important contribution to the field [4][6]. It provided insights into preventing defects and optimising manufacturing processes that involve materials that can change shape.

7.1.3 Creation and implementation of a hybrid model for enhanced interdependency modelling.

Chapter V “Hybrid computational framework” focussed on achieving the third objective: ‘*Integrate the established framework with a supervised learning algorithm to enhance the efficiency and reliability of quality control tests by predicting component states and accounting for interdependencies in the process’*.

The existing research has shown a gap in the integration of a DES model with a supervised learning algorithm through KD [53]. This combination has the potential to greatly improve the efficiency and reliability of quality control tests in manufacturing processes. While there have been studies on DES models [166], supervised learning algorithms [90], and KD techniques[72], their integration for enhancing quality control testing has not been extensively explored. Bringing together a DES model and a supervised learning algorithm using KD represents an area with significant possibilities. This merging created a framework that not only predicts component states, but also takes into account the complex interdependencies inherent in manufacturing processes. This innovative approach aims to streamline quality control tests, reducing time and costs while simultaneously strengthening manufacturing reliability and efficiency [152].

To achieve the aim of the third objective it was required to explore the integration and enhancement of the developed framework. In the manufacturing industry, it is common practice to conduct multiple quality tests after each production step to identify faults or defects [11]. However, although these methods are effective, this approach proved to be time consuming and resource intensive [44]. This integration aimed to predict the states of components and improve quality control tests by reducing testing time while thoroughly analysing how different process factors interact with each other.

Therefore, this research contributes by introducing an innovative hybrid model that implements a KD approach. This unique combination addresses the challenges of the DES model by incorporating architecture search and data augmentation techniques to improve the generalisation capacity of the student model (SML) algorithm [152]. By utilising the DES model to generate training data for the SML algorithm, advancements can be made in fault detection and prediction in machine manufacturing processes such as knowing the location, time frame and the severity of a fault created by interdependencies in an electrical component.

The advantages of this new hybrid model are numerous. First, by combining the DES and SML it reduced the simulation time in a 99% reduction from 2 minutes to less than 1 second, leading to faster production timelines. Additionally, the model's ability to enhance stator quality contributes to improved reliability and safety of the final product. However, as with any pioneering approach, there are considerations associated with this hybrid model. It is worth considering that the performance of the model heavily depends on the quality and representativeness of the training data generated by the DES model. Inaccuracies in this data could compromise fault detection and prediction accuracy. Finally, maintaining and adapting the architecture of the hybrid model might pose challenges when new data becomes available or manufacturing processes change. Updating and fine tuning the model could be more difficult compared to using standalone techniques resulting in potentially slowing down its responsiveness to changes.

7.1.4 Creation and implementation of a multi-objective optimisation model for interdependencies.

Chapter VI "Multi-Objective Optimisation for Interdependencies" focussed on achieving the last objective: *'Establish a model-based framework for Integrated Fault Detection and Parameter Optimisation in production processes'.*

The aim of the fourth objective in this research was to fill the last gap (section 2.6) by creating and implementing a multi-objective optimisation framework. This framework would seamlessly integrate fault detection and parameter optimisation with a focus on the interdependencies that exist in production processes. Bridging this gap was crucial as it has greatly improve the efficiency and effectiveness of manufacturing operations by reducing quality faults and cost in EMs where deformable material is a vital part. While methods like evolutionary learning, parallel and distributed algorithms, and the island model genetic algorithm have provided solutions for problems at various levels [103][108][137], their application has mostly been centred around design optimisation rather than process optimisation. To address this, a multi-objective framework that combines fault detection and parameter optimisation, while carefully considering interdependencies, was developed and implemented.

This research contributed to the field of multi-objective optimisation by leveraging evolutionary algorithms. These algorithms have proven to be effective in solving multi-objective problems while maintaining a level of independence between different solutions spaces [62]. In the context of optimising manufacturing processes, the NSGA-II algorithm was proposed as a technique that excelled in addressing multiple objectives such as reducing costs and enhancing quality. What made this approach innovative was its adoption of a multi-objective strategy to determine and increase the level of control in interdependencies by optimising the linear winding process using parameter optimisation.

By generating correlation matrices from optimised models, this framework uncovered insights into interactions allowing an assessment of how optimised input parameters were correlated with system faults. By minimising interdependencies within the system thanks to the use of the NSGA-II algorithm, it enhanced not only manageability and optimisation, but also holds potential for cost reduction and fault mitigation. However, it is important to consider the drawbacks associated with this approach. The computational complexity involved in algorithms, especially when working with multiple objectives, may require significant resources. Furthermore, finding the perfect equilibrium between goals and their optimisation might pose challenges, especially when there are trade-offs to consider [108].

7.2 Limitations of Research

While the previous sections have shown contributions and advancements, it is crucial to recognise and thoroughly assess limitations that are inherent in the proposed methodologies and approaches.

7.2.1 Limitation of the DES model

Firstly, it is important to recognise that the DES model was primarily focused on the linear winding technique used in electrical machine manufacturing. However, this narrow focus ignores the range of winding techniques commonly employed in the industry such as the flyer, needle and toroidal winding [5]. Consequently, the insights and recommendations provided by the model may not be universally applicable since it might have overlooked aspects of manufacturing processes associated with other winding methods. Additionally, the DES model was developed using a set of input parameters that included speed, tension, wire size and bobbin shape. However, the DES model was designed to be flexible and adaptable allowing for the inclusion of parameters and improvements as necessary to improve its precision and practicality.

While these parameters are undoubtedly relevant, this reductionist approach may not capture all the variables that influence the manufacturing process. Neglecting other important input factors could limit the accuracy of the model in representing the interplay of variables encountered in real-world manufacturing scenarios. Furthermore, when examining outputs, the DES model only considered two aspects: variation in electrical resistance, and a limited subset of geometrical faults consisting of only six types. This narrow focus may not encompass all the output variables required to assess the quality and reliability of the manufacturing process.

Lastly, the DES model only focuses on the orthocyclic scheme, which may restrict its practicality. In electrical machine manufacturing there are various winding schemes such as wild and helical [5], and solely focusing on one might limit the model's relevance and effectiveness in situations that use different winding techniques. Additionally, the simulation was limited to a maximum of five layers of winding. While this limitation may be sufficient for certain scenarios, it might not accurately represent complex manufacturing processes that involve a greater number of winding layers. This constraint could potentially make it challenging for the model to accurately replicate the intricacies of real-world manufacturing.

7.2.2 Limitation of the hybrid model

The hybrid model, although it has potential for innovation, it does have some limitations that need to be considered when interpreting its results. Firstly, one notable limitation was the comparison of SML algorithms. While this research evaluated six popular algorithms from the literature [115][137], there are actually many more SML algorithms available. This comparison might not fully capture the range of possibilities and could potentially exclude algorithms that might perform better for specific tasks. The choice of algorithms being compared could impact the effectiveness and applicability of the model raising questions about its broader usefulness. Additionally, focusing solely on tuning an SML algorithm, the Neural Network in this case, presents further limitations. Although Neural Networks are known for their versatility and effectiveness [44][68], concentrating exclusively on this algorithm may overlook insights from other algorithms. By tuning only the Neural Network, nuances and variations in prediction accuracy that could arise from other tuned SML algorithms might be missed out on, which limits the overall comprehensiveness of the model.

Another limitation stems from the size of the database used in this research, which was limited to a total of 40,000 instances. While this dataset forms a foundation for analysis, its size could impose constraints on how the model can generalise to broader manufacturing scenarios. Bigger sets of data might be able to provide more dependable results – capturing the complexities and variations found in actual manufacturing processes. Aside from these factors, it was also important to explore limitations such as biases within the dataset. These biases could unintentionally affect the predictions of the model.

7.2.3 Limitation of the multi-objective optimisation

While the multi-objective approach discussed in this research showed promise, it is important to acknowledge and critically evaluate limitations that could affect its practicality and interpretation. Firstly, one significant constraint arises from only considering two objectives in the objective approach. Manufacturing processes often involve competing objectives, such as: reducing costs, enhancing quality, improving energy efficiency, and promoting sustainability [62][108]. By focusing on only two objectives, the approach may not fully capture the range of objectives that manufacturers typically strive to optimise. This limitation could lead to a representation of the trade-offs and complexities involved in manufacturing decision-making.

Another noteworthy limitation stems from using the NSGA-II algorithm as the genetic algorithm employed. Although NSGA-II is well regarded and has proven effective in solving objective optimisation problems [108], solely relying on this algorithm might overlook other potentially superior alternatives. The performance of algorithms can vary depending on problem characteristics. Exclusively utilising NSGA-II may neglect other algorithms that offer better convergence rates or solutions.

Moreover, the performance of the NSGA-II algorithm depends on its parameter settings. Without parameter settings, tuning the algorithm may not achieve its optimal performance potential, reducing its effectiveness in generating high-quality solutions for objective optimisation problems. Finally, using correlation matrices to understand how input parameters interact also has a limitation. These matrices are created based on the input parameters, and while they provide valuable insights, they might not include other parameters that could affect the manufacturing process. Ignoring these parameters could compromise the accuracy and depth of our understanding gained from the correlation matrices.

7.3 Proposed Future Work

In this section, future directions that can build upon the findings of this research and tackle the limitations that have been identified were discussed.

7.3.1 Proposed work for the DES model.

Moving forward, there are ways to enhance the capabilities of the DES model. One possible approach is to broaden the scope by incorporating a range of winding techniques into machine manufacturing. As a result, this expansion would provide additional insights into the interconnections between manufacturing processes. For this research it would be beneficial to consider more input parameters such as friction, and not just be limited to speed, tension, wire size and bobbin shape. By considering a far larger range of input variables, the model would improve its understanding of the aspects of manufacturing and their impact on product quality. Additionally, exploring output variables that go beyond electrical resistance variation and geometrical faults could enhance the capabilities of the DES model. This exploration could reveal insights about the manufacturing process, ultimately leading to quality control and more accurate defect prediction.

7.3.2 Proposed work for the Hybrid model.

To further enhance the capabilities of the hybrid model, there are potential future avenues that can be explored. These include: improving the algorithm comparison process, tuning algorithms to analyse how their performance improves, and considering a far larger range of datasets. By expanding the comparison of SML algorithms beyond the six evaluated, it could be possible to gain a more comprehensive understanding of which approach is most suitable for specific manufacturing contexts. A broader comparison implementing algorithms such as Gradient Boosting, XGBoost and LightGBM would help uncover nuances that may not be apparent in the evaluation. Additionally, conducting parameter-tuning exercises like Random search or Bayesian optimisation for SML algorithms is another important area to focus on as future work. This would enable the identification of configurations that maximise prediction accuracy and enhance performance of the hybrid model. It is crucial to ensure that the selected algorithm truly aligns with the requirements of each manufacturing application. Lastly, obtaining a more diverse dataset for training and validation purposes is an aspect to consider for future improvements. An extensive dataset would provide a better representation of real-world manufacturing scenarios' variability and complexity, resulting in more accurate and reliable predictions from the hybrid model.

7.3.3 Proposed work for the multi-objective optimisation process.

In the field of multi-objective optimisation, several potential areas can be explored in order to enhance the comprehensiveness and effectiveness of this approach. One possible approach involves going beyond simply reducing costs and improving quality. By incorporating objectives related to energy efficiency, resource utilisation, and environmental impact, it could be possible to create an optimisation framework that aligns with sustainability goals. Another promising direction is to further explore the use of other evolutionary algorithms apart from NSGA-II, like SPEA2 or MOEA/D. The performance of algorithms can be compared to determine which one is best suited for a specific optimisation problem. This analysis would provide insights into convergence properties, exploration capabilities, and solution quality.

Furthermore, it would be beneficial to conduct parameter tuning and sensitivity analyses for the chosen algorithm. This would help in understanding how different parameter settings affect the outcomes of optimisation. To further advance this understanding, expanding the set of input parameters in the correlation analysis should be considered. Additionally, including more variables can lead to more insightful correlation matrices and optimised manufacturing solutions. Finally, it is crucial to validate the viability and effectiveness of the multi-objective optimisation approach through real-world manufacturing scenarios and case studies across industries. This validation process would offer evidence of its applicability in manufacturing operations while guiding its implementation effectively.

7.4 Conclusions

The increasing global focus on sustainable and eco-friendly technologies, such as electric vehicles, has created a higher demand for electrical products [24]. As a result, there is a pressing need for improvements in the manufacturing process of EM. Therefore, it becomes crucial to meet the growing demand [4][43] while ensuring high quality standards, reducing the time required for end-of-line testing, and supporting the expansion of the friendly green industrial revolution.

Previous research has emphasised the importance of comprehending parameter interdependence to achieve optimised results [6]. However, there is a lack of established approaches that investigate how interdependencies in deformable materials affect EM faults. This research aims to bridge this gap by introducing a framework that enhances the EM manufacturing processes. It considers the influence of deformable materials, such as copper wire, on the creation of faults and optimises the overall production process.

The main focus of this PhD research was to detect and tackle the interconnections between components that involve deformable materials during the manufacturing of EM. Unlike existing literature, this research by providing a new perspective to defect analysis in the manufacturing of EM. Instead of focusing on individual components this research took a more comprehensive approach. It carefully examined how electrical components made with flexible materials such as copper wire interacted throughout the entire manufacturing process. This unique holistic approach provided insights and understanding on the influence that interdependencies have on the creation and severity of faults. Traditionally, defects in EM were often addressed later in the production or during EoL testing (winding resistance test), increasing costs [11]. In contrast, this research placed emphasis on early fault detection by understanding how various input parameters (i.e., winding speed and tension) influenced the final production quality of a stator.

By embracing this viewpoint, defects (electrical and geometrical) were detected earlier in the production process (winding process), but their underlying causes were also identified. This proactive approach allowed for solutions to be developed to minimise defects and optimise the manufacturing process. To accomplish this, four main objectives were defined: identifying characteristics of the process, creating a model-based framework that explains how various variables contribute to defects, integrating this framework with a machine learning algorithm for quality control purposes and, finally, establishing a model-based approach for parameter optimisation.

Advanced techniques such, as precedence graphs and graph networks were initially incorporated to detect and examine these interdependencies comprehensively. While precedence graphs and graph networks are useful, for modelling and analysing connections there might be some limitations that it should be consider:

- These techniques rely on data, which could overlook any dynamic variations and necessitate the use of high-quality data to achieve accuracy.
- To gain a comprehension of manufacturing processes it may be beneficial to adopt a multifaceted strategy that integrates both modelling and empirical data along with real time monitoring.

To overcome these limitations, it could be advantageous to complement these techniques with methods or techniques such as digital twins that are capable of anticipating and addressing defects by analysing real time data utilising machine learning algorithms or incorporating simulations, thereby making important contributions to the field of manufacturing science and engineering practices. Through the use of digital twins, this framework has the potential to analyse real time data and offer insights, into possible problems.

This research contributed with three innovative frameworks:

The first framework allowed the thorough investigation into how the interaction of input parameters directly affects the occurrence of flaws during the linear winding process. By focusing on this aspect, the research deepens our comprehension of how defects are formed, which opens up opportunities for better strategies in preventing defects and improving overall quality in manufacturing industries. Therefore, a framework was developed by implementing a DES method to examine the interactions between processes involving deformable materials with a specific focus, on noncircular orthocyclic coils. This DES model is capable of detecting faults and areas of increased resistance, which are commonly referred to as "hotspots".

In addition, with the DES model it is now possible to thoroughly analyse manufacturing processes that involve materials that can change shape and accurately evaluate how interconnected factors contribute to the occurrence of faults. This framework provided the creation of a dataset that enables the examination of how different input parameters interact and lead to defects giving insights, into the manufacturing process. These insights helped identify the process step and approach to implement corrective measures ultimately minimising and eliminating faults to improve the overall quality of products.

The second framework combined the previously developed DES model with an SML algorithm via KD. This combination has led to the development of a framework that predicts component states while taking into account complex process interdependencies [152]. This approach tackles the challenges that the DES model has, by conducting architecture searches and employing data augmentation to enhance the student model's ability to generalise. By utilising a DES model to generate training data it enhances the detection of faults in machine manufacturing which could result in a shorter manufacturing time, better stator quality, increased reliability, and greater safety.

The third framework improved the area of parameter optimisation by using an evolutionary algorithm, which has a proven track record in solving problems, with multiple objectives independently [108]. It introduced the NSGA-II algorithm, showing innovation by applying a multi-objective approach to linear winding processes. This approach focuses on identifying connections and interdependencies between input parameters and system faults, which can lead to management optimisation, decreased costs and effective fault handling.

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