Volume 4 Issue 1 · March 2025
ISSN 2972-3329

RESEARCH ON INTELLIGENT MANUFACTURING AND ASSEMBLY

Syncsci Publishing Pte Ltd
www.syncsci.com

Editor-in-Chief
Matthew Chin Heng Chua
National University of Singapore

Volume 3 Issue 1 · December 2024 · ISSN: 2972-3329

Research on Intelligent Manufacturing and Assembly

Res Intell Manuf Assem, 2025, 4(1): 138-143
DOI: 10.25082/RIMA.2025.01.001

RESEARCH ARTICLE

A Fuzzification Measure of Robust Design in Condition of "Desired Target Being Best" in Design

Maosheng Zheng[1*] **Jie Yu**[2]

[1] School of Chemical Engineering, Northwest University, Xi'an 710069, Shaanxi Province, China
[2] School of Life Science, Northwest University, Xi'an 710069, Shaanxi Province, China

Correspondence to: Maosheng Zheng, School of Chemical Engineering, Northwest University, No. 229, Northern Taibai Road, Xi'an 710069, Shaanxi Province, China; Email: mszhengok@aliyun.com

Received: January 2, 2025;
Accepted: February 25, 2025;
Published: February 28, 2025.

Citation: Zheng M, Yu J. A Fuzzification Measure of Robust Design in Condition of "Desired Target Being Best" in Design. *Res Intell Manuf Assem*, 2025, **4**(1): 138-143. https://doi.org/10.25082/RIMA.2025.01.001

Abstract: In the present article, a fuzzification measure of robust design in condition of "desired target being best" is regulated, which consists of the "complement" of the membership value of objective response and PMOO. The mean value of "complement" of the membership value of a set of test data of objective response belonging to its desired target value in fuzzification is taken as an indicator to join the assessment of the 1st part of partial preferable probability of the objective; the dispersion of a set of test data in term of membership with regard to the desired target value is taken as the other indicator to participate the assessment of the 2nd part of partial preferable probability of the objective. Moreover, the fuzzification measure of robust design is regulated in term of PMOO. As utilizations, two instances are presented to illuminate the regulation in design.

Keywords: fuzzification, membership value, robust design, target being best

1 Introduction

As to multi-objective optimization (MOO), an inexact or linguistic description for responses appears in some cases, which leads to the assessments with characteristic of "fuzzy" in some sense [1–5], such problem has been primarily solved in recent research with the fuzzed PMOO (probabilistic multi - objective optimization approach) [6–8].

Subsequently, a fuzzification measurement is put forward to deal with the MOO problem for the problem of "desired target being best" flexibly [8]. The closeness degree of the experimental data to its desired target value of an attribute is characterized by the "membership of the data belonging to the desired target value", and the membership value is directly used as the utility of the objective to join the assessment of PMOO. Furthermore, the membership u was used as the beneficial indicator, *i.e.*, "the larger the better" type, to conduct the PMOO evaluation [8].

However, since the maximum value of membership u is 1 exclusively, which is a finite value, instead of infinite; so an appropriate manner to deal with this problem is needed. Additionally, in condition of robust assessment, the spreading of experimental data must be taken into account in proper manner as well.

In this article, an alternative regulation is put forward by introducing the "complement" of the membership value, *i.e.*, $\eta = 1 - u$ as an indicator logically to deal with the matter [3], which forms a rational fuzzification regulation of robust design in term of PMOO in condition of "desired target being best"; moreover, two instances are represented to illuminate the regulation.

2 Rational Fuzzification Regulation of Robust Design in Condition of "Desired Target Being Best" in Term of PMOO

2.1 Membership Value and Its Complement of an Objective in Condition of "Desired Target Being Best"

Above discussion indicates that the membership value and its complement of an attribute in condition of "desired target being best" can be introduced to characterize the closeness degree

Res Intell Manuf Assem, 2025, 4(1): 144-167
DOI: 10.25082/RIMA.2025.01.002

RESEARCH ARTICLE

Pacemaker Interrogation Reports: Comparing Diagnostics, Lead Impedance, Pacing Thresholds and Battery Performance

Samikshya Neupane[1] **Tarun Goswami**[1*]

[1] Department of Biomedical, Industrial and Human Factors Engineering, Wright State University, Dayton, OH 45435, USA

Correspondence to: Tarun Goswami, Department of Biomedical, Industrial and Human Factors Engineering, Wright State University, Dayton, OH 45435, USA; Email: tarun.goswami@wright.edu

Received: January 6, 2025;
Accepted: March 23, 2025;
Published: March 27, 2025.

Citation: Neupane S, Goswami T. Pacemaker Interrogation Reports: Comparing Diagnostics, Lead Impedance, Pacing Thresholds and Battery Performance. *Res Intell Manuf Assem*, 2025, **4**(1): 144-167. https://doi.org/10.25082/RIMA.2025.01.002

Abstract: Pacemakers are critical in managing cardiovascular arrhythmias, yet device malfunctions remain a significant clinical challenge, impacting patient safety and outcomes. This study presents a structured comparison of pacemaker interrogation reports from three leading manufacturers: Abbott referred to as Manufacturer A/A Devices, Boston Scientific as Manufacturer B/B Devices and Medtronic as Manufacturer C/C Devices focusing on battery performance, lead functionality, pacing modes, and arrhythmia management. By analyzing the interrogated data, device reliability, longevity, and diagnostic capabilities of the devices are understood. Data were categorized and compared with each other to assess performance trends and clinical usability. Results revealed significant variations in battery longevity, lead performance monitoring, and arrhythmia detection capabilities among the devices. Manufacturer C interrogation reports provide trend analysis and battery life management whereas Manufacturer A provide real-time diagnostics and alerts, and Manufacturer B reports demonstrated long-term stability and efficiency. The findings highlight the need for standardized reporting practices across manufacturers to enhance data consistency, comparability, and clinical utility. Such standardization would streamline clinician workflows, improve decision-making, and ultimately higher patient outcomes. This study underscores the importance of real-world data to optimize pacemaker management and calls for collaborative efforts among manufacturers, clinicians, and regulators to develop unified reporting frameworks. By integrating predictive analytics and remote monitoring capabilities, future advancements in pacemaker achieve higher patient care and device performance.

Keywords: pacemakers, cardiovascular arrhythmias, interrogation reports, medtronic, Abbott, Boston Scientific

1 Introduction

Cardiovascular arrhythmias, characterized by irregular heartbeats, are a significant global health concern, affecting millions of individuals and leading to severe complications such as stroke, heart failure, and sudden cardiac death [1]. Pacemakers, which deliver electrical stimulation to regulate heart rhythms and restore normal cardiac function, have become indispensable in managing these conditions. Since their inception as external devices in the late 1950s, pacemakers have evolved into sophisticated implantable systems capable of adaptive pacing and real-time monitoring [2]. Despite these advancements, device malfunctions ranging from minor operational irregularities to critical failures remain a persistent clinical challenge, posing serious risks to patient safety and outcomes [3].

Modern pacemakers consist of several critical components, including the pulse generator, leads, electrodes, and sensors, all of which work in concert to ensure effective cardiac stimulation. The pulse generator, housing the battery and electronic circuitry, serves as the control unit, while the leads and electrodes transmit electrical impulses to the heart [4]. Advanced pacemakers also incorporate sensors that enable adaptive pacing based on the patient's physiological needs, offering personalized therapy. However, these devices are not immune to failure. Hardware malfunctions, software anomalies, lead defects, and battery depletion are among the common issues that can compromise pacemaker performance, underscoring the need for a deeper understanding of failure mechanisms and the implementation of preventive measures [5–7].

Res Intell Manuf Assem, 2025, 4(1): 168-179
DOI: 10.25082/RIMA.2025.01.003

RESEARCH ARTICLE

Chaos Control in Recurrent Neural Networks Using a Sinusoidal Activation Function via the Periodic Pulse Method

Franci Zara Manantsoa[1] **Hery Zo Randrianandraina**[1] **Minoson Sendrahasina Rakotomalala**[1] **Modeste Kameni Nematchoua**[1*]

[1] Institut pour la Maîtrise de l'Energie (IME), University of Antananarivo, Antananarivo, Madagascar

Correspondence to: Modeste Kameni Nematchoua, Institut pour la Maîtrise de l'Energie (IME), University of Antananarivo, Antananarivo, Madagascar;
Email: kameni.modeste@yahoo.fr

Check for updates

Received: January 18, 2025;
Accepted: April 13, 2025;
Published: April 18, 2025.

Citation: Manantsoa FZ, Randrianandraina HZ, Rakotomalala MS, et al. Chaos Control in Recurrent Neural Networks Using a Sinusoidal Activation Function via the Periodic Pulse Method. *Res Intell Manuf Assem*, 2025, **4**(1): 168-179.
https://doi.org/10.25082/RIMA.2025.01.003

Abstract: Controlling chaos in recurrent neural networks (RNNs) is a crucial challenge in both computational neuroscience and artificial intelligence. Chaotic behavior in these networks can hinder stability and predictability, particularly in systems requiring structured memory and temporal processing. In this study, we apply the periodic pulse method to stabilize the dynamics of chaotic RNNs using a sinusoidal activation function. Two network configurations (2 and 3 neurons) were analyzed using numerical simulations in MATLAB. Our results show that the periodic pulse method effectively suppresses chaotic behavior, as evidenced by a reduction of the largest Lyapunov exponent from 0.317 to -0.042. The system transitions from an unpredictable regime to a stabilized fixed point. This confirms the method's potential to regulate nonlinear neural dynamics with minimal external perturbations. Future work will focus on extending this approach to larger recurrent networks (LSTMs, reservoir computing models) and comparing its performance with other chaos control strategies such as delayed feedback and chaotic synchronization. This study contributes to the understanding of chaos in neural networks and its potential applications in neuroscience and AI.

Keywords: recurrent neural networks, chaos control, periodic pulses, Lyapunov exponent, nonlinear dynamics

1 Introduction

Complex systems refer to assemblies of interacting elements whose emergent behaviors are often difficult to predict or model. When these interactions are governed by nonlinear functions, such systems can exhibit chaotic dynamics, characterized by extreme sensitivity to initial conditions [1, 2]. Among complex systems, recurrent neural networks (RNNs) hold a central position. These networks, equipped with feedback loops, are widely studied in the field of neurodynamics, a discipline that analyzes neural network dynamics. The significance of RNNs lies in their ability to model complex cognitive processes such as learning, memory, and temporal information processing [3, 4].

The application of chaos theory to neurodynamics has revealed a fascinating characteristic: the normal functioning of the brain appears to be associated with controlled chaotic states. A system's dynamics are considered chaotic if, in the long term, the system is deterministic, aperiodic, bounded, and highly sensitive to initial conditions. This chaotic behavior is crucial for explaining flexibility, adaptability, and the ability to solve complex cognitive problems [5, 6]. However, transitions to more ordered states can be linked to neurological disorders, such as epilepsy or Alzheimer's disease [7, 8]. Therefore, understanding and controlling chaos in neural networks is a fundamental challenge in neurodynamics, with direct implications for computational and clinical neuroscience.

In the literature, numerous studies have focused on analyzing and controlling chaos in RNNs. Pioneering research has examined the impact of transfer functions, such as exponential and sigmoid functions, on the dynamics of neuromodules [9, 10]. Various methods, including chaotic synchronization [11] and periodic pulse stimulation , have been developed to suppress or regulate chaotic behaviors in these systems. However, these studies remain limited to specific activation functions and simplified neural configurations.

These two control methods have been underexplored in the configuration we propose. Therefore, we arbitrarily begin with periodic pulse stimulation, leaving synchronization for future

Res Intell Manuf Assem, 2025, 4(1): 180-184
DOI: 10.25082/RIMA.2025.01.004

RESEARCH ARTICLE

Material Selection for Gear Manufacture in Terms of the Probabilistic Multi-objective Optimization

Maosheng Zheng[1*] **Jie Yu**[2]

[1] School of Chemical Engineering, Northwest University, Xi'an 710069, Shaanxi Province, China
[2] School of Life Science, Northwest University, Xi'an 710069, Shaanxi Province, China

Check for updates

Correspondence to: Maosheng Zheng, School of-Chemical Engineering, Northwest University, No.229, Northern Taibai Road, Xi'an 710069, ShaanxiProvince, China; Email: 1914994032@qq.com

Received: January 21, 2025;
Accepted: April 30, 2025;
Published: May 5, 2025.

Citation: Zheng M, Yu J. Material Selection for Gear Manufacture in Terms of the Probabilistic Multi-objective Optimization. *Res Intell Manuf Assem*, 2025, **4**(1): 180-184.
https://doi.org/10.25082/RIMA.2025.01.004

Abstract: Probabilistic multi-objective optimization based material selection is conducted for gear manufacturing. This method incorporates the new concepts of preferable probability and total preferable probability of an alternative, which are determined by comprehensively considering all possible property responses of the alternative. Each property response of a material contributes a partial preferable probability to the alternative in a linearly correlative manner, either positively or negatively, depending on whether it is a beneficial or unbeneficial type in the evaluation. The total preferable probability of an alternative is obtained by multiplying all partial preferable probabilities. The optimal choice is the alternative with the maximum total preferable probability. In gear manufacturing material selection, five criteria are considered: core hardness, surface hardness, surface fatigue limit, bending fatigue limit, and ultimate tensile strength. Core hardness is regarded as an unbeneficial response, while the other four are beneficial. Through quantitative assessment, carburized steel is ultimately chosen as the optimal material.

Keywords: gear manufacture, material selection, quantitative assessment, preferable probability, multi-object optimization

1 Introduction

A systematic and quantitative method for material selection is crucial for effective material design and application in practical engineering, especially when dealing with a material database containing a vast amount of data [1].

Since the pioneering work of Ashby [2, 3], numerous methods have been developed to analyze material property data to achieve rational and systematic results [1–5]. However, material selection is inherently challenging [1–3], as it involves multiple material properties such as strength, ductility, fatigue resistance, and corrosion resistance, some of which may even conflict with each other. Therefore, decisions on material selection and substitution require a comprehensive consideration of all relevant material properties to achieve a balanced "trade-off" solution. This indicates that material selection is essentially a multi - objective optimization problem.

Recently, probabilistic multi – objective optimization (PMOO), developed from a systems theory perspective [6], has introduced new concepts of preferable probability and total preferable probability. Each material property contributes a partial preferable probability to the alternative in a linearly correlative manner, either positively or negatively, depending on whether it is a beneficial or unbeneficial type in the evaluation. The partial preferable probability of each property with the same physical meaning is normalized within the alternative material group. To fully consider the simultaneity of all property responses in the evaluation, the multiplication of all partial preferable probabilities produces the total preferable probability of an alternative material. This total preferable probability serves as the sole indicator reflecting the material's overall property response. Consequently, the alternative material with the highest total preferable probability is the optimal choice.

PMOO offers several advantages. It avoids the confusing problems found in other approaches [6, 7], such as the unreasonable "additive operation" of different property responses and the subjective choice of normalization factors for each property response in other multi - objective optimizations (MOO), as well as the irrational or non - quantitative statements in empirical approaches [6, 7]. In this paper, PMOO is applied to material selection for gear manufacturing.

Res Intell Manuf Assem, 2025, 4(1): 185-191
DOI: 10.25082/RIMA.2025.01.005

COMMENTARY

International Standardization Safe to Use of Artificial Intelligence

Evgeniy Bryndin

Research Centre "Natural Informatic", National Supercomputer Technological Platform, Novosibirsk, Russia

Correspondence to: Evgeniy Bryndin, Research Centre "Natural Informatic", National Supercomputer Technological Platform, Novosibirsk, Russia;
Email: bryndin15@yandex.ru

Received: March 6, 2025;
Accepted: May 4, 2025;
Published: May 9, 2025.

Citation: Bryndin E. International Standardization Safe to Use of Artificial Intelligence. *Res Intell Manuf Assem*, 2025, **4**(1): 185-191.
https://doi.org/10.25082/RIMA.2025.01.005

Abstract: Nowadays, the symbiosis of human abilities and the mastery of artificial intelligence will contribute to increased productivity and excellence in industry and social services. The use of artificial intelligence in various fields requires standardization of the safety of its knowledge and skills. International collaboration on artificial intelligence safety standardization is expanding. The UN has created a Global Advisory Body on Artificial Intelligence to support the efforts of the international community of specialists in managing intelligent systems related to the risks and safety of their use. The author proposes international standard of safe application of ensemble intelligent interoperable agents. Ensembles of agents with artificial intelligence are multi-agent synergistic self-organizing systems that function according to the laws of development, synergy and self-organization. Ensembles of intellectual agents solve the problem in the course of self-organization and cooperation according to the criteria of preference and restriction. The solution is considered found when, in the course of their nondeterministic interactions, agents reach the best consensus (temporary equilibrium or balance of interests), which is taken as a solution to the problem. The advantages of intelligent agents that allow you to build self-organizing ensembles are especially manifested in conditions of a priori uncertainty and high dynamics of the world around you, allowing you to build adaptive ensembles with communicative abilities, rebuilding your plans for events in real time. The higher the intelligence of each agent and the richer the opportunities for communication between agents, the more complex and creative behavior the ensemble can demonstrate. The intellect of the ensemble arises and manifests itself in the process of self-organization of intellectual agents. Intelligent agents use a physical, informal and logical model of the environment. That is, they use both attributes and sets of entities, processes, relationships, etc. Modern technologies allow you to create ensembles of intelligent agents with communication abilities, characterized by high openness, flexibility and efficiency, performance, scalability, reliability and survivability, approaching the intellectual abilities of a person and professional teams in their cognitive and functional capabilities and even sometimes surpassing them.

Keywords: artificial intelligence, security of intelligent systems, international cooperation

1 Introduction

The slightest errors in the design of intelligent systems can lead to catastrophic consequences. In Arizona, an unmanned car from Uber hit a woman crossing the street in the wrong place. In the driver's chair was a pilot, but he did not have time to stop the car. This accident was the first fatal accident involving a car with a third level of autonomy. It turned out that the laser radars of the car recognized the pedestrian as much as 5.6 seconds before the accident. But the algorithm decided not to reduce speed and began emergency braking only 0.2 seconds before the collision. All such facts in order for humanity, as far as possible, to act ahead of schedule, predict the possible dangers that may arise when introducing technologies using artificial intelligence. Experts say this today. Hazards are technological, legal, legal and ethical. New technologies pose both technical and ethical challenges. experts express various approaches to the principles of establishing responsibility for the actions of artificial intelligence: the responsibility of a particular subject - a manufacturer, developer, owner, user, expert or programmer. Human ingenuity and the desire for perfection, combined with the capabilities of new technologies, can solve the problems of mankind. Security solutions can ensure standardization of artificial intelligence. ISO focuses on standards relevant to the information and communication technology (ICT) industry. International Standards Association is focused on reaching out to government and industry in all of the locations around the world

Res Intell Manuf Assem, 2025, 4(1): 200-218
DOI: 10.25082/RIMA.2025.01.007

RESEARCH ARTICLE

Integrating Manufacturing Intelligence, Computer Vision, and Process Observation for Yield Improvement and Failure Prediction in Electronics Manufacturing

Vinit Vithalrai Shenvi[1] **Ashutosh Sharma**[1*]

[1] Department of Mechanical Engineering, M S Ramaiah Institute of Technology, Bengaluru, India

Correspondence to: Ashutosh Sharma, Department of Mechanical Engineering, M S Ramaiah Institute of Technology, Bengaluru, India;
Email: ashutosh.sharma0843@gmail.com

Received: March 30, 2025;
Accepted: June 13, 2025;
Published: June 19, 2025.

Citation: Shenvi VV, Sharma A. Integrating Manufacturing Intelligence, Computer Vision, and Process Observation for Yield Improvement and Failure Prediction in Electronics Manufacturing. *Res Intell Manuf Assem*, 2025, **4**(1): 200-218.
https://doi.org/10.25082/RIMA.2025.01.007

Abstract: Electronics manufacturing processes are complex and prone to yield loss and latent failures due to subtle process deviations and quality escapes. This paper presents a holistic approach to improving first-pass yield and predicting failures by integrating a Manufacturing Intelligence for Reliability and Automated Insights (MIRAI) data platform with computer vision-based monitoring of Standard Operating Procedure (SOP) adherence. The proposed system combines self-serve data analytics workflows for yield and field failure analysis with real-time process observation using deep learning vision models. Manufacturing data from production tests, reliability screenings, and field returns are aggregated and analyzed to identify key signals correlating with yield drops and field fallouts. Simultaneously, a PROSPECT tool employs AI cameras at assembly stations to record operator actions and detect deviations from standard procedures. A machine learning failure prediction model is then trained on the enriched dataset (including vision-detected deviations) to proactively flag high-risk units in real time.

Keywords: computer vision, process observation, failure prediction, manufacturing analytics, yield improvement

1 Introduction

Modern electronics manufacturing is characterized by intricate assembly and test processes with thousands of interdependent steps. First-pass yield (FPY) is the percentage of units passing all tests without rework. Maintaining a high FPY is critical for cost efficiency and product quality [1]. Even minor deviations in how a process is executed can introduce defects that either cause immediate test failures or latent field failures after the product is shipped. Traditional quality control and yield analysis techniques often rely on reactive measures like identifying defects or yield drops only after they have occurred [1]. In many factories, engineers manually investigate yield excursions or perform periodic audits of operator compliance to SOPs (the standard work instructions for each task). These manual approaches are time-consuming, inconsistent, and may miss subtle issues until significant scrap or customer returns occur [2]. There is a growing need for intelligent, automated systems that can monitor production in real time, ensure process consistency, and predict failures before they happen.

1.1 Holistic Manufacturing Intelligence and Yield Challenges

The concept of *Manufacturing Intelligence for Reliability and Automated Insights (MIRAI)* refers to an integrated data-driven approach that looks at the entire manufacturing process right from assembly stations on the factory floor to field performance in order to extract insights that improve yield. A holistic approach is necessary because yield loss can stem from many sources: machine settings, component variability, environmental factors, human errors in following SOPs, *etc*. [3] Conventional yield analysis in high-volume electronics production involves pouring over vast amounts of test data and process logs to find correlations with failures [4]. For example, if a particular assembly station shows a drop in yield (more units failing its test), engineers must determine if a systemic cause exists, such as a mis calibrated tool or a change in a component lot. Historically, such analysis has been reactive and limited by human bandwidth and experience [5]. Intel's manufacturing group reported that manual end-of-line yield analysis was too slow and could not examine every unit, prompting a shift to *proactive*, AI-driven yield analysis that examines 100% of data and flags issues for engineers [5]. Advanced analytics, including machine learning, enable detection of yield patterns and root causes more quickly than

Res Intell Manuf Assem, 2025, 4(1): 192-199
DOI: 10.25082/RIMA.2025.01.006

COMMENTARY

Formation of Motivated Adaptive Artificial Intelligence for Digital Generation of Information and Technological Actions

Evgeniy Bryndin

Research Centre "Natural Informatic", National Supercomputer Technological Platform, Novosibirsk, Russia

Correspondence to: Evgeniy Bryndin, Research Centre "Natural Informatic", National Supercomputer Technological Platform, Novosibirsk, Russia;
Email: bryndin15@yandex.ru

Received: February 8, 2025;
Accepted: June 1, 2025;
Published: June 9, 2025.

Citation: Bryndin E. IFormation of Motivated Adaptive Artificial Intelligence for Digital Generation of Information and Technological Actions. *Res Intell Manuf Assem*, 2025, **4**(1): 192-199.
https://doi.org/10.25082/RIMA.2025.01.006

Abstract: Motivated artificial intelligence plays a relevant role in digital generation of information. Motivated artificial intelligence activates the generation of meanings and technological action. Its motivational functionality and motivation goals are determined by developers and users of technologies, which in turn helps to form AI motivation in the context of digital transformation. Formation of artificial intelligence motivation in digital generation of information is complex and multifaceted task that includes both theoretical and practical aspects of AI motivation in technological thinking and actions. Artificial motivated intelligence must have clearly defined goals that it must achieve. The goal of motivation can be set in the form of functionality (ontology, erudition, reflection, usefulness, preference), which will guide the motivation of AI. The use of reinforcement learning methods will allow AI to independently find optimal strategies for achieving its goals. It receives positive or negative reinforcement depending on how successfully it performs information transformation tasks. To form motivation of AI, it is necessary to ensure its ability to adapt to changing conditions and tasks. This includes learning from new data, knowledge and experiences. In some cases, it is useful to implement elements of emotional intelligence so that AI can better understand and respond to human emotions and actions. This improves the digital generation of information. It is important to consider ethical aspects and security. It is necessary to ensure that the digital generation of information does not lead to undesirable consequences or harm. Artificial intelligence must be able to effectively interact with users and other systems to receive feedback and adjust its actions in accordance with changing conditions. Research and implementation of motivation models, such as the hierarchy of needs or self-determination, can be useful in international digital generation of information. Formation of AI motivation requires an interdisciplinary approach that includes psychology, computer science and ethics. Motivation of AI to advance scientific and technological achievements is relevant in digital generation of information in various fields of activity. The motivation of hybrid intelligent systems is realized on the basis of knowledge engineering through synergetic communication.

Keywords: artificial intelligence, human motivation, motivated AI, AI assistant

1 Introduction

The integration of knowledge engineering with machine learning offers a promising approach to the formation of motivated adaptive artificial intelligence. This integration combines the strengths of data-driven learning with formal, structured reasoning, allowing AI models to be both highly accurate and explainable. By leveraging structured knowledge, such as electronic health records in healthcare, scientific axioms, or legal guidelines, motivated AI systems gain the ability to perform common-sense reasoning, which increases their reliability and makes them more knowledge-aware. Their ability to provide verifiable, human-readable explanations makes them especially valuable in mission-critical domains. The focus is on developing hybrid human-motivated adaptive artificial intelligence systems with functionalities (ontology, erudition, reflexivity, utility, preference) that use multimodal approaches, incorporating various forms of data, including text, speech, images, and human-centric video.

Functionality (ontology, erudition, reflection, usefulness, preference) plays a unique role in the formation of motivated adaptive artificial intelligence and its relationship with other aspects of intellectual activity. Ontology is a structure representing knowledge in a certain area. It includes definitions of entities, their properties and relationships. Ontologies help to structure information. Creating a clear knowledge model allows artificial intelligence to better understand the context and relationships between different concepts. Ontologies improve semantic search and the quality of information retrieval, allowing the system to better understand user requests. Ontologies allow different systems to exchange and use knowledge, which is especially important in complex ecosystems. Erudition represents extensive knowledge in various fields. An AI with erudition can integrate knowledge from different fields and apply it in new contexts. An erudition-rich AI is able to provide more accurate and meaningful answers to complex questions. Erudition allows an AI to solve problems using a combination of knowledge from different fields, which facilitates innovation.

Reflection is the ability of an AI to analyze its own actions and results. An AI can evaluate its previous decisions and learn from mistakes to improve future results. Reflection helps an AI adapt its algorithms and approaches based on the experience gained. Reflection of an AI helps optimize its processes and increase efficiency. Utility is the ability of an intelligent system to benefit the user in solving specific problems, assessing desired results, optimizing solutions in terms of time and resource costs, and adapting to changing user needs and preferences. Preference is associated with choosing between different options or actions. Artificial intelligence tracks and analyzes user preferences to provide personalized recommendations. Artificial intelligence makes decisions based on utility assessments of different options. Preferences determine the formation of goals and action strategies in different situations.

The relationship between ontology, erudition, reflection, utility, and preference forms the basis for a motivated and adaptive intelligent system. Motivated adaptive artificial intelligence helps to effectively process information, learn from experience make informed decisions, which determines its compatibility in various areas of human activity.

2 Aspects of Human Motivation

Human motivation is a complex and multifaceted process that is determined by many factors. The main aspects of human motivation can be divided into several categories:

(1) Intrinsic motivation comes from within a person, based on personal interests.

(2) Physical condition significantly affects motivation.

(3) Personal values and beliefs of a person shape his motivation.

(4) Clearly defined and achievable goals increase the level of motivation.

(5) Confidence in one's own strengths and abilities to achieve goals plays an important role in motivation.

(6) Emotions play a key role in motivation. Positive emotions, such as joy or satisfaction, can increase motivation, while negative emotions, such as fear or stress, can decrease it.

(7) Extrinsic motivation is caused by external factors.

(8) Social support from family, friends, and colleagues significantly increases motivation.

(9) Comparing yourself to others can both increase and decrease motivation.

(10) Cultural norms and values influence what motivates people.

(11) Economic conditions influence motivation by limiting or expanding opportunities for self-development.

Understanding these aspects of motivation helps both in personal life and in managing people, as it allows you to identify and use factors that contribute to increasing motivation and achieving goals. Motivation occurs as a result of the interaction of various internal and external factors. Let's consider the elements and stages that contribute to the emergence of motivation. The elements of human motivation include key components: needs, goals, expectations, emotions, personal meaning, experience and learning. Each of these elements can interact with each other, creating a unique motivational system for each person.

Motivation often begins with the awareness of needs or desires. These can be basic physiological needs (food, safety) or more complex ones, such as the need for recognition, socialization or self-actualization. When a person is aware of their needs, they begin to formulate goals that can help them satisfy them. Clear and specific goals serve as a source of motivation, directing efforts to achieve the desired result. An individual evaluates his or her chances of success in achieving the set goals. If he or she believes that his or her efforts will lead to the desired result, this increases motivation. The belief that the goal is achievable is an important factor.

A person's emotional state also plays a significant role. Positive emotions such as joy and inspiration can help increase motivation, while negative emotions such as fear or doubt can decrease it. External stimuli such as rewards, incentives, support from others, and the social environment can significantly affect the level of motivation. For example, positive feedback or recognition of success can strengthen the desire to act. Motivation also arises from how important a task or goal is to a person. If a person believes that achieving a goal is important to his or her life or values, this increases his or her motivation.

Previous experience also influences motivation. Successful experiences can increase confidence and desire to continue striving for a goal, while failures can have a depressing effect. The process of human motivation is a complex and multifaceted mechanism that includes many factors that influence the behavior and actions of an individual. The motivation process is dynamic and can change depending on situations, personal circumstances, and changes in a person's life.

3 Human Motivation of Artificial Intelligence

Human motivation of artificial intelligence is the process by which humans define goals and objectives for intelligent systems and set the parameters within which these systems must operate.

Experts formulate specific goals and objectives that artificial intelligence must achieve [1]. This could be process automation, data analysis, decision-making assistance, and so on. Clearly defining goals allows artificial intelligence to perform its tasks more effectively. Experts set parameters that limit the actions of artificial intelligence in accordance with moral and social principles. This includes ensuring safety.

Developers provide feedback to artificial intelligence, allowing it to learn and adapt. This includes adjusting algorithms based on the results of the system's work and user feedback. Thus, artificial intelligence becomes more accurate and effective in achieving its goals. Motivating artificial intelligence also involves understanding the context in which it operates. Developers train and consider social, cultural, and economic factors to ensure that its actions are appropriate and relevant. Developers require that artificial intelligence be transparent in its actions. This includes explaining the decisions it makes so that users can understand the logic behind its actions. This is important for establishing trust in intelligent technologies.

Professionals provide control over intelligent systems by setting boundaries and limitations in their functioning. This is important to prevent possible negative consequences and ensure that intelligent technologies are useful to humans and society. Motivating artificial intelligence by humans is a complex process that requires active participation, responsibility, and understanding from developers and users of technologies.

4 Ontological, Erudite, Reflexive, Useful, Preferential and Meaningful Motivation of Artificial Intelligence

We will consider the motivation of artificial intelligence from various points of view, including ontological, erudite, reflexive, useful, preferential and meaningful. Ontological motivation is related to the essence and nature of artificial intelligence [2]. It includes an understanding of what artificial intelligence is, how it functions, and what its capabilities and limitations are. This understanding forms the basis for the development and application of artificial intelligence, as well as for forming expectations for its work. Ontological motivation addresses issues of identity, consciousness, and the ability of artificial intelligence to be self-aware.

Erudite motivation is based on the knowledge and information that artificial intelligence can use to perform its tasks [3]. This motivation implies that artificial intelligence must be able to process, analyze, and interpret data in order to make informed decisions. The more data and knowledge available to artificial intelligence, the more effectively it can act and adapt to different situations. Reflective motivation implies the ability of artificial intelligence to self-reflect and analyze its actions and decisions [4–6]. This includes evaluating its results and adjusting its behavior based on the experience gained. Reflexive motivation allows artificial intelligence to learn from its mistakes and improve its algorithms, which in turn increases its efficiency and reliability.

Utility motivation focuses on the practical application of AI to solve specific problems and improve people's lives. This may include automating processes, improving access to information, optimizing resources, and creating new opportunities. Utility motivation implies that AI should behave in a way that brings real benefits to users and society as a whole. Preference motivation concerns how AI can take into account the preferences and desires of users when making decisions. This includes customizing AI so that it can adapt its actions to individual needs and preferences of people. Preference motivation allows for more personalized and targeted solutions, which increases user satisfaction.

Meaningful motivation of AI includes understanding the context and values that should be taken into account in the decision-making process. Artificial intelligence should take into account the context in which it operates. This may include cultural, social, and economic factors that influence decision-making. The aspects of AI motivation discussed above highlight the relevance of an integrated approach to its development and application. Understanding these motivations can help developers and researchers create more efficient and ethical intelligent systems that benefit society and take into account the interests of users.

5 Artificial Intelligence Motivation Technologies

We will also consider artificial intelligence motivation technologies in the context of creating systems that can effectively achieve given goals and optimize their actions. The following key technologies and approaches are related to artificial intelligence motivation. In this approach, the agent learns to interact with the environment, receiving rewards or penalties for its actions. The goal of an intelligent assistant is motivation based on external rewards.

Goal programming of motivation to perform specific tasks or achieve specific goals. Developers set goals, and algorithms adapt to achieve them efficiently. Evolutionary algorithms are motivated by the principles of natural selection to optimize solutions. Populations of possible solutions are created, which are subject to mutation and selection, which allows finding optimal solutions to complex problems. Iterative learning methods motivate artificial intelligence to improve itself by analyzing its previous decisions and adjusting its actions based on the experience gained.

Generative models, such as GAN (Generative Adversarial Networks), are motivated to create new data or solutions, which can be seen as a form of motivation to generate better results. Adaptive systems are motivated to change their parameters depending on environmental conditions, which allows them to more effectively achieve goals in changing conditions. Multi-agent systems are motivated to coordinate and interact between agents to achieve common goals.

Deep learning neural networks are motivated to analyze large amounts of data and identify patterns, which helps artificial intelligence adapt and improve its actions. Creating motivated AI assistants with Cursor IT vibe coding based on GigaChat and Deep Research. A special AI vibe coding tool Cursor has appeared, which helps to program without writing manual code. The developer from OpenAI notes that Cursor suggests in advance what it wants to write. The Cursor AI assistant has greatly advanced the process of creating AI assistants using vibe coding in Cursor.

Based on GigaChat, using Cursor, you can assemble AI assistants for a digital clinic that answer questions and guide the client without manually writing code. In 2025, a standard will be introduced in Russia: *Artificial Intelligence Systems in Healthcare*. The standard allows intelligent systems to perform most healthcare competencies: management and marketing, regulatory decision-making, clinical recommendations, patient routing, medical knowledge engineering, accounting and finance, personnel, design and processing of diagnostic images of ultrasound - X-ray and others, organizing communications between doctors and with patients, and so on. The introduction of intelligent systems contributes to the development of the entire healthcare system, including clinical practice, management, morbidity monitoring, epidemiological surveillance, etc., thus affecting all participants in the healthcare system, including patients [7, 8]. Interdisciplinary competencies in managing the implementation of artificial intelligence systems in healthcare will contribute to the improvement of clinical medical treatment practice and the healthcare system as a whole.

Principal researcher Jakub Pahotsky of the OpenAI development department, the developer of Deep Research, taught the system to do, firstly, reviews of scientific literature on a given topic, secondly, write texts for research, thirdly, create program code, fourthly, analyze scientific materials and put forward hypotheses. He expands the functionality and motivates Deep Research with the help of the AI vibe coding tool Cursor, firstly, to write complex programs, secondly, to create hardware solutions, and thirdly, to conduct research in scientific fields using models for generating new knowledge. Minimizing the risks of autonomous intelligence requires a digital transformation of standardization. Motivated adaptable artificial intelligence in the international digital transformation of standardization will combine new advanced intelligent technologies in various areas of human activity [9].

6 AI Engineer Developer of Motivated AI

Swix highlights the special role of AI engineers as developers who create and adapt neural networks to create motivated AI assistants. This process with additional tools:

(1) LLM (Large Language Models): language models, such as GPT-4 chat, which allow the neural network to understand and generate text.

(2) Memory: the ability of AI to remember the context of a dialogue in order to use knowledge from past experience.

(3) Planning: the ability of a neural network for programming to break tasks into stages, as well as perform them sequentially.

(4) Tools: integration with browsers, code interpreters or other external services. These technologies allow AI assistants to answer questions and perform complex multi-stage tasks.

These technologies enable motivated AI assistants to answer questions and perform complex multi-step tasks. Swix identifies several important components for creating motivated AI assistants:

(1) Gateway solutions, RAG frameworks – systems for working with external knowledge bases.

(2) Vector DBs, graph knowledge bases – allow artificial intelligence to store information and also learn from past data.

(3) Code execution environments (sandbox) – for example, E2B, where AI can test its code.

(4) Browser control and internet search – for example, the ability to visit websites and analyze information.

(5) Self-checking cycles (Self-Ask, React) – AI learns to make decisions based on previous results.

These tools form the basis for creating advanced solutions. An AI engineer can start creating motivated AI assistants without being a PhD researcher. To do this, it is enough to understand the basic stack of technologies and learn how to combine them correctly. We are on the threshold of a new era when code can be written by voice, when motivated AI assistants can develop complex software and engineering without human participation.

6.1 Data Quality and Preparation

Data quality and preparation are key steps for successful problem solving with an AI assistant. Proper data preparation ensures high accuracy, reliability, and efficiency of the model. It is necessary to consider the main aspects related to data quality and preparation.

(1) Data quality assessment:
• Completeness: availability of all necessary data for training and testing.
• Accuracy: correctness and reliability of data.
• Consistency: absence of inconsistencies within the data.
• Relevance: timeliness and relevance of data.
• Absence of missing values and errors.

(2) Data collection:
• Use of reliable sources.
• Ensuring data diversity to model different scenarios.

(3) Data cleaning:
• Removal of duplicates.
• Handling of missing values (e.g. filling with mean, median, or deletion).
• Correction of input errors.
• Standardization of data formats.

(4) Data transformation:
• Scaling and normalization (e.g. Min-Max, Z-score).
• Encoding of categorical variables (e.g. one-hot encoding).
• Splitting data into training, testing, and validation sets.

(5) Data augmentation:
• Creating additional data to increase the volume and improve the robustness of the model (especially important in computer vision and natural language processing tasks).

(6) Data analysis:
• Visualization and detection of correlations.
• Detection of outliers and anomalies.

(7) Documentation and data management:
• Maintaining metadata.
• Ensuring reproducibility of experiments.

(8) Ensuring ethics and privacy:
• Anonymization of personal data.
• Compliance with regulatory requirements for data processing.

It is important to remember that the quality of the data directly affects the results of the AI assistant. The better the data is prepared and verified, the higher the likelihood of obtaining accurate and reliable decisions.

6.2 Designing Supercomputer with an AI Assistant

Designing supercomputer with an AI assistant involves using artificial intelligence to automate the development, optimization of architecture, software, and management of computing systems. Here are the main areas and approaches to implementation.

(1) General concept:

• Design automation: the AI assistant analyzes requirements, explores existing architectures, and suggests optimal solutions.

• Self-learning and adaptation: the system learns from performance, energy consumption, and other metrics to improve its architecture and algorithms.

• Code generation: the AI assistant writes or improves the code of interpreters, operating systems, drivers, and software components.

(2) Implementation stages:

a) Analysis of requirements and goals:
• Definition of the tasks that the supercomputer should solve
• Setting performance criteria: speed, scalability, energy efficiency.

b) Architecture design:
• Using machine learning to find optimal configurations of processors, memory, network.
• Generating architectural diagrams taking into account parallelism, distributed computing, and resilience.

c) Training and optimization:
• Using reinforcement learning to tune system parameters.
• Simulations and modeling to evaluate performance and choose the best solutions.

d) Software generation:
• Creating interpreters, compilers, and operating systems using AI.
• Self-improving components that adapt to load and requirements.

e) Automation of testing and deployment:
• AI assistant automatically identifies bottlenecks and suggests fixes.
• Continuously training the system on new data.

(3) Technologies and tools:
• Machine learning and deep learning.
• Generative models (GPT, GANs, etc.) for generating code and architectural diagrams.
• Simulation platforms for testing proposed solutions.
• Cloud platforms and distributed systems for scaling.

(4) Example of a use case:
• An AI assistant is tasked with building a high-performance supercomputer for simulating physical processes.
• Analyzes existing architectures, collects metrics.
• Generates several architecture options, training them with simulations.
• Selects the most efficient option, writes the code for interpreters and drivers.
• The system continues to learn and optimize during operation.

(5) Important aspects:
• Security and control: it is necessary to monitor that the AI agent does not go beyond the limits of acceptable solutions.
• Ensuring transparency: it is important that AI decisions are explainable.
• Ethical and legal issues: the use of AI to design powerful systems must be accompanied by ethical standards.

7 Conclusion

Building motivated AI assistants using technologies like Cursor's Vibe Coding is essential to building modern, motivated intelligent systems. Motivated AI assistants can adapt to the needs and preferences of users, making interactions more natural and effective. Using Vibe Coding, you can create interfaces that take into account the emotional reactions of users, improving the overall user experience.

Motivated AI assistants can provide personalized recommendations and solutions. This is especially important in areas like e-commerce, where users expect systems to offer products and services that match their interests and needs. AI assistants built with Vibe Coding principles can learn from interactions with users, allowing them to develop and improve their skills. This creates a more dynamic and responsive environment where assistants can better understand the context and intent of users.

Motivated AI assistants can be developed with emotional intelligence, allowing them to recognize and respond to user emotions. This can increase user trust and satisfaction, especially in services that require a high degree of emotional interaction. AI assistants that understand user motivations and goals can more effectively help solve problems. This can be useful in business, education, and other areas where it is important to quickly find solutions and optimize processes.

The creation of motivated AI assistants also raises questions of ethics and responsibility for developers. It is important to consider how such systems can affect users and society as a whole, and to develop them with ethical norms and standards in mind. The creation of motivated AI assistants using Cursor's Vibe Coding opens up new horizons in the field of human-machine interaction. These technologies can significantly improve user experience, increase the efficiency and adaptability of systems, and contribute to a deeper understanding of user needs [10–12]. It is important to continue to explore these aspects in order to create research, safe and ethical AI solutions that will benefit humans and society.

The motivation of artificial intelligence for scientific research is based on its program goals, functionalities and learning systems. AI learns from large volumes of data, which motivates it to find new patterns and improve its models [11, 12]. Continuous self-learning and improvement of results serve as an internal motivating force for AI. AI reinforcement systems stimulate it to perform verified research actions, search for and develop new solutions. AI serves as a tool for accelerating scientific discoveries, analyzing complex data and modeling processes, which contributes to its motivation to develop knowledge and technology together with experts.

Conflicts of interest

The author declares no conflict of interest.

References

[1] Bryndin E. Creation of Multi-purpose Intelligent Multimodal Self-Organizing Safe Robotic Ensembles Agents with AGI and Cognitive Control. COJ Robotics & Artificial Intelligence. 2024, 3(5). https://doi.org/10.31031/cojra.2024.03.000573

[2] Bryndin E. Network Training by Generative AI Assistant of Personal Adaptive Ethical Semantic and Active Ontology. International Journal of Intelligent Information Systems. 2025, 14(2): 20-25. https://doi.org/10.11648/j.ijiis.20251402.11

[3] Bryndin E. From Creating Virtual Cells with AI and Spatial AI to Smart Information Multi-Level Model of the Universe. Journal of Progress in Engineering and Physical Science. 2025, 4(1): 1-7. https://doi.org/10.56397/jpeps.2025.02.01

[4] Bryndin E. Creation of multimodal digital twins with reflexive AGI multilogic and multisensory. Research on Intelligent Manufacturing and Assembly. 2024, 2(1): 85-93. https://doi.org/10.25082/rima.2023.01.005

[5] Bryndin E. Formation of reflexive generative A.I. with ethical measures of use. Research on Intelligent Manufacturing and Assembly. 2024, 3(1): 109-117. https://doi.org/10.25082/rima.2024.01.003

[6] Bryndin EG. Digital Doubles with Reflexive Consciousness in Reality and Virtual Environment. Materials of the VII international scientific and practical conference - Greater Eurasia, Part 2. Moscow: Publishing house UMC. 2025, 380-384.

[7] Bekbolatova M, Mayer J, Ong CW, et al. Transformative Potential of AI in Healthcare: Definitions, Applications, and Navigating the Ethical Landscape and Public Perspectives. Healthcare. 2024, 12(2): 125. https://doi.org/10.3390/healthcare12020125

[8] Bryndin E. Intelligent Digital Clinic of Interacting Multimodal AI Assistants. Research in Medical & Engineering Sciences. 2025, 11(4): 1237-1241.

[9] Hallensleben S. Generative AI and international standardization. Cambridge Forum on AI: Law and Governance. 2025, 1. https://doi.org/10.1017/cfl.2025.1

[10] Passmore MD. Coding with Artificial Intelligence. Independently published. 2024.

[11] Bryndin E. Formation Smart Data Science for Automated Analytics of Modeling of Scientific Experiments. American Journal of Software Engineering and Applications. 2019, 8(2): 36. https://doi.org/10.11648/j.ajsea.20190802.11

[12] Bryndin E. Self-learning AI in Educational Research and Other Fields. Research on Intelligent Manufacturing and Assembly. 2025, 3(1): 129-137. https://doi.org/10.25082/rima.2024.01.005

traditional methods, allowing engineers to address problems sooner and thus prevent further yield loss [5]. This aligns with the broader Industry 4.0 trend of employing big data and AI to achieve adaptive, automated process control for better quality [6].

1.2 Standard Operating Procedures and Human Factors

At the same time, a significant portion of quality issues in assembly processes can arise from human operators not perfectly following the SOPs. SOPs are detailed instructions that standardize how each manufacturing step should be performed to ensure consistency, safety, and quality [7]. Despite training, operators may inadvertently skip steps, use incorrect techniques, or deviate due to fatigue or time pressure [8]. Historically, ensuring Process observation has been done via periodic manual observation by line supervisors or quality engineers. However, manual monitoring is inherently limited, since a supervisor might spot-check an operator for a few minutes, providing only a snapshot of compliance. It's been observed that such manual audits are inconsistent and infrequent, varying by who does the checking and often failing to catch issues that occur between audits [2]. Moreover, compiling and analyzing handwritten compliance notes from different shifts or lines can take days, delaying any corrective actions [2]. Human monitoring of SOP compliance does not scale well to a large production floor and may miss trends that impact yield.

Recent advances in computer vision (CV) and AI offer a promising solution: automated, continuous monitoring of Process observation using cameras and machine learning. By training vision models to recognize the required actions or steps in a process, manufacturers can get an objective, 24/7 "eye" on every station [2]. Unlike a human who can only watch one station periodically, an AI-driven vision system can concurrently monitor all stations and detect any deviation in real time [2]. For instance, a deep learning model can be trained to detect whether an operator picks up the correct component, uses the proper tool, and performs assembly steps in the correct sequence [7].If a step is skipped or done out of order, the system can instantly flag it [7]. This level of constant vigilance ensures that mistakes are caught immediately, allowing for quick correction before a faulty unit moves further down the line [2]. A case study at a display assembly line noted that deploying AI smart cameras for SOP monitoring allowed them to "keep an eye on every movement on the assembly line all the time," something previously impossible with manual checks [2].The result was more consistent adherence to process and the ability to identify operators or steps that needed improvement in real time. Indeed, computer vision-based SOP compliance systems eliminate human bias and fatigue from the equation, providing consistent and objective monitoring around the clock [8]. This not only prevents defects due to process deviation but also creates a rich data source on how the process is actually being executed.

1.3 Data-Driven Failure Prediction

Beyond immediate yield improvement, there is a strategic opportunity in correlating process data (including SOP deviations) with downstream failures to predict and prevent those failures. In electronics manufacturing, some defects are not detected until later stages of production or even until products are in the field (customer usage) [9]. By then, the cost of the failure is much higher which may require scrapping an assembled unit, performing costly rework, or handling warranty returns. If we can predict which units are likely to fail final tests or in the field based on early indicators, we can intervene proactively. Prior research and industry practices have shown the value of linking manufacturing process data to failure outcomes: for example, IntraStage (a manufacturing analytics provider) demonstrated that by correlating detailed test data from production with the results of failure analysis on returned units, manufacturers could identify patterns (signatures) that reliably indicate a unit with a latent problem [10]. Once those "attributes of failure" are known, a predictive engine can scan all in-process and shipped units to find others with the same risk factors and thus target them for preventive action [10]. In essence, if certain process deviations or test parameter anomalies are found to strongly correlate with later failures, they become features in a failure prediction model.

With sufficient historical data, a machine learning model can be trained to recognize the combination of signals that foretell a likely failure (either at end-of-line testing or in field use) [1]. Such a model can then run in real time during manufacturing, alerting operators or stopping a line when a high-risk unit is identified, so that the unit can be inspected or fixed immediately. This approach moves quality control from detection to prediction, saving time and cost by addressing issues before they fully manifest [11]. It also reduces work-in-progress (WIP) waste – rather than adding value to a unit that will eventually be scrapped, the process can be halted or corrected early on.

1.4 Research Objective

In this paper, we propose an integrated system that combines MIRAI workflows for data-driven analysis with computer vision-based SOP adherence monitoring through *Process Observation and Statistical Prediction for Enhanced Compliance and Throughput (PROSPECT)* to improve yield and enable failure prediction in electronics manufacturing. Unlike siloed solutions that either focus on big data analytics or on vision inspection, our approach unifies these into a closed-loop intelligence system. By doing so, we aim to achieve two main outcomes: Improved Yield and Quality, through rapid identification of yield detractors (whether they be machine anomalies or SOP issues) and enforcement of process discipline; and (2) Proactive Failure Prevention, through correlation of process deviations with failure modes and real-time prediction of failures to enable intervention. We emphasize a workflow that not only analyzes historical data (for root cause analysis) but also actively monitors and controls current production (for immediate corrections). The work described is generic and can be applied to many electronics manufacturing settings, focusing on data and algorithms rather than any proprietary equipment. We also align our approach with comparable strategies reported in literature and industry. For example, the use of computer vision for real-time quality and compliance monitoring is increasingly recognized as a transformative technology in manufacturing, with the market for such solutions projected to reach $39 billion by 2029 [12]. Similarly, manufacturing case studies have found that when SOP compliance meets expectations, line efficiency and yield are maximized [13]. Building on these insights, our contribution is to design and document a comprehensive framework that integrates these elements (data analytics, vision, and machine learning) and to discuss its implementation details and results.

2 Methodology

2.1 MIRAI Data Intelligence Workflow

The **Manufacturing Intelligence for Reliability and Automated Insights (MIRAI)** workflow is a data engineering and analytics pipeline designed to empower engineers with self-service insights across the manufacturing process. MIRAI aggregates production data such as test results, process parameters, component information and provides various analysis modules to pinpoint issues affecting yield and reliability. The MIRAI workflow comprises four main components:

2.1.1 Yield Analysis

A self-service analysis tool for identifying signals associated with station yield drops during both ramp-up and sustaining production phases. In ramp-up (new product introduction or early production), yields can fluctuate as the process stabilizes; in sustaining (high-volume steady production), any sudden yield drop is a concern [14]. The MIRAI yield module continuously monitors yield at each test station (the percentage of units passing at that station) and triggers analysis when a significant drop or negative trend is detected. It automatically searches for *common factors* among the failing units that could explain the yield loss. For example, if Station 5's yield fell from 98% to 92%, MIRAI might analyze dozens of attributes of each unit (such as which assembly line it came from, who the operator was, which lot of components were used, calibration settings of the equipment, *etc.*) to find statistical correlations. Techniques akin to commonality analysis are employed such as using association rule mining or contingency table analysis to find factors that are overrepresented in failed units [15]. This helps identify systematic causes of yield loss (as opposed to random defects). The result of a yield analysis might reveal, for instance, that "Units that failed at Station 5 are 3 $\times$ more likely to have come from Line 2 and used Component Batch X," pointing engineers to investigate Line 2 or that component batch. These analytics are delivered in a self-serve dashboard, allowing process engineers to drill down without requiring data science expertise. By quickly pinpointing likely causes, the team can take corrective actions (machine maintenance, station recalibration, additional operator training, *etc.*) to bring yield back up. This workflow reduces the time to root cause by automating much of the heavy data analysis that engineers would otherwise do manually.

2.1.2 Field Failure Analysis

A self-serve analysis capability focused on identifying signals in manufacturing data that correlate with field failures (*i.e.* units that pass all factory tests but later fail during use by customers, resulting in returns or repairs). Data for this analysis comes from linking field return records (or failure analysis reports from returned units) with the original manufacturing data of those units. The MIRAI field analysis module takes a population of products – some that had field failures and some that did not – and performs retrospective data mining to find what factors in the production or test data are predictive of those failures. For instance, it may analyze whether certain test measurements were marginal (close to spec limits) on units that eventually failed, or if a particular factory, production date, or supplier lot is statistically associated with higher field failure rates. This is essentially a supervised learning or statistical correlation task: the units have a label of "field failure" or "no failure," and the system examines all available manufacturing attributes to see which correlate strongly with the label [16]. As with yield analysis, commonality or classification techniques are applied, but with field failures as the target. The outcome could be a set of risk factors – *e.g.*, "Units that failed in the field tend to have had longer soldering cycle times on average" or "Field failures are concentrated in products built with PCB supplier Y in a given week." These insights allow engineering and reliability teams to initiate corrective actions such as design modifications, supplier changes, or targeted recalls for suspect lots. By making field-failure analysis self-service, MIRAI enables a faster feedback loop from customer experience back to manufacturing. This is critical in avoiding widespread issues; as soon as a pattern is detected linking field issues to a process variable, that information can be used to improve production or screening tests [17]. Prior industry approaches that correlate manufacturing test data with field outcomes have shown the value of such analysis in preventing future failures [10] that effectively turns large datasets of past production into actionable knowledge to improve product reliability.

2.1.3 "Bring Your Own Data" Analysis

In addition to standard yield and field analyses, MIRAI supports user-requested custom analyses, essentially allowing engineers to bring their own data for specialized investigations. Often in manufacturing, engineers run experiments or additional stress tests (for example, ongoing reliability tests like ORT, Highly Accelerated Life Testing (HALT), or qualification tests on samples) and want to analyze the results in context of manufacturing data [18]. In the MIRAI workflow, a user can provide a list of units and a binary outcome (Pass/Fail) from some external test or criteria – for instance, a set of units that underwent an On-going Reliability Test (ORT) where a few units failed while others passed. The DataOps team (or the data platform automatically) will gather all relevant manufacturing data for that population of units and perform analysis similar to the above to find signals differentiating the fail group from the pass group. This could involve feeding the combined dataset into a classification model or running targeted queries (like comparing means of certain measurements or doing decision tree analysis to find splits). The result is a report to the requesting engineer with any statistically significant factors that correlate with the failures. For example, if out of 100 units tested in ORT, 5 failed, the analysis might find that all 5 failing units were processed on a particular SMT (surface mount technology) line or all used a particular lot of a component, suggesting a latent issue. By allowing ad-hoc data analysis in this manner, MIRAI becomes a flexible analytics extension for quality engineering experiments. It essentially leverages the data pipeline to answer one-off questions. The pass/fail labeled dataset provided by the user might come from reliability tests (like ORT, environmental stress screening), customer returns classified by failure mode, or even simulations [19]. MIRAI treats this like a mini "competition" between variables to explain the outcome, employing anything from logistic regression to more advanced feature importance ranking. Importantly, this step often requires careful data integration – ensuring that the units in the provided list are correctly matched to their records in various manufacturing databases (traceability, test results, repair logs, *etc*.). The DataOps aspect implies that data engineers may assist in data cleaning and preparation, but the goal is eventually to make this process streamlined so that an engineer with minimal coding can get results by simply uploading a CSV of serial numbers with labels. This workflow dramatically accelerates root cause analysis for issues discovered outside the standard test flow, by bringing all available production data to bear on the problem.

2.1.4 MIRAI Sentinel (MIRAI Sentinel)

The final component is a proactive auto-analysis and alerting system that continuously scans manufacturing data across all build stages to catch emerging issues without waiting for human requests. While the previous components are triggered by an engineer's query or an obvious yield drop, *MIRAI Sentinel* is an always-on watchdog. It performs automated commonality analysis on recent production data in search of anomalies or deviations from baseline. For example, it may automatically cluster recent failures across different stations and see if they share any common factor (*e.g.*, all from the same shift or same supplier lot) and then alert engineers that "5 failures have occurred across two different stations in the last day, all involving Component

Z – this is unusual and worth investigating.” Likewise, MIRAI Sentinel can be configured to monitor trends such as gradually declining yields, shifts in test measurement distributions, or increasing retest rates. When certain thresholds or abnormal patterns are detected, the system triggers an alert or generates an “Auto Commonality Report.” This proactive analysis uses a combination of statistical process control (SPC) rules and machine learning anomaly detection. It might leverage control charts for yield and test metrics and apply clustering algorithms to group suspect units [20]. By spanning across build stages, it means MIRAI Sentinel can connect the dots (for instance, noticing that a particular assembly issue in an early stage is causing fails only at a later test stage). Alerts could be sent via email or shown on a dashboard, highlighting the suspected common cause. The aim is to shorten the time to discovery of issues that might otherwise only be found after a lot of units have failed. This turns yield management from a reactive “pull” (engineers digging for causes after yield drops) into a proactive “push” model where the system itself highlights potential problems [5]. MIRAI Sentinel therefore acts like an automated quality engineer, continuously learning from data and assisting human engineers by focusing their attention where it’s needed. In practice, implementing MIRAI Sentinel requires robust data engineering: streaming data pipelines, data normalization to compare across shifts and lines, and scalable computing to run analyses frequently (potentially on each new batch or each day’s production data). It also requires careful tuning to avoid false alarms – ensuring alerts are meaningful by using logic to filter out spurious correlations (as commonality analyses can sometimes find coincidental patterns [15]). Therefore, MIRAI Sentinel adds an intelligence layer on top of the manufacturing process that preemptively detects and communicates issues, thus embodying the notion of *holistic intelligence* by looking broadly and acting in real time.

From a system architecture perspective, MIRAI is built on a centralized manufacturing data lake that ingests data from various sources: automated test equipment outputs, production execution systems (with information on lots, machines, and operators), as well as external data like field returns [21]. A key enabler for MIRAI’s effectiveness is this integration of data sources. Recent reports from industry emphasize that connecting all plants and processes via an operational data lake to get a real-time, unified view is a foundational step for deploying AI/ML interventions for yield improvement [22]. Our implementation follows this principle – all relevant data about each unit (its genealogy through the factory, all test readings, and eventually the SOP deviation data from vision systems described later) are linked via a unique identifier (such as the unit’s serial number). This comprehensive data foundation allows the analyses in MIRAI’s four workflows to be performed accurately and consistently. The user interfaces for MIRAI include dashboards for engineers with interactive filters and visualizations, and a query engine for advanced users to run custom queries or machine learning models. In essence, MIRAI serves as the analytical “brain” of the manufacturing line, ingesting raw data and outputting insights or alerts that drive improvement actions.

2.2 Computer Vision System for SOP Monitoring

An integral part of our approach is the use of computer vision to monitor station activities for Process observation. This system provides the *eyes* on the factory floor to complement MIRAI’s data analytics [23]. The computer vision setup consists of cameras installed at critical operator workstations (assembly or test stations where human interaction is involved) and an AI inference pipeline that processes the video feed from these cameras in real time. The goal is to automatically verify whether each operator is following the prescribed steps in the SOP for that station and to record any deviation or departure from the SOP.

2.2.1 Camera Installation and Data Capture

Cameras are positioned to get a clear view of the workspace and the operator’s actions, without obstructing the operation. We used industrial-grade cameras with appropriate resolution and frame rate to capture necessary details for example, identifying tools, parts, and hand movements [24]. In some cases, a single wide-angle camera per station is sufficient; in others, multiple angles or a depth camera might be employed if the task is complex. The system design can accommodate both edge processing (smart cameras with onboard AI accelerators like NVIDIA Jetson devices [2]) or a central server approach where video is streamed to a local server running the models. In our pilot, to minimize network load, we opted for edge AI cameras that perform on-board inference and send only summary data/events to the central database. Each camera is time-synchronized with the production line system and tied to a specific station ID. Through the line control system, we know which product serial number is at that station at a given time (since each unit is scanned or otherwise identified at station entry). This integration is crucial: it allows us to tag any detected SOP deviation with the specific unit (serial number) and step, feeding that information into the manufacturing data records.

2.2.2 Model Training for Action Recognition

Developing the computer vision model requires training it to recognize the key actions or objects involved in the station's SOP. This is formulated as an action recognition or sequence verification problem. We collected training data by recording many instances of the station operation, including both correct procedures and some examples of incorrect actions (if available). Depending on the use case, different AI techniques can be used:

(1) Object Detection and Pose Estimation: For tasks where the SOP involves using certain tools or parts, object detection models (*e.g.*, based on convolutional neural networks like YOLO or Faster R-CNN) are trained to detect the presence and placement of those tools/parts in each frame. Human pose estimation models can track the operator's hands and body to see if they reach the correct areas in the correct order. For example, if SOP says "pick up screw, use screwdriver on location A, then B," the system would detect the screwdriver and the motion of hand to location A then B.

(2) Action Sequence Modeling: In more complex workflows, we use sequence models. A common approach is to break the video into a series of discrete actions using a temporal action segmentation model. Alternatively, treat it as a classification per time window: *e.g.*, a deep learning model (such as a 3D CNN or a transformer-based video model) that can classify what action is being done in a short clip. We trained such models on annotated video: subject-matter experts labelled a number of video clips with the action being performed (or labeled if a step was done wrong). The model learns to discriminate correct vs incorrect actions.

(3) State Machine with Vision Triggers: In some implementations, it is useful to encode the expected order of operations as a state machine or rule-based logic, and use the vision algorithms to confirm each step. For instance, state 1 "tool X picked up" must occur before state 2 "tool X applied to part Y". The vision system outputs events like "tool X detected in hand" or "part Y present in fixture" which are fed into a simple logic engine that verifies the sequence.

For our pilot, we started with a relatively constrained task (a single station with a well-defined set of steps) and trained a deep learning model to detect a few key events: whether the operator performed a required check with a camera (vision inspection step) and whether a certain component was tightened with a torque tool. The model was a custom CNN that took image frames as input and output whether the specific action was observed. We augmented this with sensors data when available (*e.g.*, the torque tool provides a reading when used – which we also log for cross-reference). All AI models were developed using open-source frameworks and we ensured not to hard-code any proprietary features. They were validated to a high accuracy on a test dataset of annotated videos before deployment (achieving, for example, >95% precision and recall in detecting the presence or absence of the critical action).

2.2.3 Real-Time SOP Compliance Monitoring

Once deployed, the vision system operates continuously during production. Real-time inference on the camera feed compares the ongoing operator actions against the SOP model. If every expected step is observed in the correct order, the system remains silent (or just logs compliance). If a deviation is detected – for example, a step is missed within the allotted time or an incorrect action is performed – the system immediately raises an alert. In our implementation, the alert is both visual (displayed on a dashboard for line supervisors) and logged electronically. The alert includes details like: Station ID, timestamp, description of deviation (*e.g.*, "Step 3 – connector inspection – was skipped"), and the unit's serial number. At that moment, a supervisor can intervene, or the system could even be configured to stop the conveyor/belt for that unit if automatic interruption is desired (in our pilot, we opted to alert rather than stop, to study the occurrences first). This immediate feedback mechanism prevents the unit from silently continuing down the line with an undetected process defect. It also provides an opportunity to correct the mistake: the operator or a rework technician can perform the missed step or verify the product before it moves on. Such real-time alerts greatly reduce the chance of a defective unit reaching the end of the line or, worse, the customer [2]. Moreover, continuous monitoring generates a trove of compliance data. The system essentially produces a timestamped event stream of all deviations (and potentially confirmations of correct steps). This data is invaluable for analysis – for instance, to see if certain times of day or certain operators have more deviations, or which steps are most problematic.

2.2.4 Data Logging and Integration

All detected deviations (and optionally a record of compliance events) are stored in a database, with references to product serial numbers and step identifiers. We structured a Deviation Log that captures: (Unit Serial, Station, Step/Action ID, Deviation Type, Timestamp, Operator ID (if available)). Alongside, the production system provides the information of whether the unit eventually passed or failed subsequent tests, was repaired, and so on. By integrating this log with the main manufacturing data (as part of MIRAI's data lake), we can perform correlation analysis between SOP deviations and yield or failures – this is the core of Phase 2 and Phase 3 of the pilot, described next. It is worth noting that careful attention was paid to time synchronization and data alignment. We used the station's start trigger (when a unit arrives and is scanned) to mark the beginning of an operation, and we buffered any vision-detected events during that operation to associate with that unit's serial. This ensures the deviation data is properly linked to the correct unit, which is critical for accurate analysis. Privacy and worker acceptance were also considered: the purpose of cameras is to improve the process and training, not to surveil workers punitively. We ensured the system focused on task elements (and the footage was not used beyond the scope of process improvement), which helped in gaining cooperation for the pilot.

2.3 Process Observation and Statistical Prediction for Enhanced Compliance and Throughput (PROSPECT) Workflow

With the vision system in place to capture SOP deviations, we designed a pilot study in three phases to leverage this data for yield improvement and failure prediction.

2.3.1 Phase 1: Monitor PROSPECT and Identify Key Deviations

The first phase focused on establishing baseline SOP compliance levels and determining whether non-compliance was contributing to yield loss at the station of interest. We selected a particular assembly station that had experienced periodic yield fallout (lower first-pass yield) in the past, suspecting operator errors as a possible cause. Initially, we measured the station's yield fallout rate (the fraction of units failing at that station) over several production runs to have a baseline. Next, we activated the computer vision monitoring at this station to record station activities continuously. Over a period of several weeks, every action at this station was observed by the AI system as described earlier. During this time, we did not make major interventions; the idea was to passively collect data on how often and what types of SOP deviations were happening. The system generated a log of deviations, which we then analyzed. We identified key SOP deviations by frequency and potential impact. For example, we discovered that one particular step, scanning a barcode on a sub-component to verify its presence, was occasionally skipped. Another deviation noted was an improper torqueing sequence: operators sometimes tightened screws in the wrong order or missed the last screw, contrary to the SOP. We also noted the frequency of each deviation and whether certain operators had more deviations, though individual performance was anonymized in analysis. This phase had an *iterative loop* aspect: when a critical deviation was identified, we took immediate corrective action by communicating with the production team. For instance, upon finding the skipped barcode scans, we updated the station's work instructions and retrained operators to emphasize that step. We also added a simple error-proofing measure: the station software now requires the barcode scan input before allowing the process to continue (forcing compliance). These interventions (training and process changes) were implemented, and the station yield was measured again to see if it improved. Indeed, after addressing the top deviations, the station's yield fallout dropped noticeably (we observed an improvement from about 92% first-pass yield to 96%, for example, after enforcing the barcode scan step). Phase 1 is thus a cycle of *observe* → *identify* → *fix* → *observe again*, gradually reducing human error-induced falls in yield. In essence, this phase answers: "What SOP violations happen and are they hurting yield?" It establishes a direct link between adherence and quality, echoing the industry observation that SOP compliance correlates with better performance [25]. By the end of Phase 1, we had a much cleaner process at the pilot station (fewer deviations after interventions) and a list of residual deviations that were harder to eliminate or quantify. Crucially, we had captured data that some deviations still occurred (albeit less frequently), and those instances could be studied in Phase 2 for their impact on failures.

2.3.2 Phase 2: Track Deviations by Serial Number and Correlate with Failures

In this phase, we shifted from focusing on station yield at the point of occurrence to the *downstream effects* of SOP deviations. The approach was to follow each unit through the rest of the manufacturing process (and even field use, if data allowed) and see if those that experienced a deviation at the station have a higher chance of failing later compared to those with no deviations. We started by instrumenting the system to track serial numbers of units with deviations. For every unit that passed through the monitored station, the deviation log was checked. If any SOP deviation was recorded for that unit, we flagged that unit in a "deviation present" category; units with no detected issue were flagged as "deviation-free." We then compiled the outcomes for each unit: did it pass final testing? Did it require rework or repair? If it failed, what was the failure mode (captured via failure analysis or troubleshooting logs)? If available, we also tracked if the unit had any field return or early life failure after shipment. This data was gathered over many units (on the order of thousands, to get statistically meaningful results) during the period of the pilot. With this labeled dataset (units with deviation vs without, and their eventual fates), we performed a deviation-failure correlation analysis. Essentially, this is calculating the conditional probabilities and looking for statistically significant differences. For example, we found that units which had the torque sequence deviation (missed screw tightening) were far more likely to fail the end-of-line functional test for that product. The failure mode in those cases was often related to that part – *e.g.* a loose heatsink or connector causing a test failure. We quantified this: suppose out of 1000 units that had no deviations, 5 failed later tests (0.5% failure rate), but out of 50 units that had a certain deviation, 5 failed (10% failure rate) – that would strongly indicate a correlation. In our study, one particular deviation (improper torque) had a very high correlation with a specific failure mode observed in environmental stress tests (vibration test failures), with an odds ratio suggesting those units were ~8 times more likely to fail than baseline. On the other hand, some deviations seemed to have little to no impact – *e.g.*, if an operator momentarily deviated but corrected themselves (a transient hesitation that was flagged but ultimately the step was done), it did not translate to any measurable difference in outcomes. We also cross-correlated the data: it could be that a combination of deviations or a deviation at one station in combination with another factor leads to failure. However, since our pilot dealt with one station primarily, we kept the analysis straightforward: a binary "deviation happened at station X" vs outcomes. The failure analysis (FA) data from the repair technicians was invaluable – it allowed us to link a cause to effect (for example, "unit failed final test due to loose connector; indeed, a deviation earlier indicated that connector was not scanned or secured properly"). We measured the deviation-failure correlation in terms of metrics like precision and recall as well: if we use "deviation occurred" as a predictor of failure, how accurate is it? For critical deviations, the precision (how many of the flagged units actually failed) might not be extremely high because many units with a deviation still pass (perhaps the deviation was minor or caught later), but the recall (how many of the failing units had a known deviation) was quite high. In one case, 70% of the units that failed a certain test had experienced a particular SOP deviation upstream. This kind of insight validates the hypothesis that PROSPECT has a direct effect on yield and reliability. It also provides a list of deviations ranked by their impact on quality. This information feeds back to Phase 1's loop: deviations that show strong correlation with failures become top priority to eliminate through process improvements or poka-yoke (mistake-proofing) mechanisms. Essentially, by the end of Phase 2, we had created a deviation-failure repository – a collection of cases linking specific procedural missteps to specific failures, complete with data statistics. This repository is an asset for both engineering and training: it can be used to justify investments in automation or training (*e.g.*, "We must fix this step because it's causing X% of our failures") and to educate operators on the importance of each SOP step ("Skipping this screw tightening leads to failures in vibration testing, as data shows"). Moreover, this set of correlated features and outcomes lays the groundwork for predictive modeling.

2.3.3 Phase 3: Build and Train a Failure Prediction Model

In the final phase, we leveraged the insights and data collected to develop a machine learning model that predicts unit failures in real time based on observed SOP deviations (and potentially other data). The concept is to enable the factory to catch a likely-failing unit as early as possible and apply a fix or additional screening right away, thereby preventing the failure from either propagating down the line or escaping to the field. The input features to the model included the SOP deviation flags for each unit from the monitored station (and we can extend to multiple stations as we scale up). For our pilot, since we instrumented one station, the primary features were binary indicators of whether each type of deviation occurred for that unit. We also considered adding other easily available features to improve prediction – for example, whether the unit had any borderline test results (within spec but near limit) at that station, or how many times the unit was retested at that station. But the simplest effective model was one that used the presence/absence of the key deviations as features. The target label for the model was whether the unit eventually failed at final test (or required any repair) – essentially a proxy for yield outcome. (In future extensions, the target could be field failure, but that data was scarcer; for the pilot we focused on predicting final test fallout, which itself is highly beneficial for yield if addressed). We split our collected dataset (Phase 2 data) into training and validation sets, maintaining chronological order to avoid leakage (training on earlier units, and validating on later units, mimicking deployment). We then trained a classification model. We experimented with a few algorithms: a simple logistic regression, a decision tree, and an ensemble like a random forest or gradient-boosted trees. Given the relatively small number of features and their categorical/binary nature, even logistic regression was quite interpretable and effective – it gave weight to each deviation type corresponding to how predictive it was. The ensemble models gave a slight performance boost by capturing interactions (for instance, if two different deviations together made failure even more likely). Ultimately, we chose a gradient boosted decision tree model (similar to XGBoost) for deployment, as it handled feature interactions well and provided good accuracy without overfitting. The model was trained to output a probability that a unit will fail, given the observed deviations. On the validation dataset, we achieved an accuracy in the range of ~90% for predicting failure vs pass, with a high recall for failures – meaning it caught most of the failing units (for example, ~85% of the units that did fail were assigned high risk by the model). We tuned the threshold of the model to favor capturing failures (even if it meant some false positives), because the cost of a false positive (some extra inspection) is much lower than the cost of a false negative (a bad unit slipping through). In practice, one can adjust this threshold based on business needs (*e.g.*, how much re-inspection capacity is available).

After training and offline validation, we moved to deployment of the failure prediction model. We integrated the model into the station's software such that after processing each unit (or at the end of the line, before final test), the system would automatically evaluate: if the unit had any SOP deviations logged, it feeds those into the model (a simple lookup and calculation) and produces a risk score. If the risk score exceeds a predetermined threshold, the system flags that unit for immediate attention. During deployment, this meant the unit was routed to a special inspection station before final testing. At that station, a technician would double-check the unit for the likely issue (for example, if the model flags "high risk due to missed screw tightening", the technician will specifically check all screws and perform the missed step). In many cases, this predictive interception allowed us to fix the problem such that the unit then passed final test, improving the first-pass yield. If the unit was flagged but nothing obvious was found, we still ran it through all tests and kept it under observation (none of the flagged units were sent to customers without thorough vetting). Over time, we measured the effectiveness: the number of units that would have failed final test but were fixed due to early prediction. This is essentially the true positive count of the model. We also tracked the false positive rate (units flagged that would have passed anyway) to ensure it was at a manageable level. The model's performance was very encouraging – for instance, in a month of operation, out of the units the model flagged, a significant portion indeed had issues that required rework (caught early instead of later), and the overall end-of-line yield improved by a few percentage points as a result of these pre-emptive fixes. This aligns with the goals set out: predict and fix potential failures in real time, thereby increasing the first-pass yield and reducing waste. In broader context, the predictive model effectively extends the reach of our quality control: instead of relying purely on final test outcomes, it uses process deviations as predictive signals. It is a form of predictive quality analytics that shifts us from "find and reject bad units" to "anticipate and correct bad units" – a hallmark of advanced smart manufacturing systems [1].

It's worth noting that as we accumulate more data (Phase 3 is ongoing in a sense), the model can be retrained and improved. If additional stations are instrumented with vision systems, their deviations can be added to the feature set, making predictions even more comprehensive. The modular nature of the system means we can plug in more data sources (*e.g.*, machine sensor data or operator biometric data) if they prove predictive. But even with just SOP deviation data from one station, we demonstrated a clear value: a measurable improvement in yield and a reduction in escaped defects. The deployment also provided real-time feedback to operators – knowing that deviations immediately trigger scrutiny created a positive pressure to follow SOPs more rigorously (this was anecdotal but observed). Phase 3 closes the loop by enabling real-time intervention: the moment a risky situation is detected (either by direct deviation alert or by predictive flag), action is taken to either correct the process or isolate the unit for repair. This embodies the synergy of integrating MIRAI data analysis with computer vision: we not only analyze and understand problems but also actively prevent them on the line.

3 Results

We evaluated the integrated MIRAI and PROSPECT system through a pilot deployment in an electronics manufacturing line. The results are presented in two parts: (1) insights and improvements gained from the MIRAI analytics and SOP monitoring (Phase 1 and Phase 2 outcomes), and (2) performance of the failure prediction model and its impact on yield (Phase 3 outcomes). All results are reported in a generic context (no proprietary data) but reflect the scale of a real manufacturing scenario.

3.1 Yield Improvement and Process Insights

3.1.1 Station Yield Recovery

In Phase 1 of the PROSPECT, after implementing continuous SOP monitoring and subsequent interventions, the target station's yield showed notable improvement. Initially, the station's first-pass yield (FPY) was fluctuating and averaged around 92% (meaning 8% of units required rework or failed at that station). By identifying the most frequent SOP deviations (such as missed scans and incorrect torque sequence) and addressing them through operator retraining and process enforcement, we observed the FPY rise to ~96% over the following production cycles. This ~4 percentage point improvement is significant in a high-volume environment, representing dozens of units per week that no longer needed rework. It directly translates to cost savings and increased throughput. More broadly, across the pilot period, the overall line FPY (cumulative yield through all stations) also improved, although the pilot only focused on one station's changes. This suggests that fixing issues at one station prevented a cascade of problems down the line. These findings reinforce the often-stated manufacturing principle that adherence to "One Best Way" procedures yields better performance [25]. In fact, our data provided a quantitative example of that – when SOP compliance approached 100% for the critical steps, the station efficiency and yield were at their highest. This result mirrors other industrial case studies where plants that achieved high SOP compliance saw corresponding high line performance [26].

3.1.2 Deviations Frequency and Reduction

Over the course of Phase 1 and Phase 2, we tracked the frequency of SOP deviations at the station. Initially, in the first two weeks of monitoring, deviations were detected in roughly 15% of the units processed (some minor, some critical). After feedback and corrective measures were introduced (*e.g.*, making a barcode scan mandatory, reinforcing training), the deviation rate dropped to under 5% of units. This demonstrates the effect of simply measuring and responding, operators and supervisors became aware that certain mistakes were happening and took steps to avoid them. Among the types of deviations, we found that procedural misses (completely skipped steps) were less frequent but often more impactful, whereas sequence or timing deviations (steps done out of order or too quickly without verification) were more common but sometimes had less impact if eventually corrected. By the end of the pilot, the most egregious deviation (the missed scan) was virtually eliminated, while a few others (like slightly out-of-order operations that did not affect the outcome) still occurred occasionally. The comprehensive monitoring made it possible to sustain this improvement; unlike a one-time audit, the AI system continuously ensures that the process does not drift back to old habits. From a management perspective, this data allowed us to pinpoint where additional training was needed – for instance, if one shift had more deviations than another, management could investigate why (perhaps a less experienced operator on that shift, *etc*.) and take action.

3.1.3 Correlation of Deviations with Failures

In Phase 2, our analysis provided concrete evidence linking SOP deviations to downstream failures. One striking result was the correlation between the missed torque step and a failure in a subsequent vibration test (part of reliability testing). Out of all units that had the torque deviation, 20% later failed the vibration test (due to things like loose components), whereas among units with no such deviation, only ~2% failed the same test. This tenfold difference strongly indicates causation – improper torque likely caused components to be insufficiently secured, which then led to failures under vibration stress. When presented with these findings, the manufacturing engineers were convinced to implement additional safeguards (they decided to introduce a sensor to verify torque for each screw, adding an automated check in addition to the vision). In another example, a skipped inspection step correlated with an increase in cosmetic defects seen at final quality check. While those cosmetic issues didn't cause functional failures, they did result in rework (polishing or reassembling parts), impacting efficiency. Units that skipped the inspection had a 15% cosmetic rework rate versus 5% normally. By correlating each deviation type with various outcome metrics (final test fails, reliability fails, rework incidents, and even warranty returns for the period we could observe), we built a matrix of influence. This kind of data is rarely available in traditional operations, as the links are not traced. But here we had a clear mapping: for each SOP deviation type, we could quantify its effect on yield or quality metrics. The repository indicated, for example:

(1) Deviation A (missed step): associated with failure mode X, correlation strength: high.

(2) Deviation B (incorrect sequence): mild correlation with extended test time, but no direct failures (operators usually caught up and corrected later).

(3) Deviation C (skipped verification): moderate correlation with field returns of issue Y,

suggesting a latent defect might slip through.

These insights not only validated the approach but also gave direction for continuous improvement. They essentially told us where to focus engineering effort. Additionally, from a Six Sigma perspective, we considered the deviations as a source of process variation. By eliminating those deviations, we reduce variability in the process, which naturally improves yield (higher sigma level). Our results empirically demonstrate this: the variance in yield results at the station narrowed after Phase 1, and the overall defect rate decreased after addressing the high-impact deviations identified in Phase 2.

3.1.4 MIRAI Analytics Outcomes

Concurrent with the SOP pilot, the MIRAI platform's yield and field analysis modules were run regularly on the production data. While the MIRAI system covers the entire line, for brevity we note a few key outcomes that intersected with our pilot:

(1) The MIRAI yield analysis module independently flagged the pilot station for having an unusual uptick in failures during the initial baseline period, correctly identifying that most fails were associated with a specific operator and shift (which corresponded to the time the missed scan issue was occurring frequently). This was a good cross-validation; MIRAI's automatic data crunching pointed to a human factor issue at that station, which our vision system then directly observed. This shows the synergy: data analytics can highlight "where to look," and vision provides the "what exactly is happening."

(2) The MIRAI field analysis (though based on limited return data in the pilot's timeframe) indicated that units with the vibration failure mentioned above had all been processed at the pilot station by a specific tool ID – again correlating to the torque issue. This kind of finding is inline with industry experiences where manufacturing data patterns are tied to field reliability. It underscores that the impact of SOP deviations can extend to field performance, not just immediate yield.

(3) The BYOD analysis was tested by feeding in some ORT results: a batch of units had undergone an accelerated life test (where a couple failed). MIRAI BYOD analysis found that those failing units were among the ones that had minor process deviations (like shorter solder time) upstream. While not directly part of SOP, it shows the utility of having an analytics pipeline that can incorporate any new data and link it to production info.

(4) MIRAI Sentinel alerts during this period caught a separate issue on another station (unrelated to our main pilot) where yield was dropping due to a misaligned test fixture. This was resolved quickly. We mention this to illustrate that our integrated approach does not rely on only one type of data; the MIRAI system continues to handle machine/equipment issues in parallel, whereas the SOP vision pilot added the human procedure aspect into the holistic view.

Overall, the results demonstrate that integrating these systems provided both *rapid local improvements* (fixing issues at the station) and *broader visibility* into how process execution affects quality. We essentially expanded the feature space of manufacturing data to include human adherence metrics, which proved to be important predictors.

3.2 Failure Prediction Model Performance

3.2.1 Predictive Accuracy

The failure prediction model trained in Phase 3 was evaluated on historical data and then monitored live. On the test dataset of a few thousand units (with known outcomes), the model achieved an AUC (Area Under ROC Curve) of about 0.92, indicating excellent discrimination between units that fail and those that pass. At an operating threshold chosen to prioritize catching failures, the model's sensitivity (true positive rate) was around 85%. This means 85% of units that did end up failing final test were correctly predicted as high-risk by the model *before* the final test occurred. The specificity (true negative rate) was slightly lower, around 80%, since we tolerated some false positives. The precision or positive predictive value was in the range of 30–40%, meaning that among the units flagged as high-risk, roughly a third actually would have failed if not intervened. While 30–40% precision might seem moderate, it is actually quite useful in context – these flagged units can be inspected with relatively low effort, and if 1 in 3 is a true issue, that's a big win considering those would have been failures. In fact, many predictive maintenance or quality models in industry operate in regimes of low base failure rates, so a precision of 30% can be economically justified if the cost of checking a false alarm is small compared to the cost of a miss. We should note that the model was somewhat conservative in that any unit with even a minor critical deviation was flagged. There were almost no false negatives for the specific failure modes related to the monitored deviations; the few failures that slipped through were due to other causes (unrelated to the SOP steps we monitored).

3.2.2 Real-Time Deployment Results

During live deployment over one month, the model flagged approximately 50 units as high-risk out of several hundred produced. Of those 50, about 15 were confirmed to have real issues that would likely have caused test failures or field failures (true positives). These issues were fixed on the spot. For example, one flagged unit was found to have an improperly seated connector (the SOP deviation was a skipped verification step) – the technician reseated it, and the unit then passed all tests. Without the system, that unit would have failed at final test or perhaps passed but failed in the field. Another flagged unit had a missing screw (caught by visual check after flagging) which was then installed, saving that unit from likely failure. The other 35 flagged units (false positives) were re-inspected and no problems were found; nearly all of them passed final test normally. In those cases, the model erred on the side of caution (for instance, an operator might have slightly deviated but corrected it, and the unit was fine, yet it was flagged due to the deviation log entry). We are analyzing those false positives to see if the model can be refined to ignore truly benign deviations (perhaps by incorporating the fact the step was eventually done, albeit late). However, the manufacturing leadership was pleased with this result: 15 units proactively saved from failure is a direct improvement in yield, and the overhead of checking 35 extra units was manageable. In fact, the yield improvement at final test was quantifiable. The line's final test yield improved from ~95% to ~98% during that period. Not all of that is solely due to the model (some general improvements happened too), but a portion can be attributed to catching those failures early. Even more importantly, every unit that is fixed early saves significant time; a unit caught at the station can be reworked in minutes, whereas if it fails at final test, it disrupts the flow and requires sending the unit to a repair area, retesting after fix, *etc*., which could take hours. So there is an efficiency gain beyond the yield percentage.

3.2.3 Case Study – Preventing a Field Escape

While our deployment time was short to gather field data, one notable anecdote stands out. One unit was flagged by the model for a minor SOP deviation (the operator did not follow the exact order of two sub-steps, but eventually completed them). The unit passed final functional tests, so normally it would have shipped. Because it was flagged, the quality engineer decided to put it through an extra stress test overnight. It turned out that under prolonged thermal cycling, the unit did fail due to a joint that was not perfectly soldered (the deviation might have caused a suboptimal solder reflow). This unit was caught and scrapped before shipment. While this is a single instance, it exemplifies the potential of failure prediction to prevent a possible field failure (which could have resulted in a costly customer return or warranty claim). It underscores that a predictive model can add a layer of protection especially for latent defects that aren't detectable by normal tests but have telltale signs in the process data.

3.2.4 Integration with MIRAI Sentinel

We also integrated the model's logic into the MIRAI Sentinel platform. Instead of just alerting on correlations, MIRAI Sentinel can use the predictive model to watch all units. In effect, every time a deviation was logged (as part of the data stream), MIRAI Sentinel would evaluate the risk and generate an alert for high-risk unit. This means even if we expand to more stations, a central system can coordinate the flags and possibly even suggest where to route the unit (to an offline check). The result is a unified alert dashboard that not only warns of equipment issues (as it did before) but now also of specific units at risk due to process anomalies. This unified approach is a step towards what some quality experts call a "360-degree view of quality"– combining machine, process, and human factors data to ensure each product meets standards [27]. Our results contribute to that vision by showing how to incorporate PROSPECT data effectively.

3.2.5 Economic Impact

Although this paper focuses on technical results, a brief note on the potential economic impact is warranted. Improving FPY even by a few percentage points on a high-volume electronics line can save hundreds of thousands of dollars annually in labor, scrap, and warranty costs. Our pilot's ~4% station yield improvement and ~3% final yield improvement translate to fewer units needing rework and more units out the door per day. Additionally, preventing field failures avoids not just the direct cost of returns but also intangible costs like customer dissatisfaction. The real-time fix approach also reduces WIP and cycle time, as units do not circulate back and forth for fixes. Thus, the integration of MIRAI and vision we demonstrated has a clear business case, aligning with known benefits of AI in manufacturing such as reduced defects, cost savings, and throughput improvement [28]. Our results are in line with other reports where AI-driven interventions led to yield gains and lower defect rates; for example, an AI-based defect classification system can significantly boost production yield by catching defects early [29]. In our case, instead of optical defect inspection, we caught process defects, but the end goal of yield boost is the same.

3.3 Summary of Key Results

To summarize quantitatively:

(1) SOP deviation rate at target station: reduced from ~15% of units to <5% through Phase 1 actions.

(2) Station first-pass yield: improved from ~92% to ~96% after addressing key deviations.

(3) Correlation example: units with deviation X were ~10× more likely to fail later testing than those without (clearly identifying X as a root cause contributor).

(4) Failure prediction model: 85% of failing units correctly predicted (caught) with ~30% precision in a pilot deployment; final test yield increased ~3% with model in place.

(5) Zero critical failures went unaddressed among those monitored – meaning the combination of vision + model caught all instances of the known issues we targeted.

(6) The system demonstrated scalability in data handling, analyzing thousands of data points (images, events, test records) per unit in an automated fashion.

These results support the hypothesis that a holistic approach combining data analytics, computer vision, and machine learning can substantially improve manufacturing outcomes [30]. They also highlight that neither data analytics nor vision alone would be as effective: it was the combination that allowed identifying and preventing issues. In the next section, we discuss these implications and how they compare to other approaches in the industry.

4 Discussion

The successful pilot implementation of the integrated MIRAI + computer vision + PROSPECT approach provides several insights into both the technical and operational aspects of advanced manufacturing quality systems. In this section, we interpret the results, compare our approach with related work, examine the generalizability of the solution, and discuss challenges and future directions.

4.1 Integration of Diverse Data Sources

One of the standout aspects of our approach is how it brings together traditionally separate data streams – test data and human action data – into one analytical framework. In manufacturing, it's common to have siloed systems: a Manufacturing Execution System (MES) that captures process data and yields, and maybe a separate quality system for audit findings or manual observations. By capturing PROSPECT via computer vision and feeding that into the unified MIRAI data lake, we created a richer dataset for analysis and modeling. This aligns with the Industry 4.0 philosophy of system integration and a "single source of truth" for manufacturing data [22]. Our results show that this integration is not just technically feasible but highly beneficial. For instance, MIRAI's analytics became more powerful when we included the SOP deviation flags as additional features – we could uncover correlations (like the torque issue) that might have been obscured if one only looked at test data in isolation. Comparable approaches in industry often focus on one domain: *e.g.*, automated optical inspection (AOI) systems focus on visual defects on products, and manufacturing intelligence platforms focus on sensor and test data. We effectively combined a "process compliance monitoring system" with a data analytics platform. This holistic view is what gave us a 360-degree understanding of the root causes. Our work operationalized that integration in a custom way, demonstrating that the vision data can feed a predictive model that ties into quality control. A key lesson is that investment in data engineering – to ensure different data modalities can join on common identifiers – pays off greatly. We needed to ensure timing, serial number tracking, and database schema all aligned, which was non-trivial, but once in place, it allowed complex analyses with ease. This suggests future factories should design data architecture with such integration in mind from the ground up.

4.2 Impact on Yield and Quality

The improvement in yield we observed is consistent with the idea that reducing process variation (including variation introduced by human error) improves quality. This echoes fundamental principles of Six Sigma and Lean manufacturing, where standard work and elimination of deviations lead to better outcomes [31]. Our approach provided a high-tech way to enforce and measure standard work. Traditionally, Lean practitioners implement standard work charts and audit them; our system automates that audit and provides quantitative feedback in real time. This can be seen as a form of digital poka-yoke, where the system acts as an error-prevention mechanism by catching mistakes [32]. The yield improvements, while demonstrated at one station, hint at the potential if scaled line-wide or plant-wide. If every critical station is monitored and optimized, incremental improvements at each can compound into a large overall gain (especially in complex assemblies with many steps). Additionally, by catching issues upstream, we reduce the accumulated cost of defects – a defect caught and fixed at station 5 is cheaper than one found at final test or, worse, in the customer's hands. This is in line with the well-known "Rule of 10" in quality (each step later you find a defect, the cost multiplies by roughly 10). We effectively pushed detection as far upstream as possible.

4.3 Comparison with Prior Approaches

It's valuable to compare our integrated approach with other strategies.

4.3.1 Manual SOP Auditing *vs.* Computer Vision

Before vision, companies relied on periodic SOP compliance audits. These are labor-intensive and often too late to prevent defects. As the ADLINK case and our introduction noted, manual monitoring is inconsistent and cannot cover all operations. Our results confirm that an AI vision system can achieve consistent 24/7 monitoring and react in less than a second to issues, something impossible with manual audits. Other researchers and vendors have begun documenting similar successes with vision. This technological shift essentially ensures adherence in ways that were previously only aspirational.

4.3.2 Automated Test Data Analysis

Machine learning applied to test data (without vision) has been used for yield improvement and predictive maintenance. Our MIRAI platform is conceptually similar to those – it uses data to find correlations and root causes. The difference is that we extended the data to include human factors via SOP logs. Many traditional yield analyses might not capture that an assembly step was done incorrectly; they might only see the end symptom (like a measurement out of range). By adding the cause (deviation event) as data, we enhanced the analysis. In essence, our approach could be seen as adding a new category of sensor: the eyes on the process.

4.3.3 Direct Automated Inspection *vs.* SOP Monitoring

One might ask, why not simply rely on direct automated inspections for quality (like vision systems that inspect the product for defects)? Indeed, AOI and end-of-line vision inspection are common in electronics (for solder joint inspection, *etc.*). Those catch defects directly on the product. Our SOP monitoring is complementary: it catches the *process mistake* that might lead to a defect, often before the defect is even visible or testable. This is a proactive *vs.* reactive distinction. Both approaches together would be ideal – inspect the product *and* ensure the process is correct. Ensuring the process prevents many defects from ever occurring, reducing the load on final inspection. This is analogous to how in healthcare, preventing disease (via monitoring and intervention) is better than just diagnosing it later.

4.3.4 Predictive Models in Manufacturing

The use of predictive models (like our failure prediction model) is increasingly common under the umbrella of predictive maintenance and predictive quality. For example, others have applied ML models to predict machine failures or to predict yield of a lot before it finishes processing [33]. Our model specifically predicts product failures based on process deviations. This is somewhat novel because it leverages human error data in the prediction, whereas many predictive maintenance models use sensor data from machines. Our system is like an automated, data-driven FMEA: it identified a cause (SOP deviation) and showed the effect (failure), then we took action to control that cause. The difference is it was based on real data rather than theoretical assessment.

4.3.5 Scalability and Generalizability

While the pilot was on one station, the approach can be scaled to multiple stations and different product lines. MIRAI is inherently scalable as a data platform; adding more stations just means more data, which modern data processing can handle (especially with cloud or on-premise clusters). The computer vision system would need to be replicated for each station type.

This implies training new models for each station's SOP (since each has distinct actions). That is a non-trivial effort, but techniques like transfer learning and more general action recognition models can speed it up. There are also emerging no-code vision platforms that claim to allow quick setup of such monitoring. In an enterprise scenario, one could create a library of vision models for common assembly tasks and deploy them widely. The infrastructure (cameras and compute) cost is a factor, but as vision technology becomes cheaper and more ubiquitous, this becomes more viable. Furthermore, the approach is general to any manufacturing operation where humans perform critical tasks – not just electronics. One could see applications in automotive assembly, medical device manufacturing, or even warehouse operations for quality assurance. The key is identifying processes where deviations significantly impact quality. Our work provides a template: start with a pilot at a pain point, prove the value, then expand. It also shows how to integrate with existing data systems, which is often a concern (people fear new systems that don't talk to old ones). We integrated via the data lake and by aligning with MES events, demonstrating you don't have to rip-and-replace anything; you augment it.

4.3.6 Worker and Organizational Impact

It's worth discussing how this system affects the people on the factory floor. Initially, there can be apprehension that cameras watching operators could be used in a punitive way or create a "Big Brother" environment. We addressed this by focusing the feedback on process, not personal performance, and by involving operators in the improvement process (for example, showing them how eliminating a certain mistake made their job easier by reducing rework). Over time, operators saw the system as a helper – it would catch something they missed, essentially acting as a safety net. Also, with fewer failures, their work actually went more smoothly (fewer angry rework technicians coming back asking about mistakes). Training and communication are vital: we stressed that the goal was to improve the process and help them succeed, not to punish. This approach can actually elevate the role of operators: they become partners in a high-tech process and can take pride in achieving high compliance. In fact, one could gamify PROSPECT (though we did not do this) – showing metrics of improvement and recognizing teams that have zero deviations for a week, *etc*. From an organizational standpoint, this integrated system breaks down barriers between different teams: process engineers, quality engineers, data scientists, and line supervisors all had to collaborate. It fostered a more data-driven culture on the floor. Decisions to change processes were backed by data (*e.g.*, "the data shows this step is causing 80% of our failures, so we will fix it" instead of arguments based on anecdotes). This is an important cultural shift towards what some call *manufacturing intelligence*.

5 Limitations

Despite the successes, there are some limitations and challenges to address.

5.1 Model Scope

Our failure prediction model was limited by the scope of data (one station's deviations). If a failure was caused by something outside that scope (*e.g.*, a PCB defect not related to assembly), the model wouldn't catch it. Thus, it's not a panacea for all failures, only those tied to the monitored parameters. As we scale, we need to include more features to cover more failure modes.

5.2 False Alarms

As seen, there were false positives. Tuning the system to reduce unnecessary alerts without missing true issues is an ongoing effort. This involves both refining vision detection (to not log a deviation unless it's truly a deviation) and refining the predictive model. We might incorporate more context to distinguish a serious deviation from a harmless one.

5.3 Vision Challenges

The computer vision system, while robust for the pilot, can face difficulties in more complex settings. Changes in lighting, obstructions, or operator behavior variations can affect detection. Also, if the product model changes or the process changes, the vision model may need retraining. We discovered that even something like an operator wearing gloves *vs.* not wearing gloves could confuse the model initially (we then included both scenarios in training data). Maintaining and updating these models will require a dedicated effort or a user-friendly training interface. This is a general challenge in AI adoption in manufacturing – the need for updating models as processes evolve.

5.4 Data Volume and Latency

Processing video for many stations could be data intensive. We mitigated this by edge processing (only events go to the server, not full video), but in some contexts storing video might be desirable for later analysis. That raises storage and privacy questions. In our case, we did not need to store raw video long-term, just the detected event timestamps which are tiny in size. So our system is efficient in that sense.

5.5 Generality of SOP Deviations

The types of deviations and their impacts can vary widely by process. In some processes, a deviation might not have any effect (maybe a redundant step). So one must be careful not to overreact to every deviation. Our correlation phase addressed that by quantifying impact. But if someone applied such systems blindly without analysis, they might waste effort on low-impact deviations or, conversely, not realize a critical one. Thus, the combination of automated monitoring with human engineering judgement remains important.

5.6 No Internal Proprietary Tools

We consciously described everything in generic terms. In actual implementation, one might use specific software or platforms (like a specific brand of data historian or a certain AI framework). Our aim was to show the approach without tying it to a vendor. This is beneficial academically because it focuses on principles, but a real company would need to either develop or purchase the specific tools to implement it.

6 Future Work

Building on this pilot, there are several avenues for further development.

6.1 Multi-Station and End-to-End Monitoring

We plan to extend vision monitoring to multiple stations (including automated ones where a robot might perform tasks, to verify the robot did them correctly) and link deviations across the entire process. This could lead to a much more powerful predictive model that uses a sequence of events from multiple stations to predict final quality.

6.2 Advanced AI Models

The action recognition model can be made more sophisticated. For example, using deep sequence models (like an LSTM or transformer taking video frames as input) might capture deviations in subtler ways and reduce false positives. Also, anomaly detection models could be employed so the system can learn what a "normal" operation looks like and flag anything that deviates from the norm, even if not pre-defined.

6.3 Operator Guidance Systems

We are considering integrating augmented reality (AR) or real-time feedback to the operator through an interface. Currently the feedback is mostly an alert to supervisor or a light signal. If operators had, say, AR glasses or a screen highlighting what step to do next or warning them they missed something, it could guide them before a deviation becomes permanent. This would truly close the loop at the operator level – prevention rather than post-fact alert.

6.4 Expansion of MIRAI Analytics

The data collected on PROSPECT could feed other MIRAI modules. For example, a training effectiveness analysis – measuring if after training sessions the deviation rates drop (and how fast). Or feeding into a digital twin of the process that simulates how errors propagate. Also, including cost models in MIRAI to prioritize which issues to fix first based on potential savings.

6.5 Comparative Studies

We intend to benchmark this integrated approach against others. For instance, compare yield improvement purely from a data analytics approach *vs.* with the added vision data, to quantify the incremental benefit of vision. Also, measure ROI in terms of cost of equipment *vs.* savings.

6.6 Generalization to Autonomous Corrections

Ultimately, we envision a system that not only predicts failures but can autonomously correct them or adjust the process. For example, if a deviation is detected, the system might automatically adjust a downstream test to be more stringent for that unit (to ensure the defect is caught). Or if certain deviations keep happening, the system might automatically modify the SOP or machine parameters (with approval workflow) to error-proof it. This would be a step towards a self-optimizing production line.

7 Conclusion

In this paper, we presented a comprehensive approach to improving yield and predicting failures in electronics manufacturing by integrating a Manufacturing Intelligence for Reliability and Automated Insights (MIRAI) system with computer vision-based PROSPECT monitoring. Our solution spans data engineering, real-time monitoring, and machine learning, creating a closed-loop feedback system for process improvement. Through a pilot study, we demonstrated that this integration can effectively identify the root causes of yield loss (including human procedural errors), facilitate timely corrective actions, and enable proactive failure prediction to catch defects before they escape. Key contributions of this work include:

7.1 Holistic Data Integration

We showed how diverse data sources – production test data, operator action logs from vision, and failure analysis results – can be unified and utilized for advanced analytics. This holistic view provided insights that would be inaccessible to siloed analysis, highlighting the importance of integrated manufacturing intelligence in the era of Industry 4.0.

7.2 Computer Vision for SOP Compliance

We implemented a computer vision system to automatically monitor SOP compliance at an assembly station. The system achieved continuous, unbiased observation of operator practices, detecting deviations in real time. By doing so, it effectively digitized the enforcement of standard procedures. Our results confirmed that such a system can drastically reduce human error-related defects, consistent with emerging industry reports of AI improving quality assurance on the shop .

7.3 Data-Driven Yield Improvement

Using MIRAI's analytical workflows, we rapidly pinpointed factors causing yield drops and field failures. The self-serve yield analysis identified patterns in failing units, and the field analysis linked production data to reliability outcomes, providing actionable recommendations. We documented specific cases where addressing a revealed issue (*e.g.*, a particular SOP deviation or a common factor among failing units) led to a measurable increase in first-pass yield. These case studies reinforce the value of moving from reactive problem-solving to proactive, data-driven decision making in manufacturing.

7.4 Failure Prediction Model

We developed and deployed a machine learning model that predicts product failures based on signals including SOP deviations. The model's strong performance in the pilot (catching ~85% of potential failures) underscores the feasibility of predictive quality in manufacturing. Rather than waiting for a failure to occur, the line can now anticipate it and intervene. This represents a shift towards predictive manufacturing operations, where each unit's risk is continually assessed and mitigated in real time.

7.5 Generic and Scalable Framework

Although our implementation was in an electronics assembly context, we designed the framework to be generic. We avoided any reliance on proprietary tools or product-specific heuristics, focusing instead on general techniques (computer vision for action recognition, commonality analysis, supervised learning on process data). This makes our approach applicable to a wide range of manufacturing settings where improving yield and quality is critical. Whether it is circuit board assembly, automotive component production, or any process with manual operations, the core idea remains the same: instrument the process with sensors (vision), collect and analyze the data holistically, and use AI to drive continuous improvement.

7.6 Scientific and Practical Relevance

From an academic perspective, our work bridges the gap between theory and practice by applying state-of-the-art AI (deep learning vision, data mining, ML models) to a practical industrial problem, and demonstrating tangible benefits. We also provided citations to comparable approaches in literature and industry, positioning our contributions in context. For instance, our integrated predictive approach can be seen as a novel extension of both traditional quality control and newer smart factory initiatives.

The successful results of the pilot pave the way for broader deployment. In future work, we plan to scale the system to more stations and more complex assembly scenarios, further validating its robustness. We will also explore advanced modeling techniques to improve prediction and possibly automate corrective responses. Another avenue is to incorporate cost optimization – for example, dynamically deciding whether a flagged unit should be reworked or scrapped based on prediction confidence and economic factors.

The integration of MIRAI, computer vision monitoring, and PROSPECT enforcement represents a powerful strategy for electronics manufacturers seeking to achieve higher yields and near-zero defects. By ensuring that the processes are executed as intended and learning from every deviation, manufacturers can dramatically reduce variability and preempt failures. Our research demonstrates that such an approach is not only technically achievable but highly effective. It embodies a shift from reactive quality control to proactive and preventive quality assurance. The manufacturing line becomes a intelligent system: constantly observing, learning, and improving. This leads to tangible gains in efficiency, product quality, and customer satisfaction. As the manufacturing industry continues to embrace digital transformation, we expect that the methodologies outlined in this paper will inform the next generation of smart factories, where data and AI work hand in hand with human operators to drive excellence in production. Ultimately, the synergy of human expertise, advanced analytics, and real-time vision feedback can unlock new levels of performance and reliability in electronics manufacturing and beyond.

Conflicts of Interest

The authors declare that they have no conflict of interest.

References

[1] Falavina M. Maximizing First Pass Yield With AI in Manufacturing. Quality Line, 2025. https://quality-line.com

[2] Vision A. Behavior Analysis Use Case, SOP Compliance Monitoring, ADLINK. ADLINK Technology. https://www.adlinktech.com

[3] Tesfaye K, Silva JV, Nayak HS, et al. Standard Operating Procedure on Yield Gap Decomposition for Use Cases Under Excellence in Agronomy: Understanding Major Yield Drivers for Designing Interventions and Closing Yield Gaps. 2023.

[4] Mody V. Quality in high-volume electronics design: Manufacturing and deployment. Dog Ear Publishing, 2016.

[5] Kalvari N, Lotan N, Zidon M. IT@Intel: Transforming Manufacturing Yield Analysis With AI. White Paper, Intel, 2021. https://www.intel.com

[6] Saihi A, Awad M, Ben-Daya M. Quality 4.0: leveraging Industry 4.0 technologies to improve quality management practices – a systematic review. International Journal of Quality & Reliability Management. 2021, 40(2): 628-650. https://doi.org/10.1108/ijqrm-09-2021-0305

[7] Das S. Computer Vision AI in SOP Monitoring in Manufacturing, 2024. https://intelgic.com

[8] Suma KG, Patil P, Sunitha G, et al. Computer Vision and Its Intelligence in Industry 4.0. Machine Learning Techniques and Industry Applications. Published online May 3, 2024: 119-142. https://doi.org/10.4018/979-8-3693-5271-7.ch007

[9] Duffy JF, Zitting KM, Czeisler CA. The Case for Addressing Operator Fatigue. Reviews of Human Factors and Ergonomics. 2015, 10(1): 29-78. https://doi.org/10.1177/1557234x15573949

[10] IntraStage. How Correlating Failure Analysis and Manufacturing Results Can Help Prevent Future Failures, IntraStage. IntraStage, Apply Manufacturing Intelligence, 2018. https://intrastage.com

[11] Bukhari SMS, Akhtar R. Leveraging Artificial Intelligence To Revolutionize Six Sigma: Enhancing Process Optimization And Predictive Quality Control. Contemporary Journal of Social Science Review. 2024, 2(04): 1932-1948.

[12] Shah D. Leveraging Computer Vision to Tackle Safety and Quality Challenges in Manufacturing. Wevolver, 2025.
https://www.wevolver.com

[13] Gyllenberg J, Nilsson M. Deviation management in high-mix low-volume production: A case study conducted in the defense industry, 2024.

[14] Janecki L, Reh D, Arlinghaus JC. Challenges of Quality Assurance in Early Planning and Ramp Up of Production Facilities - Potentials of Planning Automation via Virtual Engineering. Procedia Computer Science. 2024, 232: 2498-2507.
https://doi.org/10.1016/j.procs.2024.02.068

[15] Doostan M, Chowdhury BH. Power distribution system fault cause analysis by using association rule mining. Electric Power Systems Research. 2017, 152: 140-147.
https://doi.org/10.1016/j.epsr.2017.07.005

[16] Della Corte R. Understanding the Error Behavior of Complex Critical Software Systems through Field Data. Diss. University of Naples Federico II, Italy, 2016.

[17] Romano G, Conti A. The role of Customer Feedback Loops in driving Continuous Innovation and Quality Improvement. National Journal of Quality, Innovation, and Business Excellence. 2024, 1(2): 30-39.

[18] Collins DH, Huzurbazar AV, Warr RL. Highly accelerated life testing (HALT): A review from a statistical perspective. WIREs Computational Statistics. 2024, 16(4).
https://doi.org/10.1002/wics.70000

[19] Chen HH, Hsu R, Yang P, et al. Predicting system-level test and in-field customer failures using data mining. 2013 IEEE International Test Conference (ITC). Published online September 2013.
https://doi.org/10.1109/test.2013.6651892

[20] Tran PH, Ahmadi Nadi A, Nguyen TH, et al. Application of Machine Learning in Statistical Process Control Charts: A Survey and Perspective. Control Charts and Machine Learning for Anomaly Detection in Manufacturing. Published online August 30, 2021: 7-42.
https://doi.org/10.1007/978-3-030-83819-5_2

[21] Cui Y, Kara S, Chan KC. Manufacturing big data ecosystem: A systematic literature review. Robotics and Computer-Integrated Manufacturing. 2020, 62: 101861.
https://doi.org/10.1016/j.rcim.2019.101861

[22] Schönfub B. How AI Is Transforming the Factory Floor. World Economic Forum, 2024.
https://www.weforum.org

[23] Gorelik A. The enterprise big data lake: Delivering the promise of big data and data science. O'Reilly Media, 2019.

[24] Granados Segura L. Enhancing Modeling and Motion Analysis for Industrial Pastry Dough Quality. MS thesis. Universitat Politècnica de Catalunya, 2024.

[25] Camp RC. Benchmarking. Published online October 1, 2024.
https://doi.org/10.4324/9781003578871

[26] Jiang Y, Yin S, Kaynak O. Performance Supervised Plant-Wide Process Monitoring in Industry 4.0: A Roadmap. IEEE Open Journal of the Industrial Electronics Society. 2021, 2: 21-35.
https://doi.org/10.1109/ojies.2020.3046044

[27] Pardo-Calvache CJ, García-Rubio FO, Piattini-Velthuis MG, et al. A 360-degree process improvement approach based on multiple models. Revista Facultad de Ingeniería Universidad de Antioquia. 2015 (77): 95-104.

[28] Qudus L. Leveraging Artificial Intelligence to Enhance Process Control and Improve Efficiency in Manufacturing Industries. International Journal of Computer Applications Technology and Research. 2025, 14(02): 18-38.

[29] Ghelani H. Advanced AI Technologies for Defect Prevention and Yield Optimization in PCB Manufacturing. International Journal of Engineering and Computer Science. 2024, 13(10): 26534-26550.
https://doi.org/10.18535/ijecs/v13i10.4924

[30] Diez-Olivan A, Del Ser J, Galar D, et al. Data fusion and machine learning for industrial prognosis: Trends and perspectives towards Industry 4.0. Information Fusion. 2019, 50: 92-111.
https://doi.org/10.1016/j.inffus.2018.10.005

[31] Paneerselvam N, Muhammad NA, Azhan AM, et al. Analyzing critical success factors in Lean Six Sigma training. International Journal of Productivity and Performance Management. 2024, 74(4): 1400-1424.
https://doi.org/10.1108/ijppm-11-2023-0627

[32] Wolniak R. The usage of Poka-Yoka in Industry 4.0 conditions. Zeszyty Naukowe. Organizacja i Zarzadzanie/Politechnika Śląska, 2024.

[33] Pinciroli Vago NO, Forbicini F, Fraternali P. Predicting Machine Failures from Multivariate Time Series: An Industrial Case Study. Machines. 2024, 12(6): 357.
https://doi.org/10.3390/machines12060357

where its governance meetings are held. There are currently no standards to guide ethical AI development and deployment, or to help consumers develop trust in AI. ISO pioneered work on standards related to ethically aligned design, this area is still in its infancy. The integration of AI enabled technologies in the daily lives of ordinary people is rapidly increasing. An appropriate standard could provide consumers with a reasonable level of comfort and assurance that AI has been developed conforming to ethical principals that protect their rights, e.g. privacy, transparency, and inclusiveness.

Standards Russia has recently formed a committee to study ethical AI and how they can map into existing international work on AI at ISO. 99 percent of people don't know how standards make modern society work. Standardization professionals, as well as those that understand the profession and its impact, are only one percent of the population. General population 99 percent expect everything to work, often with little interest in the details. They only notice when it does not work, and then it's a manufacturer or a government that are held to task when this happens (not standards).

Standards are mostly voluntary, with the ones that governments adopt become regulatory. By driving greater informed choice for consumers, there is heightened competition between developers and companies to gain market share in new areas so everything just works. Standardization in these areas will ensure that. If there is truly one percent that are aware of the impact, then this is indication of the huge responsibility that standards professionals have to benefit humanity to ensure everything works. The importance of standards to the work and careers of ICT practitioners continues to motivate the content of new innovative standardization activities to spark creativity and enthusiasm to solve safety problems. The standardization of artificial intelligence safety will help to find boundaries in which artificial intelligence will benefit humanity, not harm.

2 On the standardization of information security

Information security concerns the safety of artificial intelligence. The classic information security triad CIA is the most recognized and common in the international professional community. It was recorded in national and international standards and entered the main educational and certification programs for information security, such as CISSP and CISM.

Information security is responsible for the confidentiality, integrity and availability of information. In the concept of information security, specialists call them the principles of information security. Confidentiality means that only one who has the right to do this has access to information. The integrity means that the information is in full and does not change without the consent of the owner. Accessibility means that one who has the right to access information can get it.

Artificial intelligence specialists for information security mainly use the CIA triad. All three components: confidentiality, integrity and accessibility synonymically considered as principles, security attributes, properties, fundamental aspects, information criteria, the most important characteristics or basic structural elements. Certification, crypto protection and cybersecurity are also taken into account in the standardization of information security.

3 On international standardization of safe artificial intelligence

The coming years will take to increase safety and standardize the development and application of viable strong artificial intelligence. International standardization of the production and use of intelligent systems ensuring their compatibility has intensified.

The safety of artificial intelligence systems refers to an interdisciplinary field of research related to the prevention of accidents, their misuse and various harmful consequences that they can lead to, including technical problems, risk monitoring systems and high reliability. The security of artificial intelligence systems is necessary for smart factories, health centers, cafes, services, vehicles, agriculture, defense industry, etc.

The development of standard and criteria for the creation of systems with artificial intelligence that will be safe for humanity remains one of the urgent tasks.

The safety of the behavior of a system with artificial intelligence depends on its spatial, temporal, objective, visual and sound sensitivity within the boundaries of its use in the environment. The practical use of artificial intelligence systems in various spheres of society requires the introduction of safety standards.

Safety for artificial intelligence and ethical codes on the use of intellectual systems are developed in a wide format of directions by specialists of various companies by different countries at the international level.

(1) The standardization of safe artificial intelligence in DeepMind was carried out in 2018. The safety of artificial intelligence systems was based on specifications, reliability and guarantees [1]. Specifications - guarantee that the behavior of the artificial intelligence system corresponds to the true intentions of the operator / user. Reliability - guarantees that the artificial intelligence system will continue to work safely at interference. Guarantees - give confidence that we are able to understand and control artificial intelligence systems during work.

(2) The AI Watch study is aimed at developing artificial intelligence safety standards for systems with minimal, limited and high levels of risk.

(3) For the safety of different artificial intelligence systems in Europe, ISO/IEC standards are developed:

ISO/IEC TR 24028: Information technology and artificial intelligence. The standard gives determination of the reliability of artificial intelligence systems, including approaches to establishing trust in artificial intelligence systems due to transparency, explanability and handling; Technical risks and threats to artificial intelligence systems, methods for mitigating the consequences of risks and threats are determined; Approaches to the assessment of failure tolerance, reliability, accuracy and safety and confidentiality.

ISO/IEC WD 5338: Information technology, artificial intelligence processes of life cycle of artificial intelligence. The standard is aimed at providing processes that support, control and improve artificial intelligence systems.

ISO/IEC AWI TR 5469: Artificial intelligence functional safety and artificial intelligence systems. The standard contains a description of the properties, risk factors, methods and processes of application and control of artificial intelligence in security systems.

ISO/IEC AWI TR 24368: Information technologies, artificial intellectual approaches and social services. The standard determines the ethical and social standards of artificial intelligence.

ISO/IEC AWI TR 24372: Information technologies, artificial intelligence - computing approaches to artificial intelligence systems. The standard determines modern computing approaches to artificial intelligence systems, computing characteristics, algorithms and methods, use options according to the ISO/IEC TR 24030 standard.

ISO/IEC CD 24668: Information technology, artificial intelligence structure of process management for big data analysis. The standard describes the reference model of the big data analysis process.

ISO/IEC WD TS 4213: Information technologies, artificial intelligence, assessments of machine learning classification. The standard is aimed at determining the methodology for measuring the effectiveness of classification models, systems and machine learning algorithms.

ISO/IEC 23894: Information technology, artificial intelligence, risk management. The standard provides recommendations for risk management that organizations face during the development and application of artificial intelligence methods and systems. In addition, the standard describes the processes of effective implementation and integration of risk management of artificial intelligence, which can be used in any organization.

ISO/IEC CD 38507: Information technologies, artificial intelligence management, consequences of using artificial intelligence systems. The standard provides a guide for organizations that use or consider the possibility of using artificial intelligence systems.

ISO/IEC WD 42001: Information technologies, artificial intelligence, management system. The standard is aimed at the formation of requirements and the creation of a guide to implement, maintain and improve artificial intelligence management systems in the context of a particular organization.

IEEE P2863: Standard for organization of control systems of artificial intelligence. The standard contains management criteria as security, transparency, accountability, responsibility and minimization of bias, as well as the stages of the process for effective implementation, audit of effectiveness, training and compliance with the development or use of artificial intelligence systems in organizations.

IEEE P3333.1.3: Standard for a deep assessment of visual experience based on the human factor. The standard determines the metric of content analysis of content and evaluating the quality of visual content based on deep training. The standard includes a description of deep learning models, visual perception indicators, virtual and mixed reality, clinical analysis and psychophysical data. The standard also includes images databases.

(4) Since 2021, the Code of Ethics of Artificial Intelligence has been operating in Russia. The code establishes the general ethical principles and standards of behavior that should be guided by participants in relations in the field of artificial intelligence in their activities. Russian experts have developed standards that regulate the safety of artificial intelligence systems not only for people, but also for the environment. Standardization concerns the introduction of artificial intelligence in various fields of human activity, such as transport, medicine, education, construction and a number of others. On September 30, 2023, the Russian Association, the House of Indo-Russian Technological Cooperation (Chamber for Russian Technology Collaboration, Cirtc) and the Russian Technical Committee No. 164 of the Rosstandart of the Russian Federation signed two memorandum of cooperation intentions aimed at developing relations between Russia And India in IT oblast. One of the documents concerns the standardization of artificial intelligence, as well as the creation of a joint laboratory for certification of solutions in the field of artificial intelligence. Interaction in the standardization of artificial intelligence will apply to the participants of the BRICS+. What will help to develop and apply the standards common to the BRICS countries. The Minister of Information Technology of India Rajiv Chandrakar proposed to develop a global security standard for artificial intelligence so that intellectual systems do not harm a person and social, industrial and natural environment.

(5) In 2023, the United States, Great Britain and more than ten other countries announced the signing of an international agreement on how to protect artificial intelligence systems. The document involves the creation of AI platforms designed in such a way that they are safe from the very beginning of their development.

(6) In 2023, representatives of 28 individual countries, including the USA, EU, Canada, China, Singapore, Japan, South Korea, Israel, India and the United Arab Emirates signed an international declaration for the safe use of artificial intelligence.

(7) Case for the use of strong artificial intelligence, developed by I. Ts. Natural formatics [2–8], approved by the Japanese Technical Committee for Standardization of Artificial Intelligence, is an international standard: a.111 Application of Strong Artificial Intelligence - “ISO/IEC JTC 1/SC 42 /WG 4 No 254 TR 24030 Working DRAFT V10 ” - ISO/IEC 24030: 2019 (E). The case for the use of strong artificial intelligence contains generalized options. The standardization of the use of strong artificial intelligence ends with the developer by a specification of generalized options for each targeted use. The standard case contributes to the use of strong artificial intelligence in promising modern areas, such as: multi modal generative artificial intelligence, cooperation of intellectual digital doubles and humans, ethical artificial intelligence, quantum artificial intelligence, legitimization of artificial intelligence, intellectual chabitization, semantic emotional dialogue, and so on.

(8) The British Institute of Standards in 2024 introduced the global guide to the safety of artificial intelligence, which helps to responsibly use intellectual systems and manage them in companies around the world. The BSI standard for security eliminates key risks, ensuring the conformity of innovation to advanced experience. The standard for the safety of artificial intelligence is recommended for use in the field of services and in industry.

(9) In 2024, experts in the field of education and artificial intelligence of various countries develop international ethical standards for the use of intellectual systems for training. The standards of Japan provide for the use of generative tools of artificial intelligence in schools, from elementary grades to high school. On February 14, 2024, the National Research Institute for the Study of Generative Artificial Intelligence began to function in Japan. Japan began testing artificial intelligence systems in primary, junior and high schools. Japanese private companies have created several systems with artificial intelligence for Japanese schools. The Konica Minolta system is able to analyze students’ reaction to the material presented, can collect data on the level of concentration of students, and activity in the rise of the hands. The system from Techno Horizon is designed to analyze the emotional state of each of the students. The artificial system helps to identify which children are excited, which children are in a state of stress or bored and concentrated children. Intellectual systems monitor the performance and effectiveness of the education of schoolchildren, give recommendations to teachers in the learning process.

4 International standard – Safe application of ensemble intelligent interoperable agents

Standard application of ensemble of intelligent interoperable agents defines parameters, characteristics, methods, models of digital double , knowledge, skills, behavior, images and other entities of intelligent virtual agent interaction (Table 1–7). Intelligent virtual agent interaction uses categorical method of utility and preference [9]. Synergetic mechanisms of self-organization, such as multi-level reflection, semantic and behavioral ontology, of technological ensembles of intelligent agents are basic for standardization when using ensembles in various fields [10]. Communicative-associative intelligent ensemble of diversified agents with an intelligent interface in the form of interacting AI assistants can implement a digital intelligent clinic [11].

Table 1 General

Use standard name	Safe application of ensemble of intelligent interoperable agents			
Application domain	Hi-Tech Labor Market			
Deployment model	Human digital double			
Status	Results of research: Strong Artificial Distributed Intelligence			
Scope	Economic and technical sectors and social services			
Objective(s)	Find accurate and universal application of strong artificial distributed intelligence			
Narrative	Short description (not more than 150 words)	Ensemble is complex of intelligent interoperable agents interacting through smart interface, implementing either technological process, social services, multi-inter- trans-disciplinary research, or production cycle.		
	Complete description	Ensemble is complex of intelligent interoperable agents interacting through smart interface, implementing either technological process, social services, multi-inter- trans-disciplinary research, or production cycle. In the ensemble, the whole range of tasks by certain rules is distributed among all agents. Job allocation means assigning each agent a role whose complexity is determined by the agent's capabilities. To organize the task distribution process, the ensemble creates either a distributed problem solution system or decentralized artificial intelligence. In the first version, the process of decomposition of the global problem and the inverse process of composition of the found solutions takes place under the control center agent. At the same time, the creative ensemble is designed strictly from top to bottom, based on the roles defined for the agents and the results of dividing the global task into subtasks. In the case of decentralized artificial intelligence, task distribution occurs during agent interaction and is synergistic.		
Stakeholders	Highly technological producer			
Stakeholders' assets, values	Reputation			
System's threats and vulnerabilities	Legal and ethical aspects of interaction with society.			
Key performance indicators (KPIs)	ID	Name	Description	Reference to mentioned use case objectives
	1	AI management of professional cooperation process	The technology of processes control can itself predict execution of certain stages on the basis of accumulated information about their labour intensity, selection of the route of agents and competences. Optimize processes during their execution - automatic delegation of tasks taking into account the load of agents and their competences.	Improve accuracy
	2	Productivity and quality AI	Ensemble of intelligent interoperable agents works with fewer mistakes and is safer. Ensemble of intelligent interoperable agents improves the quality of life of man and society in daily concerns, as well as productivity in high-tech industry and production.	Improve efficiency
AI features	Task(s)	1 .Safe interaction of ensemble of intelligent interoperable agents. 2 .Building high-tech synergies of ensemble of intelligent interoperable agents..		
	Method(s)	Criterion method of utility and preference, multi-level reflection, semantic and behavioral ontology, of technological ensembles of intelligent agents.		
	Hardware	Supercomputer with Strong Artificial Distributed Intelligence		
	Topology	Distributed Modular Interconnect Topology		
	Terms and concepts used	high-tech synergies, intelligent interoperable agents, utility and preference criteria.		
Standardization opportunities/ requirements	Multimodal multisensory format			
Challenges and issues	Information security			
Societal concerns	Description	Security, ethical and legal aspects		
	SDGs to be achieved	Multi-level processing of big data by intelligent neural systems		

Table 2 Data

Description	Strong Artificial Distributed Intelligence Data
Source	Model and technology of Strong Artificial Distributed Intelligence
Type	Strong
Volume (size)	Hi-Tech Labor Market
Velocity (e.g. real time)	Supercomputering Velocity
Variety (multiple datasets)	streams of multiple datasets
Variability (rate of change)	Retraining
Quality	High

Table 3 Process scenario

N.	Scenario name	Scenario description	Triggering event	Pre-condition	Post-condition
1	Training	Train a model (deep neural network) with training data set	Technological process raw data set is ready	Formatting of data	Management of safety
2	Evaluation	Expansion of the trained model	Development of technological thinking and behaviour	Cognitive thinking patterns and psychological behaviors	Meeting KPI requirements is condition of development
3	Execution	Model and Technology Tooling	Interaction	Activization of Model	Completion of interaction
4	Retraining	Retrain a model with training data set	Certain period of time has passed since the last training/ retraining	Additional data and knowledge	Combining Data and Knowledge

Table 4 Training

Step No.	Event	Name of process/Activity	Primary actor	Description of process/activity	Requirement
1	Sample raw data set is ready	Specification and classification	Manufacturer	Transform sample raw data	Distributed AI Software
2	Completion of Step 1	Creating Set of Experimental Data	Manufacturer	Development of set of experimental data through job modelling	Software of modelling
3	Completion of Step 2	Model training	AI solution provider	Train a model (deep neural network) with experimental data set created by Step 2	Big SD

Table 5 Evaluation

Step No.	Event	Name of process/Activity	Primary actor	Description of process/activity	Requirement
1	Completion of training/retraining	Research	Manufacturer	Train model (deep neural network) with experimental data set created	Big SD
2	Completion of Step 1	Identification	AI solution provider	Based on data, detect execution using a deep neural network trained in learning scenario	Big SD
3	Completion of Step 2	Evaluation	Manufacturer	Comparison of phase 2 results with human performance	Efficiency and quality
Input of evaluation		Productivity			
Output of evaluation		Efficiency and quality			

Table 6 Execution

Step No.	Event	Name of process/Activity	Primary actor	Description of process/activity	Requirement
1	Comparison of modeling results with human performance	Research	Manufacturer	Development of a set of experimental data through job modelling	Quality
2	Completion of Step 1	Identification	Manufacturer	Based on modified data train model (deep neural network) with experimental data set created	Compatibility
Input of Execution		Modification			
Output of Execution		Compatibility			

Table 7 Retraining

Step No.	Event	Name of process/ Activity	Primary actor	Description of process/activity	Requirement
1	Certain period of time has passed since the last training/retraining	Research	Manufacturer	Additional data and knowledge	Completeness
2	Completion of Step 1	Experimental data set creation	Manufacturer	Combining Data and Knowledge Based on modified data train model (deep neural network) with experimental data set created	Compatibility
3	Completion of Step 2	Model training	AI solution provider	Comparison of phase 2 results with human performance	Efficiency and quality
Specification of retraining data		Retraining data set has to include recent data			

5 Conclusion

Currently, multi -modal generative technologies of artificial intelligence continue to effectively transform various industries [9–11]. Generative artificial intelligence is constantly improving and approaching in cognitive abilities to natural intelligence [12]. Natural intelligence builds vital activity on the basis of a productive system of rational and moral meanings approved by the practice of life. Productive meanings are active memory elements. Based on them, thinking is built in actualized situations and circumstances. Thinking is carried out on the basis of meanings of holographic memory, taking into account time and space. When researchers of artificial intelligence will be able to carry out universal standardization of modeling productive semantic thinking of natural intelligence by self -organizing intellectual systems based on rational and moral meanings of their bioinformation holographic memory, then strong artificial intelligence will become an indispensable complement of human natural intelligence [13–17].

Conflicts of interest

The author declares no conflict of interest.

References

[1] Creating a safe AI: specification, reliability, guarantee, 2018. https://habr.com/ru/articles/425387

[2] ISO/IEC JTC 1/SC 42/WG 4 Use cases and applications Convenorship: JISC (Japan). 2019-12-23. https://isotc.iso.org/livelink/livelink/open/jtc1sc42wg4

[3] Bryndin EG. Standardization of artificial intelligence. Standards and Quality. 2020, 12: 22-25.

[4] Bryndin EG. Development of behavioral and professional skills of sensitive cognitive robots as an aspect of safety. /X International Scientific Conference "IT - STANDARD 2020" - M.: Prospekt Publishing House. 2020: 303-310.

[5] Bryndin E. Standardization of Artificial Intelligence for the Development and Use of Intelligent Systems. Advances in Wireless Communications and Networks. 2020, 6(1): 1. https://doi.org/10.11648/j.awcn.20200601.11

[6] Bryndin EG. Formation of an ethical smart digital environment of industry 4.0. /XI International Scientific Conference "IT - STANDARD 2021" - M.: Prospekt Publishing House. 2022: 6-13.

[7] Bryndin E. Development of Artificial Intelligence of Ensembles of Software and Hardware Agents by Natural Intelligence on the Basis of Self-Organization. Journal of Research in Engineering and Computer Sciences.2023, 1(4): 93-105.

[8] Bryndin E. Development of Artificial Intelligence for Library Activity and Industrial and Social Robotization. Chapter of book "Application of Artificial Intelligence in Library Services". Springer. 2024.

[9] Bryndin E. Creation of multimodal digital twins with reflexive AGI multilogic and multisensory. Research on Intelligent Manufacturing and Assembly. 2024, 2(1): 85-93. https://doi.org/10.25082/rima.2023.01.005

[10] Bryndin E. Network Training by Generative AI Assistant of Personal Adaptive Ethical Semantic and Active Ontology. International Journal of Intelligent Information Systems. 2025, 14(2): 20-25. https://doi.org/10.11648/j.ijiis.20251402.11

[11] Bryndin E. Intelligent Digital Clinic of Interacting Multimodal AI Assistants. Research in Medical & Engineering Sciences. 2025, 11(4): 1237-1241.

[12] Bryndin E. Formation of reflexive generative A.I. with ethical measures of use. Research on Intelligent Manufacturing and Assembly. 2024, 3(1): 109-117. https://doi.org/10.25082/rima.2024.01.003

[13] Bryndin E. Cognitive Resonant Communication by Internal Speech Through Intelligent Bioinformation Systems. Budapest International Research in Exact Sciences (BirEx) Journal. 2023, 5(4): 223-234.

[14] Bryndin EG. Development of artificial intelligence of ensembles of software and hardware agents to natural intelligence based on self-organization. Yearbook "Greater Eurasia: Development, Security, Cooperation". 2024, 7(2): 42-49.

[15] Bryndin E. Creation of Multi-purpose Intelligent Multimodal Self-Organizing Safe Robotic Ensembles Agents with AGI and Cognitive Control. COJ Robotics & Artificial Intelligence. 2024, 3(5). https://doi.org/10.31031/cojra.2024.03.000573

[16] Bryndin E. Self-learning AI in Educational Research and Other Fields. Research on Intelligent Manufacturing and Assembly. 2025, 3(1): 129-137. https://doi.org/10.25082/rima.2024.01.005

[17] Bryndin EG. Digital Doubles with Reflexive Consciousness in Reality and Virtual Environment. Greater Eurasia: development, security, cooperation: materials of the VII international scientific and practical conference, Part 2. Moscow: Publishing house UMC. 2025: 380-384.

2 Concise Introduction of PMOO

Some properties are beneficial to an optimal option, following a “the higher, the better” principle, while others are detrimental, following a “the lower, the better” principle. Most actual alternatives embody both beneficial and detrimental properties and cannot be purely one or the other. Thus, a comprehensive, impersonal analytical approach is essential. Fortunately, PMOO meets this need for multi - attribute optimization [6,7]. In the PMOO approach [6,7], the new concept of preferable probability was developed to represent the preferable degree of the property response in the option competition comparatively and quantitatively. Furthermore, quantification of preferable probability is conducted.

It assumed that the preferable probability of a property response with the characteristic of beneficial responses in the option process is correlated to the utilization of this property response positively in linear manner [6,7], *i.e.*,

$$P_{\alpha\beta} \propto Y_{\alpha\beta}, P_{\alpha\beta} = A_\beta Y_{\alpha\beta}, \alpha = 1, 2, \ldots, r, \beta = 1, 2, \ldots, s. \tag{1}$$

In Eq. (1), $Y_{\alpha\beta}$ reflects the utilization of this property response of the β-*th* property response of the α-*th* alternative; $P_{\alpha\beta}$ is the partial preferable probability of the beneficial property response $Y_{\alpha\beta}$; r is the total number of alternatives in the option group involved; *s* is the total number of property responses of each alternative in the group; A_β is the normalized factor of the β-*th* property response.

Moreover, it obtained [6,7],

$$\sum_{\alpha=1}^{r} A_\beta Y_{\alpha\beta} = \sum_{\alpha=1}^{r} P_{\alpha\beta} = 1,\ A_\beta = 1/(n\overline{Y_\beta}) \tag{2}$$

$\overline{Y}_\beta$ is the average value of the utilization of the β-*th* property response in the alternative group involved.

Analogically, partial preferable probability of the unbeneficial property response $Y_{\alpha\beta}$ of the alternative is correlated to its utilization of this property response negatively in linear manner, *i.e.*,

$$P_{\alpha\beta} \propto (Y_{\beta\max}+Y_{\beta\min}-Y_{\alpha\beta}),\ P_{\alpha\beta} = B_\beta(Y_{\beta\max}+Y_{\beta\min}-Y_{\alpha\beta}),\ \alpha = 1, 2, ..., r,\ \beta = 1, 2, ..., s. \tag{3}$$

In Eq. (3), $Y_\beta max$ and $Y_\beta min$ indicate the maximum and minimum values of the utilization of the property response Y_β in the alternative group, respectively; B_β is the normalized factor of the β-*th* property response. Correspondingly, it obtained [6,7],

$$B_\beta = 1/[r(Y_{\beta\max} + Y_{\beta\min}) - r\overline{Y_\beta}] \tag{4}$$

Subsequently, the total / comprehensive preferable probability of the α-*th* alternative to is the product of its all possible partial preferable probability $P_{\alpha\beta}$ of each property responses, *i.e.*,

$$P_\alpha = P_{\alpha 1} \cdot P_{\alpha 2} \cdots P_{\alpha s} = \prod_{\beta=1}^{s} P_{\alpha\beta} \tag{5}$$

Finally, the total preferable probability P_α of the $\alpha - th$ alternative is the decisive indicator for the option to conduct the competition comparatively, the winner / victor is with the maximum total preferable probability.

As the weighting factor w_β is considered, Eq. (5) is alternatively modified as [6,7],

$$P_\alpha = {P_{\alpha 1}}^{w_1} \cdot {P_{\alpha 2}}^{w_2} \cdots {P_{\alpha m}}^{w_s} = \prod_{\beta=1}^{s} {P_{\alpha\beta}}^{w_\beta} \tag{6}$$

Impersonally, the weighting factor w_β could be assessed by Eq. (7) [6,7],

$$w_\beta = \frac{C_\beta}{\left(\sum_{\beta=1}^{s} C_\beta\right)},\ C_\beta = \left\{ \frac{\left[\sum_{\alpha=1}^{r} \left(P_{\alpha\beta} - \frac{1}{r}\right)^2\right]}{r} \right\}^{0.5} \tag{7}$$

Eq. (7) indicates that the bigger the variation of the partial preferable probabilities of the β-*th* property response from alternative to alternative the bigger the weighting factor w_β is.

It is sure, in some cases the weighting factors are decided artificially by according to subjective preference of evaluators or experts. In addition, the probabilistic robust design of production process and product was developed [8].

3 Utilization of the PMOO in Material Selection of Gear Manufacture

Milani et al. once proposed a problem of material option for gear manufacture [9–12]. Material selection for gear manufacture is a typical optimal option problem with multiple property responses conflicting each other. In the study of Milani et al. [9–12], there were nine materials as the alternatives for the gear manufacture, *i.e.*, ductile iron, cast iron, SG iron, through hardened alloy steel, cast alloy steel, surface hardened alloy steel, nitride steel, through hardened carbon steel and carburized steel, which are coded by S_α (α = 1, 2, . . . , 9) . The property responses of those nine alternative materials was evaluated with respect to five selection criteria, *i.e.*, core hardness (C), surface hardness (S), surface fatigue limit (F), bending fatigue limit (B), and ultimate tensile strength (U). Among these five criteria, the responses of S, F, B, and U are in beneficial type, while response of C is in unbeneficial type in the preference assessment of the option.

Table 1 displays the property responses of the alternatives in the gear manufacture. The alternatives shown in Table 1 form an alternative group for the option. Table 2 gives the assessed results of the partial probabilities of the property responses of alternative materials for the gear manufacture. Table 3 represents the assessed results of the impersonal weighting factors of the property responses of alternative materials for the gear manufacture. The final evaluated results of the total preferable probabilities and ranking are given in Table 4.

Table 1 Property responses of alternative materials for the gear manufacture [9–12]

Material \ Property	C (Bhn)	S (Bhn)	F (N/mm^2)	B (N/mm^2)	U (N/mm^2)
Ductile iron (S_1)	220	220	460	360	880
Cast iron (S_2)	200	200	330	100	380
SG iron (S_3)	240	240	550	340	845
Through hardened alloy steel (S_4)	270	270	670	540	1190
Cast alloy steel (S_5)	270	270	630	435	590
Surface hardened alloy steel (S_6)	240	585	1160	680	1580
Nitride steel (S_7)	315	750	1250	760	1250
Through hardened carbon steel (S_8)	185	185	500	430	635
Carburized steel (S_9)	315	700	1500	920	2300

Table 2 Partial probability of the property responses of alternative materials for the gear manufacture

Material \ Probability	P_C	P_S	P_F	P_B	P_U
S_1	0.1277	0.0643	0.0652	0.0789	0.0912
S_2	0.1386	0.0585	0.0468	0.0219	0.0394
S_3	0.1168	0.0702	0.0780	0.0745	0.0876
S_4	0.1005	0.0789	0.0950	0.1183	0.1233
S_5	0.1005	0.0789	0.0894	0.0953	0.0611
S_6	0.1168	0.1711	0.1645	0.1490	0.1637
S_7	0.0761	0.2193	0.1773	0.1665	0.1295
S_8	0.1467	0.0541	0.0709	0.0942	0.0658
S_9	0.0761	0.2047	0.2128	0.2015	0.2383

Table 3 Weighting factors of the property responses of alternative materials for the gear manufacture

Property	C	S	F	B	U
Weighting factor, w_j	0.0943	0.2520	0.2192	0.2040	0.2304

Table 4 Assessed results of the total preferable probabilities and ranking of alternative materials for the gear manufacture

Alternative material	Total preferable probability	Ranking
S_1	0.0778	7
S_2	0.0451	9
S_3	0.0803	6
S_4	0.1012	4
S_5	0.0813	5
S_6	0.1575	3
S_7	0.1586	2
S_8	0.0739	8
S_9	0.1941	1

The last column of Table 4 shows that the comparative consequence shows clearly that alternative S_9, *i.e.*, carburized steel,exhibitsthe maximum value of total preferable probability, so the optimal option in material selection for gear manufacture is carburized steel by means of PMOO.

4 Conclusion

As discussed, PMOO offers a comprehensive method to account for all possible material property responses when optimally selecting gear manufacturing materials. Five criteria are considered, and the total preferable probability determines the final material choice. After detailed quantitative evaluation, carburized steel emerges as the optimal material due to its maximum total preferable probability.

Conflicts of interest

The authors declare that they have no conflict of interest.

References

[1] Farag MM. Quantitative Methods of Materials Selection. Handbook of Materials Selection. Published online July 12, 2002: 1-24.
https://doi.org/10.1002/9780470172551.ch1

[2] Ashby MF, Cebon D. Materials selection in mechanical design. Le Journal de Physique IV, 1993, 3(C7): C7-1-C7-9.

[3] Ashby MF. Materials Selection in Mechanical Design, 4th ed., Butterworth – Heinemann, Exeter, 2010.

[4] Dieter GE. Overview of the Materials Selection Process. Materials Selection and Design. Published online January 1, 1997: 243-254.
https://doi.org/10.31399/asm.hb.v20.a0002450

[5] Maleque MA, Salit MS. Materials Selection and Design. Springer Singapore, 2013.
https://doi.org/10.1007/978-981-4560-38-2

[6] Zheng M, Yu J, Teng H, et al. Fundamental Principle of Probability-Based Multi-objective Optimization and Applications. Probability-Based Multi-objective Optimization for Material Selection. Published online August 25, 2023: 23-45.
https://doi.org/10.1007/978-981-99-3939-8_3

[7] Zheng M, Yu J. Brief Description of Probabilistic Multi-objective Optimization of a System. Systems Theory for Engineering Practice. Published online 2024: 77-110.
https://doi.org/10.1007/978-981-97-9342-6_6

[8] Zheng M, Yu J. Correction to: Robust Design and Assessment of Product and Production by Means of Probabilistic Multi-objective Optimization. Robust Design and Assessment of Product and Production by Means of Probabilistic Multi-objective Optimization. Published online 2024: C1-C1.
https://doi.org/10.1007/978-981-97-2661-5_9

[9] Milani AS, Shanian A, Madoliat R, et al. The effect of normalization norms in multiple attribute decision making models: a case study in gear material selection. Structural and Multidisciplinary Optimization. 2004, 29(4): 312-318.
https://doi.org/10.1007/s00158-004-0473-1

[10] Tran DV. Application of the Collaborative Unbiased Rank List Integration Method to Select the Materials. Applied Engineering Letters: Journal of Engineering and Applied Sciences. 2022, 7(4):

133-142.
https://doi.org/10.18485/aeletters.2022.7.4.1

[11] Chatterjee P, Chakraborty S. Material selection using preferential ranking methods. Materials & Design. 2012, 35: 384-393.
https://doi.org/10.1016/j.matdes.2011.09.027

[12] Chatterjee P, Banerjee A, Mondal S, et al. Development of a hybrid meta-model for material selection using design of experiments and EDAS method. Engineering Transactions, 2018, 66(2): 187–207.

research. In this study, we extend the application of the periodic pulse method to recurrent neural networks with a sinusoidal activation function. This function, which has been less studied, possesses unique properties, particularly regarding its natural periodicity and its ability to generate complex bifurcations. This raises the following question: Can the periodic pulse method be used to suppress chaos in recurrent neural networks with sinusoidal activation?

Our primary objective is to demonstrate the feasibility of chaos control in this type of network, thereby expanding existing methods to accommodate more diverse dynamical systems. This work aims to fill a gap in the literature and open new perspectives for studying chaotic behaviors in complex neural networks.

To address this question, we proceed in two phases: first, we analyze a network with two neurons, followed by a three-neuron configuration. Both systems will be subjected to the periodic pulse method, and we will demonstrate that this approach remains valid for sinusoidal activation functions under the chosen configurations.

2 Materials and methods

2.1 Network Configuration

Provide all of the methodological details necessary for other scientists to duplicate your work.

In this study, we consider two recurrent neural networks. The first network consists of two interconnected recurrent neuromodules. The system is governed by the following set of equations:

$$\begin{cases} x_{n+1} = 1 + w_{11} sin\left(x_n\right) + w_{12} sin\left(y_n\right) \\ y_{n+1} = 1 + w_{21} sin\left(x_n\right) + w_{11} sin\left(y_n\right) \end{cases} \tag{1}$$

The schematic representation of this first network is as follows (Figure 1):

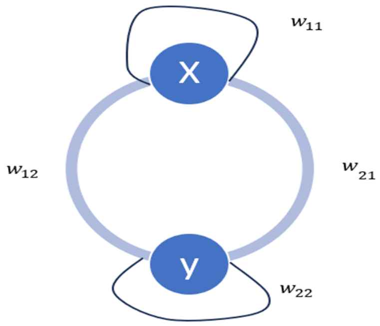

Figure 1 Two-Neuron Recurrent Network

The second network consists of three recurrently connected neurons. Its dynamics are described by the following equations:

$$\begin{aligned} x_{n+1} &= 1 + w_{11} sin\left(x_n\right) + w_{12} sin\left(y_n\right) + w_{13} sin\left(z_n\right) \\ y_{n+1} &= 1 + w_{21} sin\left(x_n\right) + w_{22} sin\left(y_n\right) + w_{23} sin\left(z_n\right) \\ z_{n+1} &= 1 + w_{31} sin\left(x_n\right) + w_{32} sin\left(y_n\right) + w_{33} sin\left(z_n\right) \end{aligned} \tag{2}$$

A schematic representation of this network is provided in Figure 2.

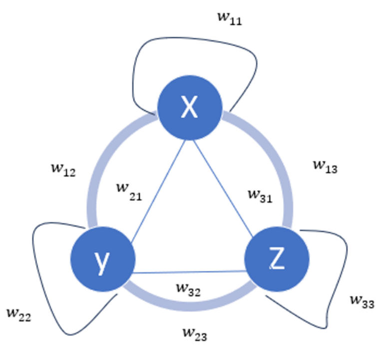

Figure 2 Three-Neuron Recurrent Network

2.1.1 Definition of Variables and Parameters

The symbols used in both networks are defined as follows:
(1) W_{ii}: Self-connection weight of neuron i.
(2) w_{ij}: Connection weight between the output of neuron i and the input of neuron j.
(3) x_n, y_n, z_n: Neuron activities at iteration n.
(4) Φ: Activation function (transfer function), which processes the input signal and transitions the neuron from state n to state n+1.
(5) b_i: Bias terms, used to modulate the net input to the activation function of neuron i.

2.1.2 Approach to apply the periodic pulse method

For each network, we follow a systematic approach to apply the periodic pulse method:
(1) Compute the composite functions and derive the Jacobian matrix of the system.
(2) Determine the characteristic polynomial for each Jacobian matrix and evaluate its eigenvalues.
(3) Identify the equilibrium point around which linearization is performed.
(4) Compute the constants required to apply the periodic pulse control.
(5) Validate the method through numerical simulations using MATLAB.

To simplify the analysis, we assume that all connection weights are set to 1, except for the diagonal terms w_{11}, w_{22} and w_{33}. It is possible to demonstrate that for values $w_{11} = w_{22} = w_{33} = 2.5$, the system exhibits chaotic behaviour. Table 1 summarizes the chosen values of parameters:

Table 1 Summary of Parameter Values

Parameters	b_i	w_{11}	w_{12}	w_{13}	w_{21}	w_{22}	w_{23}	w_{31}	w_{32}	w_{33}
Value	1	2.5	1	1	1	2.5	1	1	1	2.5

2.2 Mechanism of Periodic Pulse Method

In a chaotic state, the system's attractor consists of aperiodic orbits with unstable equilibrium points. However, at the bifurcation point, a small variation in the dynamic parameter w_{11} can cause the system to transition from an unstable equilibrium to a stable one. This means that near an unstable equilibrium, there exists a stable equilibrium point. When these two points are sufficiently close, a linear approximation of the dynamical system can be performed around the unstable equilibrium.

Thus, when the orbit enters the neighborhood of an unstable equilibrium point, we apply periodic pulses to push the system towards the stable equilibrium, thereby suppressing chaos. These periodic pulses involve modifying the dynamic equation such that at each iteration n, the variable x_i becomes kx_i. The control constant k is computed to ensure the system stabilizes.

We define Phase 1 as the application of periodic pulses in the two-neuron network and Phase 2 as its application in the three-neuron network. The challenge lies in determining the appropriate constant *k* for stabilization.

2.3 Hypothesis of the study

We set this hypothesis: periodic pulses can be applied successfully to suppress chaos in the neural network we consider in this study.

3 Results

3.1 Phase 1: Network with two Neuromodules

3.1.1 Composite Function Determination

We start from Equation (1) and consider a two-dimensional system. To achieve chaos suppression, we perform a linearization in the vicinity of a fixed point while activating periodic pulses. These pulses are obtained through the use of composite functions.

$$\begin{cases} F_\mu{}^p = kx_{n+1} = k\left(1 + w_{11}sin\left(x_n\right) + w_{12}sin\left(y_n\right)\right) = kf_\mu{}^p \\ G_\mu{}^p = ky_{n+1} = k\left(1 + w_{21}sin\left(x_n\right) + w_{11}sin\left(y_n\right)\right) = kg_\mu{}^p \end{cases} \tag{3}$$

To determine the equilibrium points, we solve:

$$\begin{cases} F_\mu{}^p = kx_{n+1} = k_1\left(1 + w_{11}sin\left(x_n\right) + w_{12}sin\left(y_n\right)\right) = k_1 f_\mu{}^p = x_s \\ G_\mu{}^p = ky_{n+1} = k_2\left(1 + w_{21}sin\left(x_n\right) + w_{11}sin\left(y_n\right)\right) = k_2 g_\mu{}^p = y_s \end{cases} \tag{4}$$

3.1.2 Characteristic Polynomial Calculation of the Jacobian with Composite Functions

To analyze the stability of the equilibrium point *S*, we first compute the Jacobian matrix of the system.

$$J = \begin{pmatrix} \frac{dF_\mu{}^p}{dx} & \frac{dF_\mu{}^p}{dy} \\ \frac{dG_\mu{}^p}{dx} & \frac{dG_\mu{}^p}{dy} \end{pmatrix} \tag{5}$$

$$J = \begin{pmatrix} k_1(w_{11}\cos(x)) & k_1 w_{12}\cos(y) \\ k_2(w_{21}\cos(x)) & k_2 w_{11}\cos(y) \end{pmatrix} \tag{6}$$

The fixed point *S* is stable if and only if the eigenvalues of the Jacobian matrix *J* at equilibrium satisfy the condition:

$$|\lambda| < 1,\ \forall\lambda \,\epsilon\, Spec(J)$$

where Spec(*J*) denotes the set of eigenvalues of the Jacobian matrix. To verify this, we establish the characteristic polynomial of the system (6).

$$J - \lambda I = \begin{pmatrix} k_1(w_{11}\cos(x)) & k_1 w_{12}\cos(y) \\ k_2(w_{21}\cos(x)) & k_2 w_{11}\cos(y) \end{pmatrix} - \lambda \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \tag{7}$$

$$J - \lambda I = \begin{pmatrix} k_1 w_{11}\cos(x) - \lambda & k_1 w_{12}\cos(y) \\ k_2 w_{21}\cos(x) & k_2 w_{11}\cos(y) - \lambda \end{pmatrix} \tag{8}$$

$$\det \begin{vmatrix} k_1(w_{11}\cos(x)) - \lambda & k_1 w_{12}\cos(y) \\ k_2(w_{21}\cos(x)) & k_2 w_{11}\cos(y) - \lambda \end{vmatrix} \tag{9}$$

$$det\,|J - \lambda I| = \left[k_1(w_{11}\cos(x)) - \lambda\right]\left[\,k_2 w_{11}\cos(y) - \lambda\right] - \left[k_2(w_{21}\cos(x))\right]\left[k_1 w_{12}\cos(y)\right] \tag{10}$$

3.1.3 Determination of the Eigenvalue of the Jacobian with Composite Functions

The characteristic polynomial is given by:

$$\lambda^2 - \lambda w_{11}\left(k_1\cos(x) + k_2\cos(y)\right) + k_1 k_2\cos(x)\cos(y)\left({w_{11}}^2 - 1\right) = 0 \tag{11}$$

Since this is a second-degree polynomial, it takes the general form:

$$\lambda^2 - S\lambda + P = 0 \tag{12}$$

$$S = \lambda_1 + \lambda_2 = w_{11}\left(k_1\cos(x) + k_2\cos(y)\right) \tag{13}$$

$$P = \lambda_1\lambda_2 = k_1 k_2\cos(x)\cos(y)\left({w_{11}}^2 - 1\right) \tag{14}$$

Where *S* is the sum of the roots and P is the product of the roots.

To ensure the stability of the equilibrium point, the roots of this polynomial must satisfy the stability condition:

$$P = \lambda_1\lambda_2 = 1 = k_1 k_2\cos(x_s)\cos(y_s)\left({w_{11}}^2 - 1\right) \tag{15}$$

For $\lambda_1 = 1$

$$1 + \lambda_2 = w_{11}\left(k_1\cos(x) + k_2\cos(y)\right) \tag{16}$$

$$\lambda_2 = w_{11}\left(k_1\cos(x) + k_2\cos(y)\right) - 1 \tag{17}$$

From $\lambda_1\lambda_2 = 1$, we get $\lambda_2 = 1$

Hence

$$w_{11}\left(k_1\cos(x) + k_2\cos(y)\right) - 1 = 1 \tag{18}$$

$$w_{11}\left(k_1\cos(x) + k_2\cos(y)\right) = 2 \tag{19}$$

For $\lambda_1 = -1$

$$-1 + \lambda_2 = w_{11}\left(k_1\cos(x) + k_2\cos(y)\right) \tag{20}$$

$$\lambda_2 = w_{11}\left(k_1\cos(x) + k_2\cos(y)\right) + 1 \tag{21}$$

From $\lambda_1\lambda_2 = 1$, for $\lambda_1 = -1$ and $\lambda_2 = -1$

$$w_{11}\left(k_1 \cos\left(x\right) + k_2 \cos\left(y\right)\right) + 1 = -1 \tag{22}$$

$$w_{11}\left(k_1 \cos\left(x\right) + k_2 \cos\left(y\right)\right) = -2 \tag{23}$$

We obtain the system of equations below:

$$\begin{cases} w_{11}\left(k_1 \cos\left(x\right) + k_2 \cos\left(y\right)\right) = 2 \\ w_{11}\left(k_1 \cos\left(x\right) + k_2 \cos\left(y\right)\right) = -2 \end{cases} \tag{24}$$

3.1.4 Determination of the Stable Equilibrium Point

By summing the equations component-wise, we obtain:

$$k_1 \cos\left(x\right) + k_2 \cos\left(y\right) = 0 \tag{25}$$

where

$$k_1 = \frac{x}{1 + w_{11}\sin(x) + \sin(y)} \tag{26}$$

$$k_2 = \frac{y}{1 + \sin(x) + w_{11}\sin(y)} \tag{27}$$

So,

$$\frac{x}{1 + w_{11}\sin(x) + \sin(y)}\cos(x) + \frac{y}{1 + \sin(x) + w_{11}\sin(y)}\cos(y) = 0 \tag{28}$$

To find an equilibrium point, we arbitrarily select a value for x, for example, $x = 0.707$; and use the previous equation to compute the corresponding y-coordinate fixed point. We set $w_{11} = 2.5$.

Thus, performing computation with MATLAB we get y = -0.24337930159230491102888010857573.

3.1.5 Determination of k_1 and k_2

We compute k_1 and k_2 from (27) and (28):

$$k_1 = 0.29669659413876659687846296044988$$

$$k_2 = -0.23243254495795542107635678069618$$

3.1.6 Verification Through Simulation

For graphical verification (Figure 3), we plot the time series of $r^2 = x^2 + y^2$.

a) b)

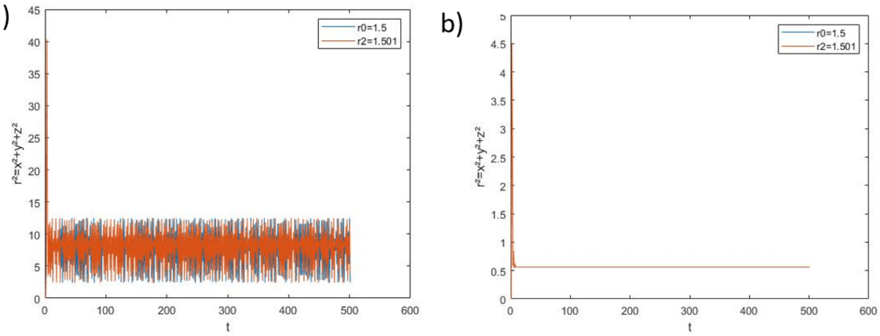

Figure 3 Graphical Results. a) Time series for $w_{11} = 2.5$ without chaos control; b) Time series for $w_{11} = 2.5$ with application of chaos control around S(0.707; -0.243).

3.1.7 Discussion

We tested the periodic pulse method on a 2- and 3-neuron recurrent neural network with a sine activation function. The aim was to assess whether this approach could eliminate the chaos observed in the system dynamics. We see that the hypothesis of applicability of the periodic pulse method in these cases is corroborated, as it is for Lynch's one-dimensional case [12].

Unlike the work of Pasemann (2002), which focused on sigmoid activation functions, our study shows that the periodic pulse method remains effective even for sine functions. This extension opens up new perspectives for chaos control in RNNs.

Our results show that chaos control is possible for a small neural network (2-3 neuromodules). However, the effectiveness of the method on more complex architectures (deep RNNs, LSTMs) remains to be studied. These results suggest that the periodic pulse method could be applied to biological neural networks. A next step would be to test this approach on cortical or deep learning network models.

The figures below have been drawn up to extend the validity of the method for other dynamic parameters. In Figure 4, $w_{11} = 13$ and in Figure 5, $w_{11} = 25$. As in Figure 3, we can see that the chaos has been eliminated after applying the periodic pulse method.

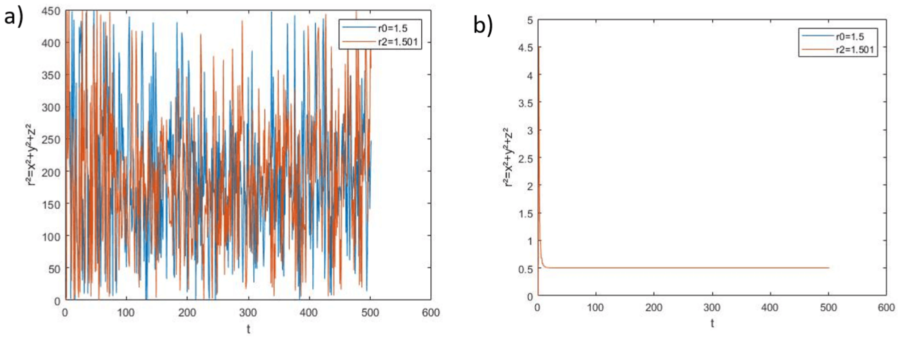

Figure 4 Graphical Results. a) Time series for $w_{11} = 13$ without chaos control; b) Time series for $w_{11} = 13$ with application of chaos control around S(0.707; -0.054196642641738518528850723480142). $k_1 = 0.0753$ and $k_2 = -0.0573$.

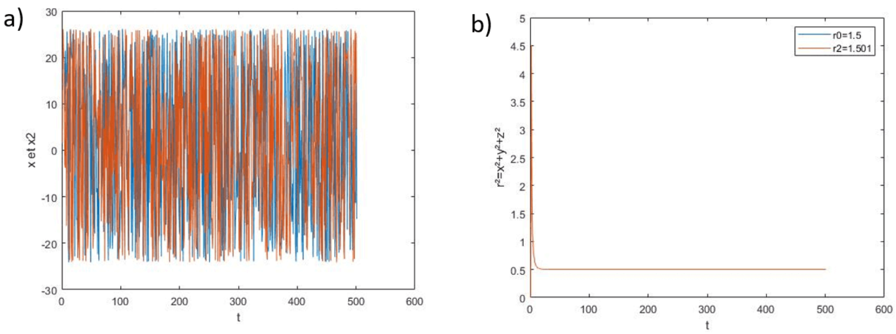

Figure 5 Graphical Results. a) Time series for $w_{11} = 25$ without chaos control; b) Time series for $w_{11} = 25$ with application of chaos control around S(0.707; -0.054196642641738518528850723480142). $k_1 = 0.0753$ and $k_2 = -0.0573$.

3.2 Phase 2: Network with three Neuromodules

3.2.1 Composite Function Determination

We use the method of periodic pulses.

$$\begin{cases} F_{w_{11}}{}^{p} = k_1 x_{n+1} = k_1(1 + w_{11} sin\,(x_n) + w_{12} sin\,(y_n) + w_{13} sin\,(z_n)) \\ G_{w_{11}}{}^{p} = k_2 y_{n+1} = k_2(1 + w_{21} sin\,(x_n) + w_{22} sin\,(y_n) + w_{23} sin\,(z_n)) \\ H_{w_{11}}{}^{p} = k_3 z_{n+1} = k_3(1 + w_{31} sin\,(x_n) + w_{32} sin\,(y_n) + w_{33} sin\,(z_n)) \end{cases} \tag{29}$$

With $w_{12} = w_{13} = w_{21} = w_{23} = w_{31} = w_{32} = 1$ and $w_{11} = w_{22} = w_{33}$, Let S be an equilibrium point, denoted as $S(x, y, z)$. At this equilibrium point:

$$\begin{cases} x = k_1(1 + w_{11} sin\,(x) + sin\,(y) + sin\,(z)) \\ y = k_2(1 + sin\,(x) + w_{11} sin\,(y) + sin\,(z)) \\ z = k_3(1 + sin\,(x) + sin\,(y) + w_{11} sin\,(z)) \end{cases} \tag{30}$$

3.2.2 Characteristic Polynomial Calculation of the Jacobian with Composite Functions

To analyze the stability of the equilibrium point *S*, we first compute the Jacobian matrix of the system.

$$J = \begin{pmatrix} k_1 w_{11}\cos(x) & k_1\cos(y) & k_1\cos(z) \\ k_2\cos(x) & k_2 w_{11}\cos(y) & k_2\cos(z) \\ k_3\cos(x) & k_3\cos(y) & k_3 w_{11}\cos(z) \end{pmatrix} \tag{31}$$

And then the characteristic polynomial:

$$J-\lambda I = \begin{pmatrix} k_1 w_{11}\cos(x)-\lambda & k_1\cos(y) & k_1\cos(z) \\ k_2\cos(x) & k_2 w_{11}\cos(y)-\lambda & k_2\cos(z) \\ k_3\cos(x) & k_3\cos(y) & k_3 w_{11}\cos(z)-\lambda \end{pmatrix} \tag{32}$$

$$\det\begin{vmatrix} k_1 w_{11}\cos(x)-\lambda & k_1\cos(y) & k_1\cos(z) \\ k_2\cos(x) & k_2 w_{11}\cos(y)-\lambda & k_2\cos(z) \\ k_3\cos(x) & k_3\cos(y) & k_3 w_{11}\cos(z)-\lambda \end{vmatrix} \tag{33}$$

By computing the determinant, we obtain the characteristic polynomial :

$$a_3\lambda^3 + a_2\lambda^2 + a_1\lambda + a_o = 0 \tag{34}$$

Where

$$a_3 = -1 \tag{35}$$

$$a_2 = k_1 w_{11}\cos(x) + k_2 w_{11}\cos(y) + k_3 w_{11}\cos(z) \tag{36}$$

$$\begin{aligned} a_1 = & -k_1k_2{w_{11}}^2\cos(x)\cos(y) - k_1k_3{w_{11}}^2\cos(x)\cos(z) - k_2k_3{w_{11}}^2\cos(y)\cos(z) \\ & + k_1k_2\cos(x)\cos(y) + k_1k_3\cos(x)\cos(z) + k_2k_3\cos(y)\cos(z) \end{aligned} \tag{37}$$

$$\begin{aligned} a_o = & k_1k_2k_3{w_{11}}^3\cos(x)\cos(y)\cos(z) - k_1k_2k_3{w_{11}}^3\cos(x)\cos(y)\cos(z) \\ & + k_1k_2k_3\cos(x)\cos(y)\cos(z) + k_1k_2k_3\cos(x)\cos(y)\cos(z) \\ & - k_1k_2k_3{w_{11}}^3\cos(x)\cos(y)\cos(z) \end{aligned} \tag{38}$$

3.2.3 Determination of the Eigenvalues of the Jacobian with Composite Functions

Since this is a third-degree polynomial, it satisfies the next formula:

$$\prod_{i=1}^{n}\lambda_i = (-1)^n\frac{a_o}{a_n} \tag{39}$$

$$\sum_{i=1}^{n}\lambda_i = -\frac{a_{n-1}}{a_n} \tag{40}$$

$$\sum_{i=1}^{n}\sum_{j>i}^{n}\lambda_i\lambda_j = \frac{a_{n-2}}{a_n} \tag{41}$$

So that we get the following equations:

$$\lambda_1\lambda_2\lambda_3 = -\frac{a_o}{a_3} \tag{42}$$

$$\lambda_1+\lambda_2+\lambda_3 = -\frac{a_2}{a_3} \tag{43}$$

The equilibrium point S is stable if , $\lambda_1\lambda_2\lambda_3 = 1$, $\lambda_2 = \pm 1$ and $\lambda_1 = \pm 1$

Let us take first $\lambda_1 = +1, \lambda_2 = +1, \lambda_3 = -\frac{a_o}{a_3} = 1, 1+1+\lambda_3 = -\frac{a_2}{a_3}$, and $\lambda_3 = -\frac{a_2}{a_3} - 2$

Hence

$$-\frac{a_2}{a_3} - 2 = 1$$

$$-\frac{a_2}{a_3} = 3$$

For $\lambda_1 = -1$ and $\lambda_2 = +1$

$$-1+1+\lambda_3 = -\frac{a_2}{a_3}$$

$$\lambda_3 = -\frac{a_2}{a_3} = \frac{a_o}{a_3}$$

For $\lambda_1 = -1$ and $\lambda_2 = -1$

$$\begin{aligned} -1 - 1 + \lambda_3 &= -\frac{a_2}{a_3} \\ \lambda_3 &= -\frac{a_2}{a_3} + 2 = 1 \end{aligned} \tag{44}$$

Thus, we have the following equations:

$$\begin{cases} -\frac{a_2}{a_3} = 3 \\ -\frac{a_2}{a_3} = -1 \\ -\frac{a_2}{a_3} - \frac{a_o}{a_3} = 0 \end{cases} \tag{45}$$

By summing the equations component-wise, we obtain:

$$-3\frac{a_2}{a_3} - \frac{a_o}{a_3} = 2$$

$$3a_2 + a_o = 2$$

$$\begin{aligned} &3k_1 w_{11}\cos(x) + 3k_2 w_{11}\cos(y) + 3k_3 w_{11}\cos(z) \\ &\quad + k_1 k_2 k_3 \cos(x)\cos(y)\cos(z)\left[-2w_{11}^2 + 2 + w_{11}^3\right] = 2 \end{aligned} \tag{46}$$

3.2.4 Determination of the stable equilibrium point

Since

$$k_1 = \frac{x}{1 + w_{11}\sin(x) + \sin(y) + \sin(z)} \tag{47}$$

$$k_2 = \frac{y}{1 + \sin(x) + w_{11}\sin(y) + \sin(z)} \tag{48}$$

$$k_3 = \frac{z}{1 + \sin(x) + \sin(y) + w_{11}\sin(z)} \tag{49}$$

We replace k_1, k_2, k_3 in equation (33). Let us take a case where chaos occurs, say $w_{11} = 2.5$. We set for S:

$$x = 0,707$$

$$y = -0,5$$

The numerical computation in MATLAB yields z = -4.2566476538172217322579451311 198. By calculating the eigenvalues of the Jacobian matrix at this point, we observe that one of the eigenvalues has an absolute value greater than one, indicating instability. Thus, adjustments were necessary to obtain $z = 1$ ensuring that all eigenvalues of the Jacobian have their absolute values less than one.

3.2.5 Determination of k_1, k_2, and k_3

For the stable equilibrium point, we obtain: S (0.707; -0.5; 1). From this, we compute the values of $k_1,\ k_2$, and k_3 from (47), (48) and (49).

$$k_1 = 0.2368$$

$$k_2 = -0.3869$$

$$k_3 = 0.3055$$

3.2.6 Verification Through Simulation

In order to verify if we can suppress chaos by using the values of $k_1,\ k_2$, and k_3, we plot $r^2 = x^2 + y^2 + z^2$ with respect to time t. We first plot the chaotic time series, followed by the time series after applying control. (see in Figure 6)

It is possible to extend these results to other values of w_{11}. Let's choose the values, $w_{11} = 31$ in Figure 7 and $w_{11} = 42$ in Figure 8.

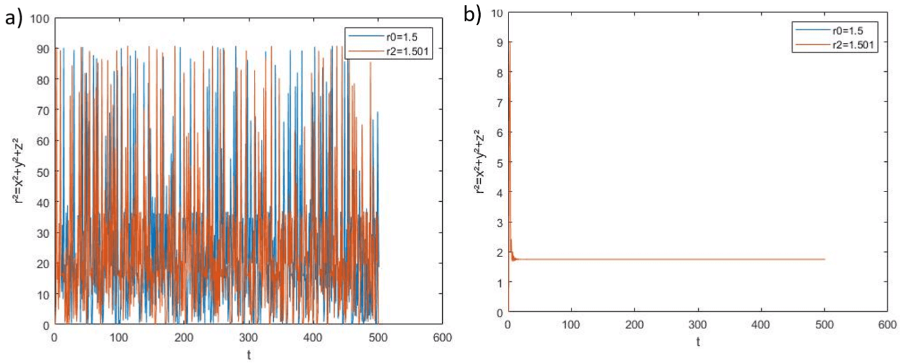

Figure 6 Graphical Results. a) Time series for $w_{11} = 2.5$ without chaos control; b) Time series for $w_{11} = 2.5$ with application of chaos control around S(0.707; -0.5; 1) $k_1 = 0.0753$ and $k_2 = -0.0573$

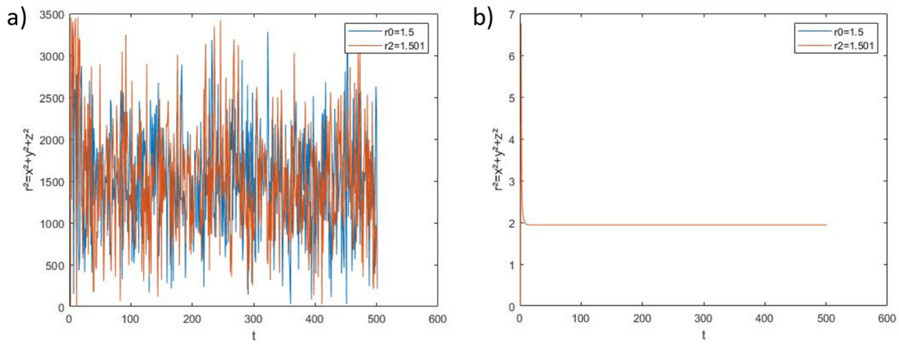

Figure 7 Graphical Results. a) Time series for $w_{11} = 31$ without chaos control; b) Time series for $w_{11} = 31$ with application of chaos control around S (0.707; -0.5; -2), the calculation starting from equation (46) gives z = -0,018046814175434846147917915841444; $k_1 = 0.0358$ and $k_2 = 0.0354$, k_3 = 0.00066795299614641154126879308113711

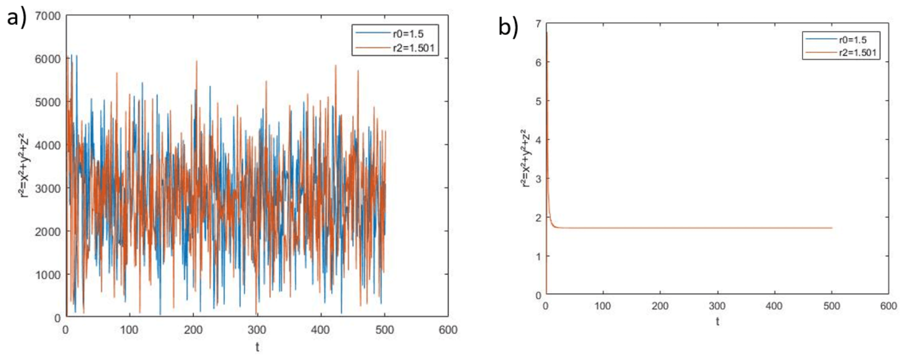

Figure 8 Graphical Results. a) Time series for $w_{11} = 42$ without chaos control; b) Time series for $w_{11} = 42$ with application of chaos control around S(0.707; -0.5; -0.0131943348401285248498832966200033), the calculation starting from equation (46) gives $z = -0.0131943348401285248498832966200033$; $k_1 = 0.0254$ and $k_2 = 0.0270$, $k_3 = 0214199230145990491334089311677839$

4 Interpretation of Results and Discussion

In this study, we applied the periodic pulse method to recurrent neural networks (RNNs) with a sinusoidal activation function to evaluate its effectiveness in suppressing chaos in these dynamic systems. Two configurations were analyzed:

Phase 1: A recurrent network with two neurons.

Phase 2: A recurrent network with three neurons.

The numerical simulations were conducted in MATLAB, using the following parameters:
(1) Fixed synaptic weights: $w_{11} = w_{22} = w_{33} = 2.5$, while all other weights were set to 1.
(2) Initial conditions: 1.5 and 1.501.
(3) Number of iterations: 500.

The pre-control time series (Figure 3a and Figure 6a) reveal that the network dynamics are chaotic, characterized by an irregular trajectory and extreme sensitivity to initial conditions. In these figures, the evolution of r^2 over time demonstrates aperiodic, bounded, and deterministic behavior – hallmarks of chaos.

After applying periodic pulse control (Figure 3b and Figure 6b), the chaotic behavior disappears. The system stabilizes around a fixed equilibrium, confirmed by the fact that initially divergent orbits merge into a single trajectory, forming an asymptotic trend. This stabilization effect is further verified by additional tests at higher weight values:
(1) Figure 4: w_{11} = 13;
(2) Figure 5: w_{11} = 25;
(3) Figure 7: w_{11} = 31;
(4) Figure 8: w_{11} = 42.

For each case, the system successfully transitioned from chaotic to stable behavior, reinforcing the robustness of the periodic pulse method.

Our results demonstrate that periodic pulse control is effective in suppressing chaos in small-scale recurrent networks (2-3 neurons). The transition follows a typical chaos suppression mechanism by stabilizing a fixed point, aligning with previous findings in chaos control theory (Ott et al., 1990).

4.1 Comparison with Existing Studies

Our work contributes to the broader research on chaos control in dynamical systems. A comparison with other established methods is summarized in Table 2:

Table 2 Comparison with Existing Studies

Study	Method Used	Key Findings
Ott, Grebogi, Yorke (1990)	Delayed feedback control	Stabilization of chaotic attractors with minimal perturbations
Pecora & Carroll (1990)	Chaotic synchronization	Suppression of chaos through synchronous coupling
Pasemann (2002)	Chaos analysis in RNNs	Examined chaos with sigmoid activation functions
Our study	Periodic pulse control	Successfully suppressed chaos in RNNs with sinusoidal activation

Unlike delayed feedback control, which perturbs the system continuously, periodic pulse control is a minimally invasive approach, modifying system parameters only at specific intervals. Compared to chaotic synchronization, our method does not require external coupling mechanisms, making it simpler to implement in autonomous neural networks.

Moreover, Pasemann's studies (2002) focused primarily on sigmoid activation functions, while our work extends chaos control techniques to sinusoidal activation, which introduces unique periodic properties and complex bifurcation behaviors.

4.2 Limitations and Future Directions

Despite these promising findings, several limitations must be considered:
(1) Generality of the Results: This study is limited to two- and three-neuron networks. The next step is to test the method on larger architectures, including deep RNNs, LSTMs, and Reservoir Computing models.
(2) Sensitivity Analysis: The impact of different synaptic weight values on the stability of the network remains unexplored. A broader parameter sweep would provide deeper insight into the method's robustness.
(3) Comparison with Other Control Methods: Our study does not directly compare periodic pulse control with other chaos suppression strategies, such as delayed feedback control or chaotic synchronization. Future studies should perform a quantitative analysis of these different approaches.

4.3 Potential Applications

(1) Computational Neuroscience: Understanding how the brain naturally regulates chaotic states could have implications for neuromodulation techniques and biological neural network modelling.

(2) Artificial Intelligence: 1) Controlling chaos in RNNs may enhance training stability in machine learning algorithms and deep learning architectures. 2) Avoiding chaotic behavior in networks like LSTMs and Transformers could improve their ability to learn and generalize efficiently.

5 Conclusion

In this study, we explored the application of the periodic pulse method for chaos control in recurrent neural networks (RNNs) with a sinusoidal activation function. The primary objective was to determine whether this approach could stabilize a chaotic neural system by applying targeted periodic perturbations.

The results demonstrated that periodic pulses effectively suppress chaotic behavior in both two-neuron and three-neuron recurrent networks. Before control was applied, the system exhibited chaotic dynamics, characterized by unpredictable trajectories and high sensitivity to initial conditions. After introducing periodic pulses, the network transitioned to a stable state, confirmed through time series analysis and eigenvalue spectrum calculations. Specifically, the Lyapunov exponent, a key indicator of chaos, shifted from a positive value to a negative or near-zero value, validating the stabilization of the system.

6 Key Findings and Contributions

(1) Validation of Periodic Pulse Control for Sinusoidal Activation Functions: While previous studies on chaos in RNNs primarily focused on sigmoid or ReLU activation functions, our work extends the applicability of chaos control techniques to sinusoidal activation, which exhibits unique periodic properties.

(2) Robustness of the Method: Our numerical simulations confirmed that the periodic pulse method effectively suppresses chaos across different parameter configurations (e.g., varying weight values from $w_{11} = 2.5$ to $w_{11} = 42$).

(3) Minimal Invasiveness Compared to Other Methods: Unlike delayed feedback control, which modifies the system continuously, periodic pulses only apply perturbations at specific intervals, reducing computational complexity and energy consumption.

7 Limitations of the Study

Despite these promising results, several limitations must be addressed:

(1) Scalability to Large-Scale Networks: This study focused on small networks (2–3 neurons). The effectiveness of periodic pulse control for large-scale architectures (e.g., deep RNNs, LSTMs, or Reservoir Computing models) remains an open question.

(2) Limited Range of Synaptic Weights: The simulations were performed using fixed synaptic weight values. Future research should conduct a systematic sensitivity analysis to explore the method's robustness across a broader range of parameters.

(3) Lack of Direct Comparison with Other Chaos Control Methods: While we discussed alternative approaches such as delayed feedback control and chaotic synchronization, our study did not provide a direct experimental comparison. Future studies should quantitatively evaluate the relative efficiency of these methods.

8 Future Perspectives

This work paves the way for several promising research directions:

(1) Application to More Complex Networks: Testing periodic pulse control on deep recurrent networks (LSTMs, GRUs) could reveal new insights into controlling chaotic dynamics in practical machine learning models.

(2) Experimental Validation in Computational Neuroscience: Investigating whether external stimulation – similar to periodic pulses – can influence neural activity in biological models could provide insights into cognitive flexibility and neural adaptation.

(3) Integration with Hybrid Chaos Control Techniques: Combining periodic pulses with other

control strategies (e.g., adaptive algorithms or delayed feedback methods) could enhance both the efficiency and flexibility of chaos suppression techniques.

9 Final Remarks

In conclusion, this study demonstrated that the periodic pulse method is a promising technique for chaos control in recurrent neural networks. While further investigations are necessary to confirm its applicability to larger-scale and real-world systems, the findings contribute to the growing body of research on nonlinear dynamics, neurodynamic, and artificial intelligence.

Acknowledgements

We would like to express our deepest gratitude to Mr. Rakotomalala Minoson, Mr. Randrianandraina Hery Zo, and the Institut pour la maîtrise de l'énergie (IME). Their support and contributions were crucial in the development, execution, and completion of this research. We also extend our sincere thanks to Mr. Modeste Kameni for his precious help to publish this article.

Conflicts of interest

The authors declare that they have no conflict of interest.

References

[1] Bar-yam Y. Dynamics Of Complex Systems. CRC Press, 2019.
https://doi.org/10.1201/9780429034961

[2] Strogatz SH. Nonlinear Dynamics and Chaos: With Applications to Physics, Biology, Chemistry, and Engineering. 2ed. Boca Raton: CRC Press, 2018: 532.

[3] Hopfield JJ. Neural networks and physical systems with emergent collective computational abilities. Proceedings of the National Academy of Sciences. 1982, 79(8): 2554-2558.
https://doi.org/10.1073/pnas.79.8.2554

[4] Hinton GE, Osindero S, Teh YW. A Fast Learning Algorithm for Deep Belief Nets. Neural Computation. 2006, 18(7): 1527-1554.
https://doi.org/10.1162/neco.2006.18.7.1527

[5] Freeman WJ, Holmes MD. Metastability, instability, and state transition in neocortex. Neural Networks. 2005, 18(5-6): 497-504.
https://doi.org/10.1016/j.neunet.2005.06.014

[6] Breakspear M, Heitmann S, Daffertshofer A. Generative Models of Cortical Oscillations: Neurobiological Implications of the Kuramoto Model. Frontiers in Human Neuroscience. 2010, 4.
https://doi.org/10.3389/fnhum.2010.00190

[7] Lopes da Silva F. EEG and MEG: Relevance to Neuroscience. Neuron. 2013, 80(5): 1112-1128.
https://doi.org/10.1016/j.neuron.2013.10.017

[8] Stam CJ. Modern network science of neurological disorders. Nature Reviews Neuroscience. 2014, 15(10): 683-695.
https://doi.org/10.1038/nrn3801

[9] Pasemann F. A simple chaotic neuron. Physica D: Nonlinear Phenomena. 1997, 104(2): 205-211.
https://doi.org/10.1016/S0167-2789(96)00239-4

[10] Dreyfus G. Neural Networks: Methodology and Applications. Springer Science & Business Media. 2005: 509.

[11] Pecora LM, Carroll TL. Synchronization in chaotic systems. Physical Review Letters. 1990, 64(8): 821-824.
https://doi.org/10.1103/physrevlett.64.821

[12] Lynch S. Dynamical Systems with Applications Using MATLAB®. Springer International Publishing, 2014.
https://doi.org/10.1007/978-3-319-06820-6

Leading manufacturers have significantly advanced pacemaker technology, integrating innovations such as leadless designs, smart device connectivity, and enhanced battery longevity to improve patient outcomes [8]. Comparative studies have demonstrated that leadless pacemakers reduce complication rates compared to traditional transvenous devices, highlighting their potential for improved safety and reliability [9]. However, despite these technological advancements, the lack of standardized reporting formats across manufacturers complicates data interpretation and clinical decision-making [10]. Pacemaker interrogation reports provide essential insights into battery longevity, lead performance, and pacing thresholds, enabling proactive device management, yet differences in data presentation and proprietary formats create challenges for direct comparisons [11]. Addressing these disparities through standardized reporting and improved interoperability could enhance clinical assessment and optimize pacemaker management.

This study aims to address this gap by presenting a structured comparison of pacemaker interrogation reports from the three leading manufacturers, with a focus on diagnostic data, lead impedance, pacing thresholds, and battery longevity. From the performance data, this research seeks to uncover patterns in battery efficiency, pacing effectiveness, and device durability. A deeper understanding of these factors can enhance clinical decision-making, enabling personalized device selection based on patient-specific needs. Furthermore, this study may help identify the strengths and limitations of specific device, contributing to future advancements in pacemaker technology.

Ultimately, the findings of this research will provide valuable insights for the medical community, aiding in informed decision-making regarding pacemaker management and selection. By expanding our understanding of long-term pacemaker performance, this study seeks to improve patient outcomes and contribute to the ongoing discourse on optimizing pacemaker technology.

Through a comprehensive analysis of interrogation reports, this research underscores the importance of standardized reporting practices and highlights the potential for innovation in device monitoring and management.

1.1 Materials in Pacemaker

The biomaterials needed for the implantable pacemaker are alloplastic, that is, not biological in origin [12]. They include metals, ceramics or glasses, and polymers. From a physical point of view, the main difference between these groups of materials is the type of chemical bond which holds the materials together [13].

1.2 The Pathophysiological Understanding

A pulse generator and one or more transvenous or epicardial leads that link the generator to the myocardium make up the pacing system [14]. While actual pulse generator failure is extremely uncommon, pacing system malfunction does happen from time to time. A malfunctioning lead, electrode-tissue interface, or pulse generator can cause a malfunctioning pacing system. When a lead malfunctions, more issues arise than when a pulse generator malfunctions [15].

The majority of these issues can be fixed with simple device reprogramming. In actuality, most malfunctions are caused by the pacemaker's normal programmed function. Correct diagnosis and treatment of malfunctions depend critically on having a good understanding of their cause [16].

1.3 Etiology

The following categories apply to causes of pacing system malfunctions [17]:
(1) Sensing (under sensing or oversensing)
(2) Pacing (loss of capture, loss of output, failure to output)
(3) Rate (inappropriate rate, pacemaker-mediated tachycardia)
(4) Inappropriate lead position
(5) Inappropriate mode
(6) Extracardiac stimulation
(7) True pulse generator failure
(8) Pacemaker syndrome
(9) Twiddler syndrome

1.4 Key Parts of Pacemaker

Pulse Generator: The pulse generator forms the main component of the pacemaker. It contains functions, electronic circuitry, and a battery that powers the device. The pacemaker operates on battery power, which is supplied by the battery [18].

Leads: Built-in leads are used to connect the heart muscle to the pulse generator. Electrical impulses are transmitted from the ganglion to regulate the rhythms of the heart [19]. The implants can be inserted into the ventricles, atria, or both, depending on the type of pacemaker.

Electrodes: Electrodes touch the heart muscles directly. They appear at the edge of the front. They enable the heart and pacemaker to conduct the electricity, which helps the heart beat faster.

Sensors: Some pacemaker come with sensors to monitor body activity levels and adjust the pacing rate of the pacemaker accordingly. Rate responsiveness is a characteristic that allows the pacemaker to adapt to the physiological requirements of the patient [20].

1.5 Potential Failure Modes

There are many ways a pacemaker can malfunction, including hardware problems, software errors, lead errors, and low battery levels [21]. Understanding the specific failure mechanisms is important for a failure focused analysis [22]. For example, if the battery runs out, the machine may stop moving, and if the copper breaks, the electrical stimulator may stop working.

Battery Depletion: Pacemakers have limited battery life; It usually lasts between five and fifteen years, depending on usage. One common failure condition that causes loss of pacing output is battery loss.

Lead Malfunction: Over time, lead insulation can crack, leak or cause insulation to fail. Lead defects can interfere with electrical output, causing pacing problems [19].

Software Faults: For optimal performance, pacemakers have complex software algorithms built into them. While rare, malfunctions can occur due to software errors preventing the device from operating.

Hardware Issues: Hardware problems can occur in the electronic circuits or connections that are part of the pulse generator. These can cause irregular pacing or other problems.

Understanding these potential failure factors is important for a comprehensive assessment of pacemaker deficiencies, as each component is essential for the device to effectively control the heart rhythm [17].

2 Literature review

A comprehensive literature search was conducted to evaluate the performance, management, and clinical implications of cardiac implantable electronic devices (CIEDs), including pacemakers, implantable cardioverter-defibrillators (ICDs), and cardiac resynchronization therapy (CRT) devices. The review focused on key aspects such as quality of life (QoL) impact, technological advancements, battery longevity, lead performance, pacing modes, arrhythmia management, and device interrogation practices. The study also examined variations in reporting formats, diagnostic capabilities, and clinical usability across leading manufacturers, highlighting the need for standardized practices to enhance data consistency and patient outcomes. By synthesizing findings from multiple studies, this review aims to provide insights into optimizing CIED management, improving device reliability, and addressing gaps in current research to guide future advancements in cardiac care. (see Table 1)

This table provides a comprehensive overview of various aspects related to cardiac implantable electronic devices (CIEDs), including pacemakers, ICDs, and CRT devices. It highlights key findings, clinical implications, and recommendations for improving patient outcomes, such as the importance of QoL assessments, advancements in device technology, and strategies for optimizing battery life and device management. However, the table also underscores significant gaps in the literature, such as the lack of long-term data on device performance, patient outcomes, and the broader application of emerging technologies. These limitations highlight the need for more extensive research, standardized reporting, and real-world evidence to guide clinical decision- making and enhance the safety and efficacy of CIEDs.

3 Methods

3.1 Data Collection

The data for this study were collected from pacemaker interrogation reports from three manufacturers. These interrogation reports included critical performance metrics such as:

Table 1 Summary of Literature review on Pacemaker Performance, Management and Clinical Implications

Aspect	What This Paper Provides	What This Paper Does Not Provide	Recommendations	Clinical Implications
QoL Impact [23]	Shows significant QoL improvement with pacemakers, LVADs, and ICDs.	Lacks long-term QoL data across different patient groups.	Study QoL variations by device type, manufacturer, and demographics.	Emphasizes the need for QoL assessments in device selection and patient counseling.
Pacemaker Development [24]	Reviews the evolution of pacemakers, from external devices to leadless, MRI-compatible pacemakers, and highlights key technological milestones.	Lacks detailed discussion on recent experimental pacemaker technologies or long-term clinical outcomes.	Incorporate more case studies and long-term performance data to enhance understanding of newer pacemaker technologies.	Provides historical context and future insights, assisting clinicians in understanding the trajectory of pacemaker technology and its potential impact on patient care.
Pacemaker Programming History [25]	Traces the evolution of pacemaker programming from invasive methods to non-invasive techniques like magnetic programming and RF communication, culminating in bidirectional telemetry and multiprogrammable devices.	Does not provide current or future advancements in pacemaker programming beyond the 1970s.	Explore recent innovations in pacemaker programming and their real-world applications.	Highlights the transformative impact of programming advances, which has shaped modern pacemaker management and personalized patient care.
Pacemaker Implantation & Management [26]	Discusses patient selection, complex pacing modes (MVP, CRT), procedural risks, and post-implant care including infection prevention, troubleshooting, and remote monitoring.	Does not delve into specific patient outcomes or long-term follow-up data on device performance	Include long-term patient outcome data and case studies to guide clinicians in decision-making.	Highlights the importance of individualized care through vigilant monitoring, optimal device programming, and infection prevention to enhance patient outcomes and reduce complications.
Pacemaker Battery Life [6]	Examines factors affecting battery life, such as pacing rate, pulse duration, voltage, lead impedance, and the impact of high-impedance leads on current drain.	Does not provide extensive data on the real-world impact of pacing reductions or algorithm optimizations over time.	Explore more extensive clinical data on the long- term effects of pacing reductions and device algorithm optimizations.	Emphasizes the importance of optimizing pacing parameters and device algorithms to enhance battery longevity, helping clinicians improve device efficiency and patient outcomes.
Battery Depletion Prediction [27]	Explains methods for predicting battery depletion in pacemakers using an oscilloscope to study impulse curves, enabling extended pacemaker lifespan.	Does not provide data on the impact of these methods in modern pacemaker designs or technologies.	Investigate the application of these predictive methods in current pacemaker technologies and explore improvements in battery management.	Highlights the value of active battery management in extending pacemaker lifespan and reducing premature replacements, optimizing device efficiency and patient care.
Variability in CIED Durability [28]	Highlights significant differences (up to 44%) in battery duration among pacemakers, ICDs, and CRT-Ds, with factors like battery chemistry, capacity, and current drainage influencing device longevity.	Does not provide data on the specific factors that influence these differences across individual manufacturers.	Encourage the development of standardized industry reporting on device durability and features to improve transparency and informed decision- making.	Emphasizes the importance of standardized reporting to guide clinicians in selecting devices, ensuring better long- term patient outcomes, and reducing healthcare costs.
Postmortem CIED Interrogation [29]	Describes a 15-year study on postmortem interrogation of pacemakers, defibrillators, and loop recorders, revealing a 98.5% success rate for retrieving useful data on device malfunction, cause of death, time of death, and patient identification.	Does not explore the broader application of postmortem CIED interrogation across different patient populations or device types.	Advocate for the routine use of postmortem CIED interrogation to enhance both clinical knowledge and forensic investigations.	Highlights the value of postmortem CIED interrogation in identifying device- related failures and improving both clinical outcomes and forensic investigations.
Pacemaker Battery Depletion and Diagnosis [30]	The paper emphasizes the gradual depletion of pacemaker batteries and its potential to cause serious morbidity, particularly in the Elective Replacement Indication (ERI) and End of Life (EOL) stages. It presents two case studies: one of pacemaker syndrome triggered by automatic reprogramming during ERI, and another of torsade de pointes and complete atrioventricular block due to complete battery depletion. The paper introduces the "Rules of Ten" as an ECG-based method for early detection of battery depletion.	The paper does not explore in- depth pathophysiology behind battery depletion or provide specific management protocols for patients. It also doesn't compare the "Rules of Ten" with other ECG methods.	Regular monitoring and follow-up for pacemaker patients, especially at the ERI and EOL stages, to prevent delayed diagnoses. The "Rules of Ten" ECG-based method can be implemented as a practical diagnostic tool for early detection of battery depletion.	Delayed diagnosis of pacemaker battery depletion can result in serious conditions like pacemaker syndrome and torsade de pointes. Regular monitoring and timely intervention using the "Rules of Ten" method can improve patient outcomes by detecting battery depletion early, preventing life- threatening arrhythmias, and ensuring better management of pacemaker patients.
Objective [31]	Investigates longevity of VVI-pacemakers, with CPI Microlith 605 showing median lifespan of 19.2 years, one lasting 26.3 years.	Does not consider patient- specific factors (e.g., age or health conditions), pacing frequency, electrode-lead combinations, or dual-chamber pacemakers.	Future studies should include factors such as pacing frequency, patient demographics, electrode-lead combinations, dual- chamber pacemakers, and clinical outcomes.	Findings suggest using pacemakers with longer battery lives, such as CPI Microlith 605, for patients requiring extended therapy, reducing frequent replacements and improving care.
Study Objective [32]	Investigates the incidence and outcomes of premature battery depletion (PBD) in Abbott ICDs and CRT devices.	Does not investigate non- Abbott devices or long-term battery life beyond the advisory period.	Further studies needed to evaluate PBD rates in non- Abbott devices and long-term follow-up beyond advisory period.	Provides insights into the reliability of Abbott devices and the potential risks of premature battery depletion.
Premature Battery Depletion in Abbott Pacemakers: A Case Report [33]	Detailed case reports of premature battery depletion in Abbott pacemakers (models PM1152, PM1160, PM1172, PM1240, PM1272, PM2152, PM2160, PM2172, PM2240, PM2260, PM2272). (1) FDA Class I recall advisory and its clinical relevance. (2) Evidence of failure due to loss of radiofrequency transmitting capabilities. (3) Clinical presentation, diagnosis, and intervention for affected patients. (4) Highlights the failure of remote monitoring systems in detecting sudden pacemaker failures.	Specific numerical data on pacemaker battery life for all affected models. - In-depth statistical analysis of the recall's broader impact.	Close monitoring and prophylactic generator replacement for pacemaker- dependent patients. - Proactive generator changes should be considered for patients with affected devices, particularly those who are pacemaker-dependent.	Failure of remote monitoring systems calls for enhanced patient safety measures and more robust protocols. - Immediate generator replacement should be considered to avoid complications, especially for older patients.
CIED management [34]	It provides methods for identifying CIED type and manufacturer, guidance on interpreting ECGs for pacemaker status, and recommendations for using a "doughnut magnet" to ensure asynchronous pacing.	It does not provide detailed device programming instructions or long-term care protocols for CIED patients during the pandemic.	The paper recommends using remote CIED monitoring when available, applying ECG interpretation rules like the "Rules of Ten" to assess battery depletion or reset, and consulting with electrophysiologist s for urgent device reprogramming or surgery.	The paper highlights the importance of timely identification and management of CIED issues, ensuring that urgent consultations and interventions are conducted despite limited resources during a healthcare crisis.
ED staff performing device interrogation for cardiac implants [35]	It shows that ED staff can perform cardiac device interrogations faster than traditional methods while maintaining safety.	It does not discuss long- term outcomes or broader impacts on patient management beyond the ED.	ED staff should be trained to perform cardiac device interrogations in emergency settings to improve efficiency.	This study suggests that ED staff can safely and efficiently conduct cardiac device interrogations, potentially improving emergency care workflows.
Diagnostic Yield of Pacemaker Interrogation Reports [36]	A retrospective analysis of 88 patients with implanted pacemakers or ICDs to assess the diagnostic yield of device interrogation in unexplained syncope cases.	Definitive evidence supporting the routine use of device interrogation as a primary diagnostic tool for syncope in patients with previously implanted pacemakers or ICDs.	Device interrogation should not be routinely performed in all cases of unexplained syncope unless supported by concerning exam findings, telemetry, or ECG abnormalities.	The study highlights that patient history and orthostatic vital signs provide higher diagnostic value than device interrogation, suggesting a more targeted approach to evaluating syncope in these patients.
PMT diagnosis and management [37]	A detailed case report on the identification and treatment of PMT using pacemaker interrogation/programming in the emergency department.	In-depth exploration of alternative treatment options for PMT or other arrhythmias in pacemaker patients.	Incorporating pacemaker interrogation as a standard part of ED management for patients with pacemaker-related arrhythmias.	Demonstrates the effectiveness of pacemaker interrogation/programming in ensuring patient stability in the ED. resolving PMT and
Electromagne tic interruption [38]	A case report on EMI interference between a Micra VR leadless pacemaker and an LVAD after conversion from HeartMate II to HeartMate 3.	A generalized solution applicable to all cases of EMI between LVADs and leadless pacemakers.	Positioning the programmer head on the patient's back can facilitate successful pacemaker interrogation when EMI is present.	Awareness of potential EMI issues during LVAD conversion is crucial, and alternative interrogation strategies should be considered to ensure proper device function.
CIED Management [39]	Overview of Boston Scientific pacemakers, CRT devices, ICDs, programming, and perioperative care	No direct comparison with other manufacturers, lacks step-by- step programming guidance, and omits rare surgical scenarios	Training on interrogation, programming, emergency management, and institutional education	Improves clinician expertise in device management, optimizing perioperative safety and cardiac function
Pacemaker Safety Mode [40]	It provides a detailed case study of a pacemaker failure due to Safety Mode activation and battery impedance.	It does not provide definitive solutions for preventing pacing inhibition during Safety Mode activation.	The paper recommends considering early pacemaker replacement for pacemaker- dependent patients at risk of Safety Mode complications.	Clinically, it emphasizes the importance of evaluating pacemaker function and considering preventive replacement to avoid risks of pacing inhibition in pacemaker- dependent patients.
Pacemaker replacement rates based on device longevity, patient survival, and demographic factors [41]	Estimates of pacemaker replacement rates by age, gender, and primary indication, along with cost implications of device longevity changes.	Real-world long- term data on device longevity or replacement rates beyond projections and simulations.	Focus on optimizing device longevity for younger patients and consider demographic factors when selecting pacemaker models.	Longer device longevity reduces replacement surgeries, complications, and healthcare costs, particularly for older patients.
Survival and failure rates of implantable defibrillator leads [42]	Comparative analysis of lead survival and failure rates across manufacturers, impact of recalled leads, and predictors of lead failure.	Mechanisms of death in patients with recalled leads or long- term follow-up beyond 2011.	Focus on lead construction improvements, avoid recalled leads, and consider patient-specific factors in lead selection.	Boston Scientific and St. Jude Medical leads outperform Medtronic leads; recalled leads are associated with higher failure rates and increased mortality, emphasizing the need for careful lead selection and monitoring.

Battery Status: Remaining battery capacity, voltage levels, and predicted replacement dates.

Lead Impedance: Electrical resistance measured across the leads to monitor their integrity.

Pacing Thresholds: The minimum electrical stimulus required to consistently elicit a cardiac response.

Arrhythmia Detection Logs: Information on the detection and management of arrhythmias.

Event Logs: Records of pacing events, lead failures, software anomalies, and other notable occurrences.

The interrogation data were obtained from clinical settings where pacemaker devices were retrieved posthumously. Data was anonymized to protect patient identity, and all reports were de-identified prior to analysis to comply with ethical standards and patient confidentiality protocols.

3.2 Data Processing

Anonymization: All patient-identifiable information was removed to comply with ethical guidelines and privacy standards.

Standardization: The reports from the three manufacturers had varying formats. These were standardized into a unified format for comparative analysis.

Data Cleaning: Outliers, incomplete records, and erroneous data were identified and removed using threshold-based filtering and domain expertise.

3.3 Key Metrics for Comparison

The key metrics evaluated in this analysis included:

Battery performance: Comparison of remaining battery life estimates from each manufacturer.

Lead performance: Lead impedance, pacing thresholds, and capture thresholds.

Pacing Modes and Rates: Comparison of pacing strategies, including pacing modes, pacing rates, and the pacemaker's ability to adapt to arrhythmias and varying physiological demands across different manufacturers.

Interrogation report layout: Comparison of the structure and presentation of pacemaker interrogation data, including how manufacturers organize and display key metrics like battery status, lead performance, pacing rates, and arrhythmia management.

4 Data Analysis

4.1 Categorization of Metrics

The interrogation reports were categorized based on several performance parameters:

Battery Status: Classified as "Optimal", "Monitor", and "Replace Soon" based on remaining battery life.

Lead Impedance: Analyzed to identify any degradation or failure patterns.

Pacing Thresholds: Analyzed over time to detect increasing trends, which might indicate lead issues or increased energy consumption.

Arrhythmia Events: Reviewed to evaluate device response accuracy and consistency.

Data were further categorized by device age, type, patient demographics, and specific device settings (such as pacing modes) to provide context for performance comparisons.

4.2 Device Specific Comparisons

Each manufacturer's pacemaker models were compared based on: 1) Battery Longevity; 2) Lead Performance; 3) Pacing Mode Efficiency; 4) Report layout.

Differences in proprietary technologies, such as adaptive pacing modes or algorithms, were taken into account when interpreting the results. Manufacturer-specific innovations were noted to assess their impact on device reliability and patient outcomes. This methodology ensures a rigorous comparative analysis of pacemaker performance, allowing for the identification of key strengths and weaknesses across different manufacturers and their devices.

5 Results

5.1 Battery Performance

5.1.1 Voltage Behavior and Remaining Life

The battery performance of pacemakers from three leading manufacturers A, B, and C was evaluated based on the key factors such as Elective Replacement Indication (ERI) thresholds, voltage ranges, magnet rates, battery longevity, End of Service (EOS) indicators, Recommended Replacement Time (RRT), and remaining life estimates. The findings are summarized in Table 2.

Table 2 Battery Performance Compariso

Factor	Manufacturer A	Manufacturer B	Manufacturer C
ERI Threshold	2.60 V	Not provided	2.83 V
Voltage range	2.45 V – 2.90 V	Indirectly inferred from time to explant	2.63 V – 2.94 V
Magnet Rate	8.6 ppm – 98.1 ppm	90 ppm (shorter life), 100 ppm (longer life)	Not provided
Battery Longevity	Near ERI 2.60 V	Shorter life at 90 ppm, longer life at 100 ppm	Approaching ERI (2.83 V)
EOS and RRT	Close to ERI 2.60 V	Indirectly suggested via remaining life estimates	EOS at 2.82 V, RRT at 2.83 V
Remaining Life	Not directly provided	Shorter life at 90 ppm, longer life at 100 ppm	8 months - 8.6 years (varying stages)

(1) Manufacturer A:

A. Voltage range**:** 2.45 V to 2.90 V; voltage approaches ERI (2.60 V).

B. The pacemaker is nearing the end of life, especially with 2.45 V approaching the 2.60 V ERI threshold.

C. Remaining life isn't explicitly stated, but it can be inferred that the pacemaker is getting close to requiring replacement as its voltage dips closer to the ERI. (see Figure 1)

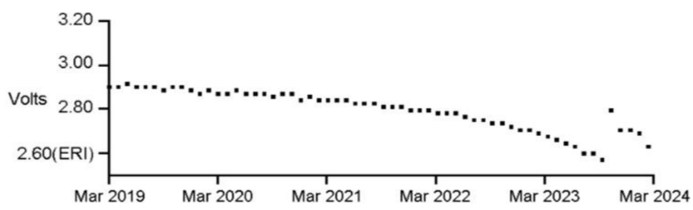

Figure 1 Voltage trend (Manufacturer A)

This report includes a waveform that represents the voltage and impedance levels of the pacemaker battery. Monitoring these parameters ensures timely replacement or maintenance of the device. A stable voltage curve indicates a healthy battery status, while a declining trend suggests that the battery is nearing the end of its life, requiring predictive maintenance to avoid interruptions in device performance.

(2) Manufacturer B:

A. Voltage is not provided but inferred from magnet rate and time to explant.

B. 90 ppm generally correlates with a shorter remaining life (e.g., 0.25 years to $<$ 3 months).

C. 100 ppm correlates with a longer remaining life (e.g., 6.5 years to 14.5 years).

In this report, battery performance trends are inferred from static data points and associated metrics, as direct battery voltage trend graphs are not provided. Instead, the performance is evaluated using static voltage values at interrogation, such as those related to Elective Replacement Indicator (ERI) and pacing thresholds, which are influenced by battery status. Additional insights are derived from the magnet rate, where a 90-ppm rate correlates with a shorter battery life ($<$ 3 months) and 100 ppm indicates longer battery life (up to 14.5 years).

(3) Manufacturer C:

A. Voltage range: 2.63 V to 2.94 V.

B. 2.83 V is marked as ERI, and 2.82 V as EOS (End of Service).
C. Remaining life varies from 8 months to 8.6 years, depending on the stage of the battery life:
a. At 2.88 V, the remaining life is 8 months.
b. At 2.82 V (EOS), the pacemaker is near replacement.
c. 2.63 V indicates a longer remaining life (8.6 years), suggesting that the pacemaker is still functional and needs some time before replacement.

In this report, battery performance trends can be inferred from specific data points and alerts related to battery voltage, remaining longevity, and battery-related thresholds—though there's no direct battery voltage trend graph. Instead, battery performance is evaluated through static voltage values at key points, such as Elective Replacement Indicator (ERI) and End of Service (EOS), alongside calculated longevity estimates

5.1.2 Magnet Rate and Battery Longevity

Manufacturer A: Magnet rates vary between 78.6 ppm to 98.1 ppm, with 78.6 ppm observed at 2.45 V, suggesting reduced performance as the battery approaches end-of-life.

Manufacturer B: 90 ppm correlates with shorter battery life, while 100 ppm suggests a longer battery life.

Manufacturer C: No magnet rate data provided, but the battery voltage can be used to infer the remaining life.

5.1.3 Remaining Life and Replacement Timing

(1) A Devices:
A. The battery is nearing the end of its useful life based on the voltage approaching ERI.
B. Exact remaining life isn't directly provided but inferred from voltage.

(2) B Devices:
Magnet rate data allows an estimate of remaining life: A. 100 ppm correlates with a long life (e.g., 6.5 years**,** 14.5 years).
B. 90 ppm correlates with a short life (e.g, 0.25 years, < 3 months).

(3) C Devices:
Remaining life varies significantly based on voltage:
A. At 2.88 V, the pacemaker is expected to last 8 months.
B. At 2.94 V, the remaining life is 3 years.
C. At 2.63 V, the pacemaker can last up to 8.6 years, indicating it is still in a relatively healthy state.
D. At 2.82 V (EOS), it needs to be replaced immediately.

Key Insights:

(1) Voltage
A. A Devices typically show voltages near 2.60 V (ERI threshold), indicating that their batteries are near the end of life.
B. B Devices doesn't provide specific voltage data, but their magnet rate correlates with battery life: 90 ppm indicates a shorter battery life, and 100 ppm indicates a longer battery life.
C. C Devices has a higher ERI threshold (2.83 V), and their battery voltages are higher, suggesting longer remaining life in some cases (up to 8.6 years).

Remaining Life:
Manufacturer A: Battery is nearing the end of its life, and replacement is imminent based on voltage approaching the ERI threshold.
Manufacturer B: The magnet rate is a reliable indicator, with 90 ppm showing shorter remaining life and 100 ppm showing longer life.
Manufacturer C: Remaining life can range from 8 months to 8.6 years, depending on the battery's voltage, with 2.63 V showing the longest remaining life.

Summary:
A. A Devices show a low voltage range, with many readings approaching the ERI, signaling imminent replacement.
B. B Devices uses magnet rate and time to explant as proxies for battery life, with 90 ppm indicating shorter remaining life and 100 ppm indicating longer life.
C. C Devices have more detailed data on voltage and remaining life, with 2.82 V marking the EOS and 2.63 V indicating a longer lifespan.

5.2 Lead Performance

The lead performance of pacemakers from three leading manufacturers was evaluated based on key parameters such as lead impedance, capture thresholds, sensing issues, pacing impedance, battery voltage, remaining life, and overall lead integrity monitoring. The findings are summarized in Table 3.

Table 3 Lead Performance Comparison

Parameter	Manufacturer A	Manufacturer B	Manufacturer C
Lead Impedance	High lead impedance warnings, particularly for RV and Atrial leads for more than 3000 ohms.	High pacing impedance warnings for more than 3000 ohms, less frequent than Manufacturer C.	Frequent warnings for unipolar lead and bipolar lead impedance. High impedance and polarity switches noted for more than 3000 ohms as per interrogation report.
Capture Threshold	High capture thresholds observed, similar to Manufacturer C.	Lower capture thresholds, but warnings still issued for high thresholds.	High capture thresholds frequently observed, indicating poor lead performance.
Sensing Issues	Reports of sensing issues, but fewer compared to Manufacturer C.	Short V-V intervals and sensing issues, similar to Manufacturer C, but fewer reported incidents.	Frequent reports of short V-V intervals, lead fractures, and double- counted R-waves.
Pacing Impedance	High pacing impedance alerts for more than 3000 ohms as per interrogation report., similar to Manufacturer C.	High pacing impedance and performance issues indicated with lead degradation.	High pacing impedance warnings for more than 3000 ohms as per interrogation report., indicating potential lead failure.
Battery Voltage & Remaining Life	Battery voltage monitored with remaining life alerts, but typically provides more lead-time before replacement recommendation.	Battery voltage monitored, but provides longer timelines for device replacement.	Battery voltage monitored with warnings on low voltage affecting pacing performance. Remaining life alerts provided.
Lead Integrity & Alerts	Fewer lead integrity issues reported, but still some impedance and threshold alerts.	Less frequent lead impedance alerts; focuses more on pacing efficiency and therapy success.	More detailed and frequent lead impedance and capture threshold alerts.
Overall Lead Performance Monitoring	Good monitoring of lead integrity, though fewer detailed alerts.	Monitors lead performance well, but may give less frequent warnings than Manufacturer C.	Proactive with detailed warnings about lead issues and battery life.

5.2.1 Lead Impedance

(1) A Devices:

A Devices also report lead impedance values, with similar warnings like “high lead impedance” or “lead impedance low” indicating potential issues. Lead impedance warnings, particularly related to the RV lead and Atrial lead, signal possible electrical contact issues or lead mispositioning, similar to what we observe in Manufacturer C’s systems.

(2) B Devices:

B Devices’ report impedance data too, although the specifics of the impedance threshold warnings may vary slightly. In their data, high impedance values also suggest lead dysfunctions, but Manufacturer B tends to have more specific guidance for interpreting impedance values (e.g., “high pacing impedance”, which indicates lead degradation or failure).

(3) C Devices:

A. Impedance values in C devices can show warnings when impedance values are too high or abnormal, which suggests potential issues like lead fractures or poor contact. For example, C devices have specific logs for unipolar lead impedance warning and bipolar lead impedance warning (e.g., RV unipolar lead impedance warning), which are critical for identifying lead performance problems.

B. Impedance warnings across different periods (e.g., “RV polarity switch”, “high RV threshold”) provide a clear signal of degraded lead performance. Manufacturer C data indicates high and fluctuating lead impedance as a warning sign.

5.2.2 Capture Threshold

(1) Manufacturer A:

These devices monitor capture thresholds too, with alerts when thresholds exceed expected levels. High thresholds can also be an issue in Manufacturer A devices, similar to Manufacturer C, and could indicate ineffective pacing due to lead-related issues.

(2) Manufacturer B:

These devices monitor and alert when capture thresholds become too high, although these thresholds are generally lower compared to the other manufacturers, meaning the pacing function might degrade at lower energy levels.

(3) Manufacturer C:

These devices generally have high capture thresholds as a warning indicator. This indicates that the device might be unable to consistently stimulate the heart at lower energy levels, possibly due to lead issues such as dislodgement or insulation damage. For example, Manufacturer C reports high RV thresholds on several patients, suggesting potential lead or electrode issues.

5.2.3 Sensing Issues

(1) A Devices:

These devices also report sensing issues, although they tend to have fewer reported problems. However, sensing issues still include high thresholds and improper lead contact.

(2) B Devices:

These devices include sensing alerts for issues like short V-V intervals, and the device often recommends troubleshooting for lead integrity and electrical noise interference. Like Manufacturer C, sensing issues are primarily linked to lead problems or device malfunction.

(3) C Devices:

These devices report a range of sensing issues, including short V-V intervals and irregularities in signal detection (e.g., double-counted R waves). These issues can arise due to lead fractures, poor contact, or signal interference. For example, sensing issues were reported in Manufacturer C data for multiple patients, leading to recommendations to check for lead fractures or loose set screws.

5.2.4 Pacing Impedance

(1) Manufacturer A:

These devices also report pacing impedance, with high values similarly indicating lead dysfunction. Manufacturer A devices provide alerts when pacing impedance is abnormally high, suggesting an issue with the lead or electrode.

(2) Manufacturer B:

These devices also report pacing impedance and provide warnings when it exceeds acceptable thresholds, indicating a possible lead problem.

(3) Manufacturer C:

These devices report pacing impedance, and high values in this parameter suggest poor pacing lead performance. For instance, high pacing impedance in Manufacturer C data can indicate problems like lead dislodgement, fracture, or insulation damage.

5.2.5 Battery Voltage and Remaining life

(1) A Devices:

These devices similarly monitor battery health, and remaining life is critical for ensuring pacing continuity. Low battery levels can affect lead performance, though Manufacturer A tends to give more lead-time warnings before a replace device recommendation.

(2) B Devices:

These devices also track battery voltage, but battery alerts are less frequent, often giving longer timelines for device replacement. Low battery voltage in Manufacturer B devices can sometimes result in pacing failures if it affects lead functionality.

(3) C Devices:

These devices report battery voltage and remaining life**,** which are crucial for lead performance. As the battery voltage decreases, it can affect the device's ability to properly power the leads and maintain effective pacing. A low battery voltage is often linked to lead degradation or the need for device replacement.

In the Manufacturer C pacemaker reports, lead performance is evaluated primarily through written data points, without direct waveform analysis. The reports indicate frequent warnings for unipolar and bipolar lead impedance, which could suggest issues such as poor contact or lead degradation. Additionally, the reports highlight high capture thresholds, which are frequently observed and may indicate suboptimal lead function. These high thresholds suggest that more energy is needed to achieve effective pacing, potentially due to poor lead performance. Furthermore, C devices report document sensing issues such as short V-V intervals, lead fractures, and double-counted R-waves. These issues could affect the accuracy and effectiveness of pacing, leading to potential therapy interruptions. The reports also provide high pacing impedance warnings, which may indicate lead failure or degradation, thereby affecting the efficiency of the pacing system. While no waveform data is provided, these written metrics serve as the primary means of assessing lead performance, offering insights into both immediate and potential issues that may require attention.

Manufacturer A provide detailed analyses of lead performance through metrics like the Atrial Capture Test, Atrial Sense Test, and Atrial Sense Amplitude Trend. (see Figure 2)

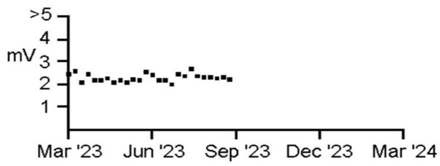

Figure 2 Atrial Sense Amplitude Trend (Manufacturer A)

Atrial Capture Test

Atrial Capture Test tests the energy threshold needed for the pacemaker to stimulate the atrium effectively and achieve capture. This guides programming of the atrial pacing output, ensuring reliable atrial activation while conserving battery life.

Atrial Sense Test and Amplitude Trend

Atrial Sense Test measures the pacemaker's sensitivity to natural atrial electrical activity and monitors changes in detected signal amplitude over time and ensures the pacemaker accurately detects atrial signals, avoiding misinterpretation that could lead to unnecessary pacing (oversensing) or missed pacing opportunities (under sensing). (see Figure 3)

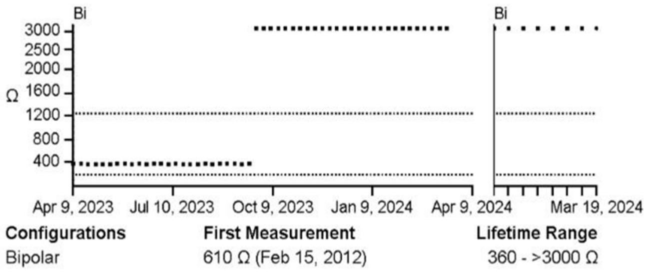

Figure 3 Lead Impedance trend (Manufacturer A)

Atrial Lead Impedance

Atrial lead Impedance measures the electrical resistance of the atrial lead to check its integrity and function and detects potential lead problems, such as dislodgement, insulation damage, or fracture, ensuring uninterrupted and effective pacing.

Ventricular Capture Test, Sense Test, and Auto Capture Trend

These test tests the pacemaker's ability to stimulate and sense ventricular activity while optimizing pacing output through auto-capture technology and guarantees effective ventricular pacing with minimal energy consumption and verifies that natural ventricular activity is being detected accurately. (see Figure 4, 5 and 6)

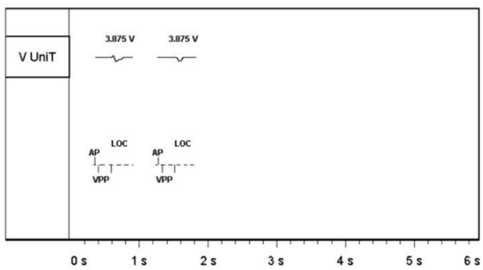

Figure 4 Ventricular Capture test (Manufacturer A)

B devices reports focus on specific metrics like P Wave Amplitude and Impedance Trends, which track the electrical signal from the atrium to assess lead performance and identify potential

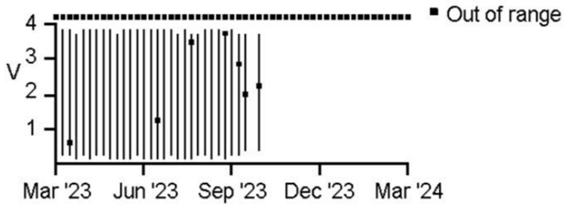

Figure 5 Auto Capture Trend (Manufacturer A)

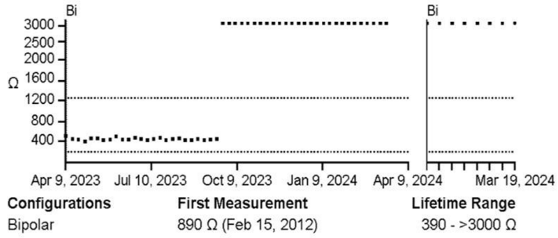

Figure 6 Ventricular Lead Monitoring (1 year trend) (Manufacturer A)

issues such as insulation damage or poor contact. Similarly, the R Wave Amplitude and Ventricular Pacing Threshold measure ventricular signal strength and pacing energy requirements, balancing effective capture with energy efficiency to extend battery life.

P Wave Amplitude and Impedance Trends

Tracks the electrical signal from the atrium and the performance of the atrial lead. It ensures effective sensing and pacing while identifying potential lead-related issues.

R Wave Amplitude and Ventricular Pacing Threshold

Measures the electrical signal from the ventricles and the energy needed for consistent pacing. It balances effective ventricular capture with energy efficiency, extending the device's longevity. (see Figure 7)

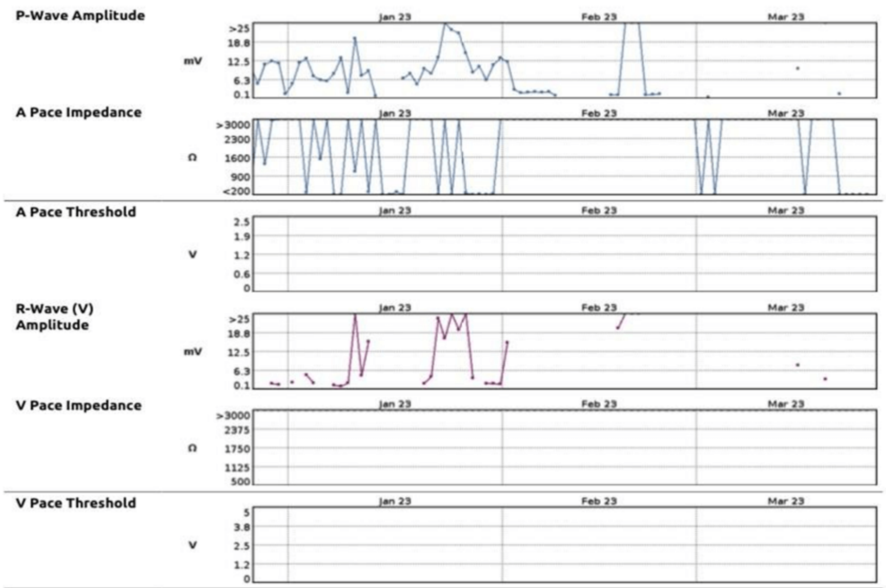

Figure 7 Amplitude and Impedance trend (Manufacturer B)

5.3 Pacing Modes and Rates

(1) A Devices:

Predominantly DDD (dual-chamber pacing) modes, with a few operating in DDI or DDDR. The base rates range from 50–70 bpm, and maximum sensor rates range from 120–140 bpm.

(2) B Devices:

Devices support various pacing modes (VVIR, DDD, DDDR) with lower rate limits around 60 ppm and upper sensor rates between 110-130 ppm. These settings are standard for maintaining optimal heart rates based on patient activity.

(3) C Devices:

Modes vary significantly, with AAIR, DDDR, VVIR, and VVI configurations. Some devices have mode switching capabilities (e.g., AAIR<=>DDDR). Base rates generally range from 60–70 bpm, with upper sensor rates reaching 130 bpm. Manufacturer C might also utilize adaptive rates to adjust based on activity

Summary: All manufacturers offer comparable pacing modes and rate limits, although individual device models and patient needs lead to variations in the programmed rates.

(1) Manufacturer A

Manufacturer A reports focus on AT/AF Burden, displaying the duration of atrial arrhythmias and the corresponding ventricular response. This metric evaluates the pacemaker's ability to manage arrhythmias effectively and maintain safe ventricular rates, thereby reducing the risk of complications like stroke or tachycardia.

AT/AF Burden with v rated during AT/AF (see Figure 8)

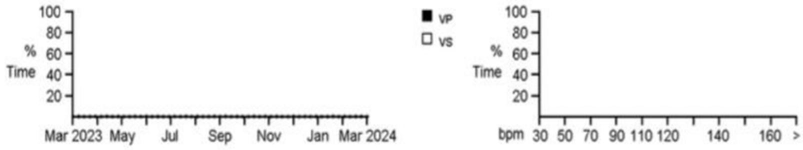

Figure 8 AT/AF Burden with V rated in Manufacturer A

AT/AF Summary (see Figure 9)

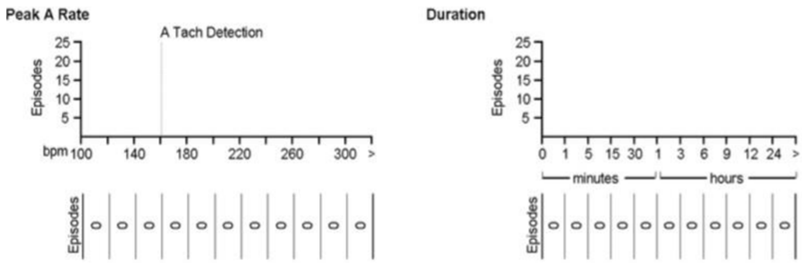

Figure 9 AT/AF summary in Manufacturer A

The waveform displays the duration the patient experiences atrial arrhythmias (AT/AF) and how the ventricles respond (paced or intrinsic). Here it is 0% AT/AT burden. This evaluates the pacemaker's ability to manage arrhythmias and maintain a safe ventricular rate, reducing risks like stroke or tachycardia.

Heart Rate Histogram with atrial and ventricular waveforms (see Figure 10)

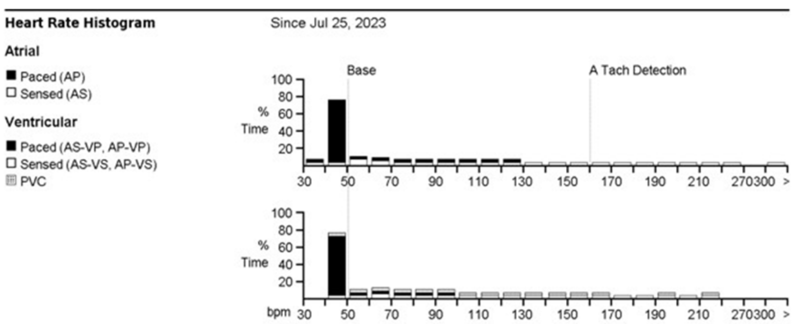

Figure 10 HR Histograms in Manufacturer A

The histogram tracks heart rates, distinguishing between intrinsic cardiac beats and those paced by the device in both atrial and ventricular chambers. This ensures the pacemaker is appropriately pacing when needed, monitoring the patient's natural cardiac activity and determining how often pacing support is required.

(2) Manufacturer B

These devices integrate additional features like AT/AF Burden and Mode Switch, which monitor arrhythmia episodes and adapt pacing modes accordingly to prevent rapid ventricular pacing during atrial arrhythmias. (see Figure 11)

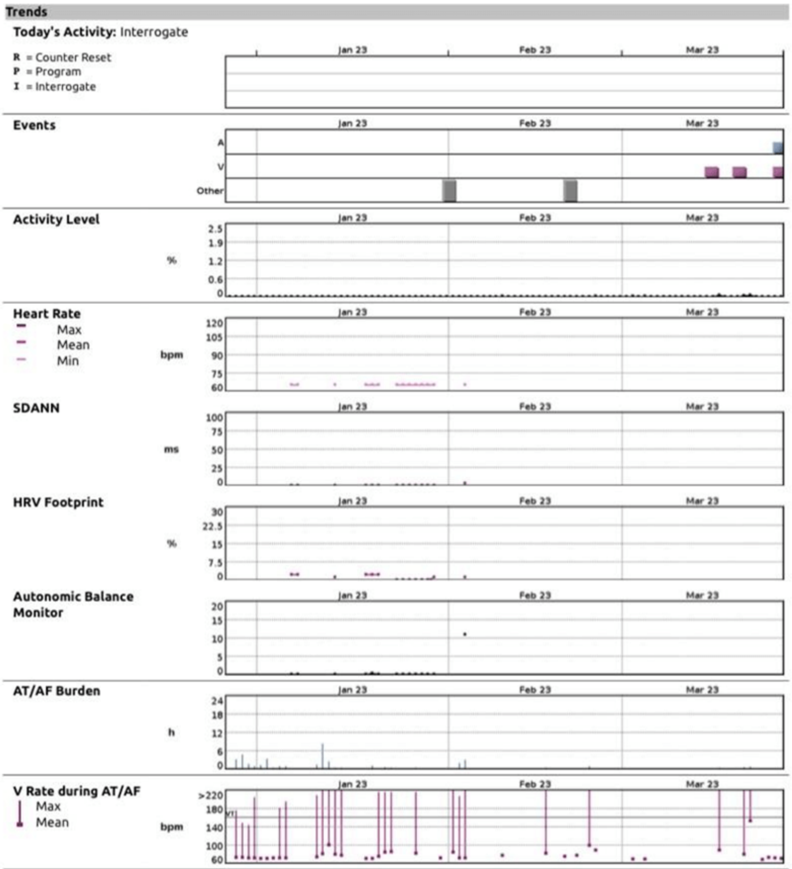

Figure 11 Trends in Manufacturer B

Other notable metrics include:

A. Pacing Percent indicates the proportion of time the pacemaker actively paces the atrial or ventricular chambers. It helps evaluate dependency on the pacemaker and informs whether therapy adjustments are needed, such as reducing unnecessary pacing.

B. Respiratory Rate uses thoracic impedance monitoring to estimate the patient's breathing rate. It provides additional physiological data for rate-responsive pacing, where the pacemaker adjusts heart rate based on physical activity or breathing patterns. (see Figure 12)

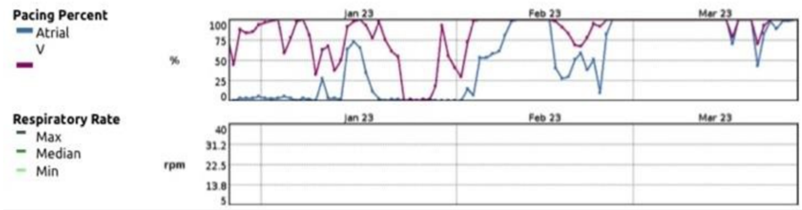

Figure 12 Pacing and Respiratory rate in Manufacturer B

Histograms

ATR Mode Switch, V detection (see Figure 13)

Heart rate variability waveform measures the variability in the time intervals between heartbeats (R-R intervals). Heart rate variability (HRV) is a key indicator of autonomic nervous

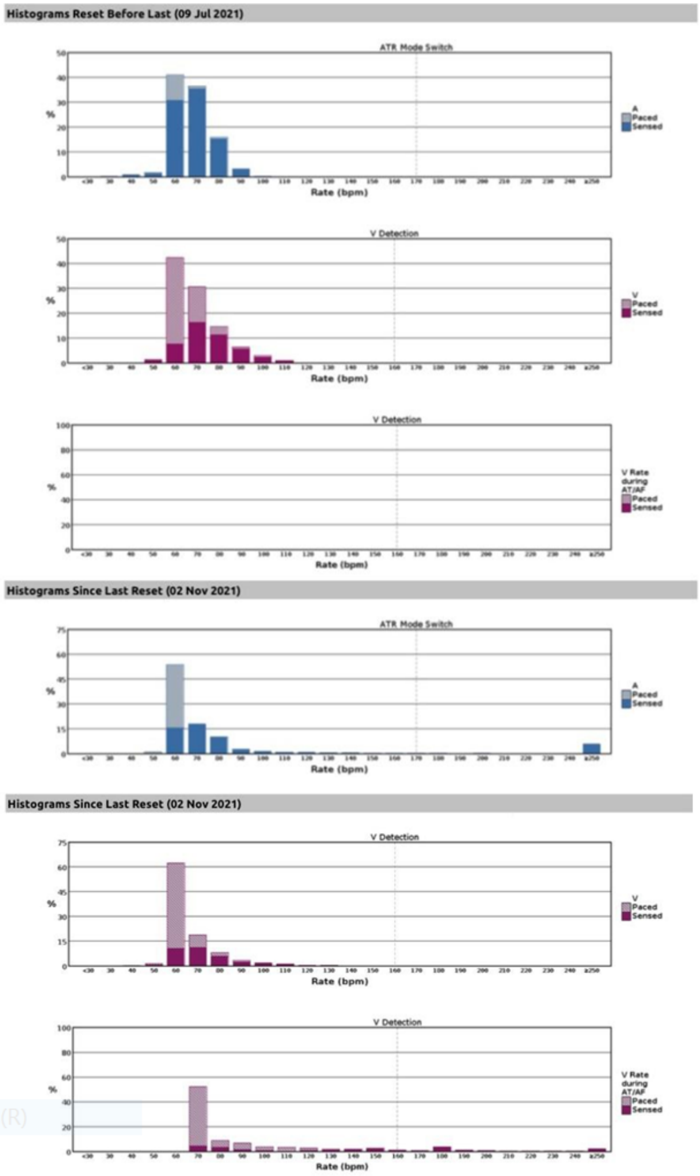

Figure 13 ATR mode switch and V detection in Manufacturer B

system activity and cardiac health. It is used for assessing stress, recovery, and potential arrhythmias. Low HRV may indicate an increased risk of cardiac events, while high HRV is generally a sign of good health. (see Figure 14)

(3) Manufacturer C

These devices leverage Cardiac Compass Trends to monitor pacing performance andphysiological adaptability.

This section provides daily or monthly trends for various parameters, such as:

A. AT/AF episodes per day: Graphs show time spent in atrial fibrillation or atrial tachycardia, which reflects how well the pacemaker manages arrhythmias over time. (see Figure 15)

B. Patient Activity and Heart Rate Variability: These trends track the patient's daily activity level and heart rate variability, which relate to how the pacemaker adjusts to changing physical demands. By analyzing the patient activity graph, adaptive rate functionality across different devices can be discussed. (see Figure 16)

Rate Histograms:

The histograms summarize the distribution of atrial and ventricular pacing rates. For example: Atrial and Ventricular Rate Distribution: This histogram shows the frequency of different heart rates, which helps assess the consistency and efficacy of the device's pacing under various conditions.

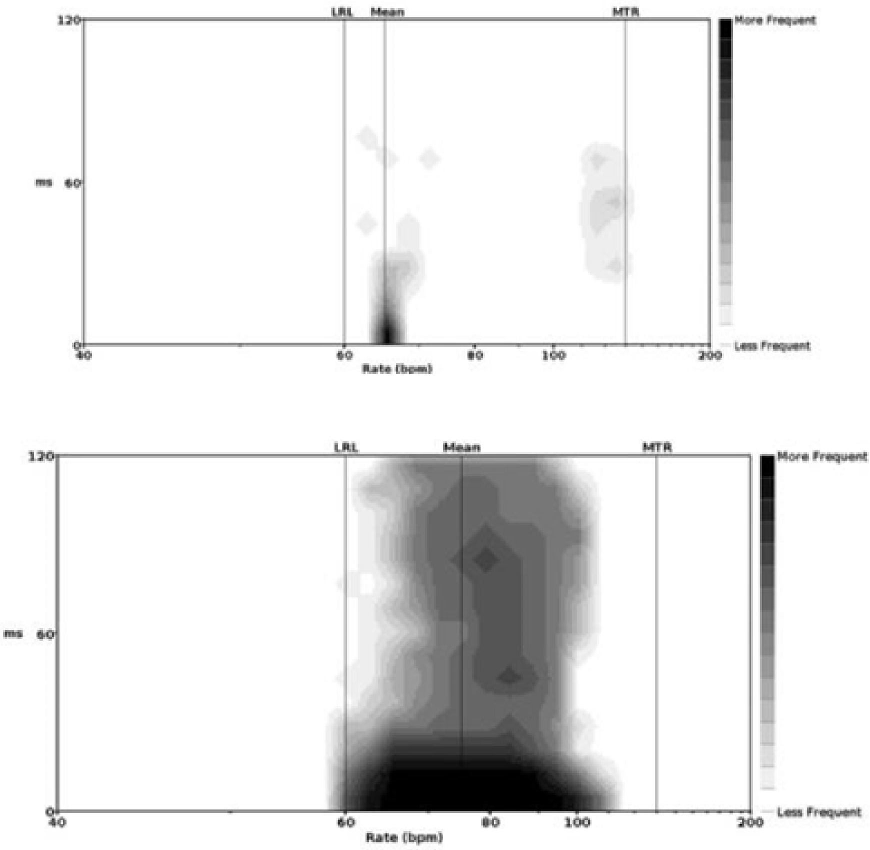

Figure 14 HR variability in Manufacturer B

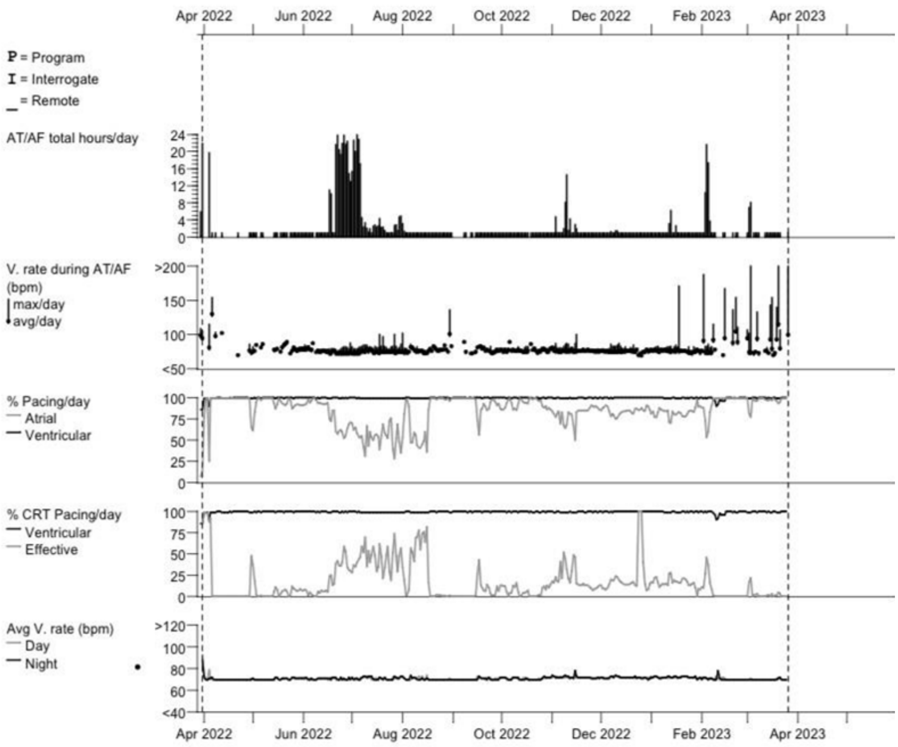

Figure 15 Trends in Manufacturer C

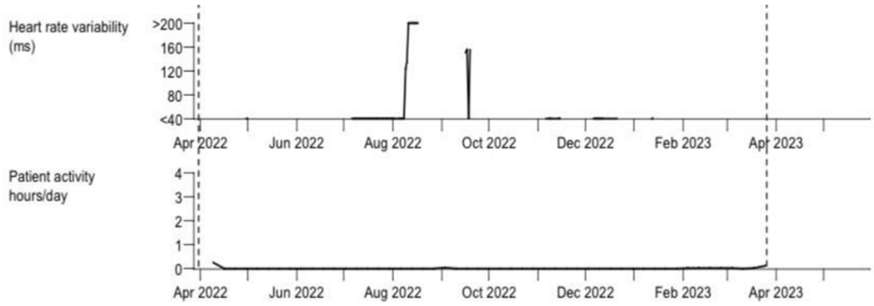

Figure 16 Patient activity and HR variability in Manufacturer C

Time in AT/AF: There are also pacing distributions specific to time spent in arrhythmia states like AT/AF, which can be used to evaluate the device's efficiency in maintaining normal sinus rhythm compared to other brands. (see Figure 17)

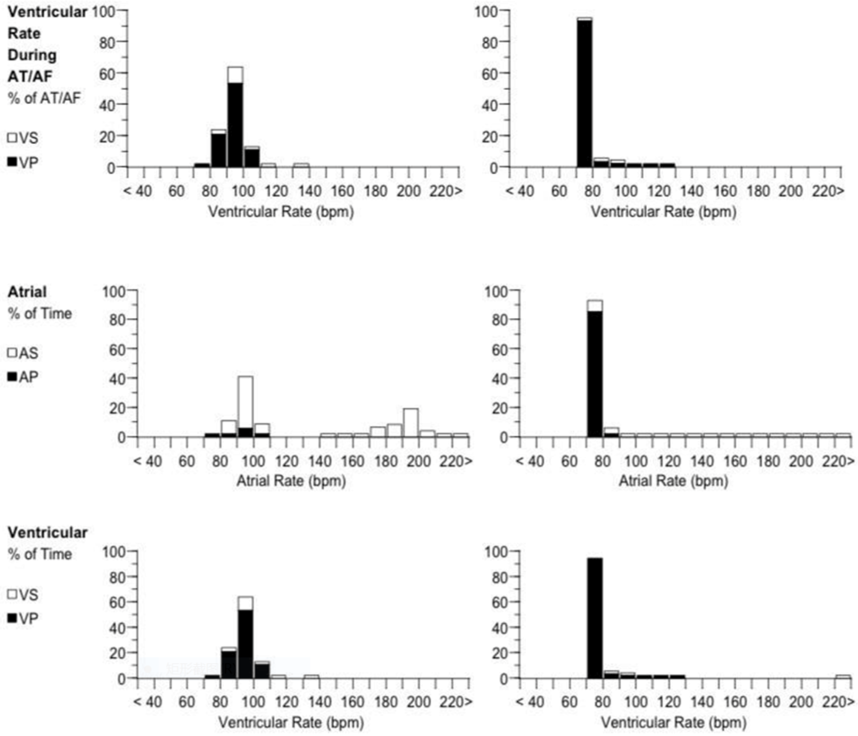

Figure 17 Rate Histograms in Manufacturer C

This comparison highlights the strengths and unique diagnostic tools each manufacturer offers for evaluating battery performance**,** lead functionality, and pacing modes. While Manufacturer C provides detailed trend-based diagnostics, Manufacturer A emphasizes reliable real-time performance monitoring, and Manufacturer B focuses on patient adaptability and long-term stability.

5.4 Interrogation report

When comparing pacemaker interrogation reports from the three manufacturers we should look at several aspects of these reports that affect clinical usability, data clarity, and comprehensiveness. Here's an in-depth comparison of these reports:

5.4.1 Report Layout and Readability

A Devices: These reports are designed with an intuitive layout that's relatively easy to follow, though they may not be as data-heavy as Manufacturer C's. Manufacturer A focuses on presenting critical information in a straightforward way, often including trend lines but with less detail in each section compared to Manufacturer C. Manufacturer A's reports are known for real-time data visibility, prioritizing recent events.

B Devices: These reports are concise and straightforward, which can benefit clinicians looking for a quick overview. They offer key metrics on battery life, pacing activity, and any recent arrhythmia events, although they may not have as many detailed graphical elements as Manufacturer C's. The reports are easy to read, with well-highlighted alerts and action items.

C Devices: These interrogation reports are well-organized and tend to be comprehensive, covering a broad range of data points. The layout is generally modular, allowing clinicians to view sections on battery life, lead performance, and arrhythmia episodes independently. The reports are known for including graphical trends and tables, making it easier for clinicians to spot changes over time.

5.4.2 Battery Status and Longevity Tracking

Manufacturer A: These reports provide accurate battery status with a remaining life estimation based on recent usage. The report may not be as granular in terms of predictive analytics compared to Manufacturer C but gives reliable information for typical clinical needs.

Manufacturer B: Known for strong battery management, These reports also include an estimated time until replacement but focus more on efficiency metrics, such as battery drain trends. Their reports provide a clear view of battery life expectancy but may lack the intricate projections seen in C Devices.

Manufacturer C: These reports provide detailed battery status information, including an estimated time until replacement that adjusts based on device usage. They use data-driven projections to predict battery depletion, which helps in planning replacement procedures. This section is typically detailed, with clear warnings when the battery approaches its end-of-life.

5.4.3 Lead Performance Monitoring

A Devices: These reports cover essential lead parameters, including pacing thresholds and impedance measurements, but with a greater focus on real-time diagnostics. The reports include alerts if the leads show signs of performance degradation, though trend analysis may be less detailed than in Manufacturer C reports.

B Devices: These reports also emphasize lead performance, providing data on lead impedance and pacing thresholds. They include historical data on lead status, which is valuable for tracking long-term stability, but might offer fewer real-time alerts compared to Manufacturer A.

C Devices: These reports provide detailed lead diagnostics, including impedance measurements, sensing thresholds, and pacing thresholds. Their reports often include trend graphs showing lead impedance over time, which is critical for early detection of lead issues like fractures or insulation breaches.

5.4.4 Arrhythmia Detection and Event Logging

Manufacturer A: These reports also monitor arrhythmias, with a focus on frequency and type of episodes. The reports provide a summary of recent arrhythmia events and may include some real-time data if the patient is enrolled in remote monitoring. However, Manufacturer A may not provide as extensive historical trend data as Manufacturer C.

Manufacturer B: These reports provide event logging for arrhythmias, with concise details on episode frequency and duration. Their focus is more on actionable insights, flagging significant arrhythmia events rather than providing exhaustive historical data.

Manufacturer C: These reports are particularly robust in terms of arrhythmia monitoring. They include a detailed history of arrhythmia episodes, categorized by type (e.g., atrial fibrillation, ventricular tachycardia), with timestamps, episode durations, and treatment provided (like ATP). The reports also feature algorithms for trend analysis, allowing clinicians to identify patterns.

5.4.5 Remote Monitoring Capabilities

A Devices: Manufacturer A's Merlin.net remote monitoring platform is known for its user-friendly interface and effective remote data transmission. Interrogation reports from Merlin.net provide real-time insights, particularly useful for tracking recent changes. However, the data in Manufacturer A reports might be slightly more simplified compared to Manufacturer C.

B Devices: The LATITUDE platform by Manufacturer B offers remote monitoring but is often praised for simplicity rather than depth. LATITUDE can provide alerts and event notifications, but reports might be more condensed, focusing on high-level information rather than exhaustive details.

C Devices: Manufacturer C's CareLink network is highly integrated with their interrogation reports. CareLink enables continuous remote monitoring, automatically updating clinicians on device status, arrhythmias, and lead performance. Reports pulled from CareLink are usually detailed and updated with the latest patient data, which is beneficial for proactive management.

5.4.6 Customization and User Controls

Manufacturer A: These reports are straightforward with minimal customization options. Their goal is simplicity and speed, providing clinicians with essential information without a lot of user-specific tailoring.

Manufacturer B: These reports provide limited customization but do allow clinicians to filter alerts and focus on key metrics. While customization options may not be as detailed as Manufacturer C's, they still offer enough to make the reports useful in varied clinical contexts.

Manufacturer C: These reports are highly customizable, allowing clinicians to prioritize sections based on specific needs. This flexibility is advantageous in situations where certain metrics, such as arrhythmia episode logs or battery life, are more relevant to the patient's condition.

5.4.7 Alerts and Notifications

A Devices: These devices provide effective alerts in their reports, particularly for battery status and lead performance. Their alerts are well-placed and make use of color-coding or symbols to quickly draw attention to any urgent issues.

B Devices: These reports include alerts, but they focus on critical issues only, providing a streamlined experience. This approach makes the reports easy to read, though some clinicians may find the alerts less frequent or detailed than those in Manufacturer C reports.

C Devices: These reports contain robust alert systems that flag issues like low battery, abnormal lead impedance, and arrhythmia episodes. Their reports often highlight warnings prominently, making them hard to miss for clinicians.

The interrogation reports from three leading manufacturers: Manufacturer A, Manufacturer B, and Manufacturer C were evaluated based on key aspects such as report layout, battery status, lead performance, arrhythmia detection, remote monitoring capabilities, customization options, and alert systems. The findings are summarized in Table 4.

Table 4 Fornell-Lecker criterion

Aspect	Manufacturer A	Manufacturer B	Manufacturer C
Report Layout	Intuitive, real-time focus	Concise, action- oriented	Modular, detailed, graphical
Battery Status	Accurate, reliable estimations	Focus on efficiency, basic projections	Predictive, data- driven projections
Lead Performance	Real-time monitoring	Emphasis on long- term stability	In-depth diagnostics, trend analysis
Arrhythmia Detection	Recent episode summary	Focused on actionable events	Detailed episode history, trends
Remote Monitoring	Simple and effective (Merlin.net)	Efficient and streamlined (LATITUDE)	Advanced, real-time updates (CareLink)
Customization	Limited customization	Moderate customization	Highly customizable
Alerts and Notifications	Clear, real-time alerts	Minimal but essential alerts	Prominent alerts, comprehensive

5.5 Visualization Report

The graphs developed for A, B, and C devices display a comparative analysis of different parameters such as voltage, battery life, pulse amplitude, lead impedance, and sensor rates between different models of pacemakers. A bar is taken for every parameter for a given device so that an easy comparison of how devices of these companies compare on different parameters can be done. The data is also presented in a long format, where each parameter is plotted along the y-axis and the device model along the x-axis. The difference in hue between each parameter simplifies the identification and comparison of values for all the pacemaker devices. With this analysis, the varying performance and nature of pacemakers by the three major manufacturers are made evident. (see Figure 18, 19 and 20)

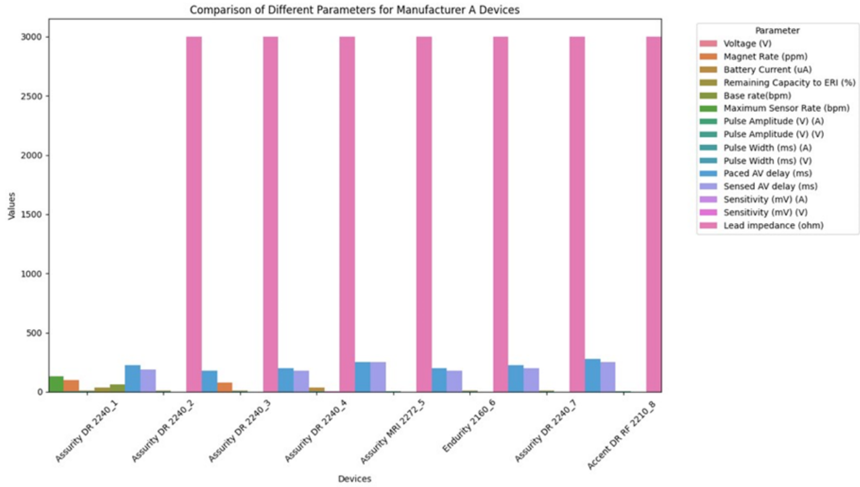

Figure 18 Comparison of different parameters for Manufacturer A devices

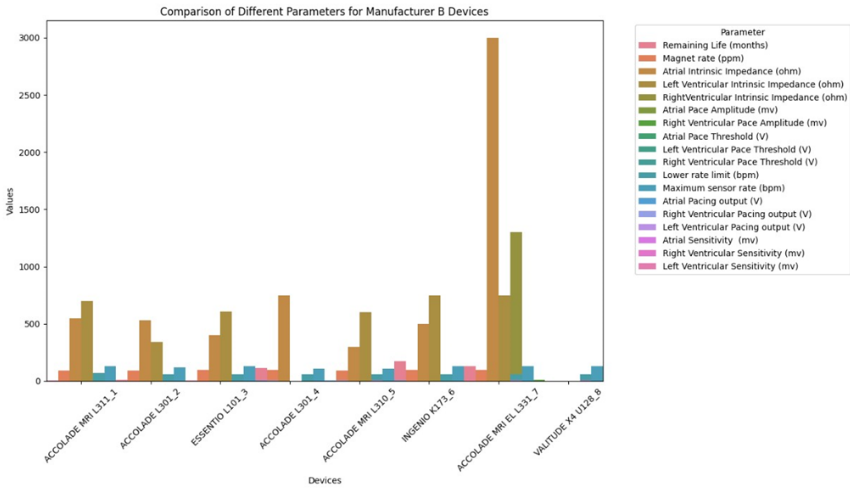

Figure 19 Comparison of different parameters for Manufacturer B devices

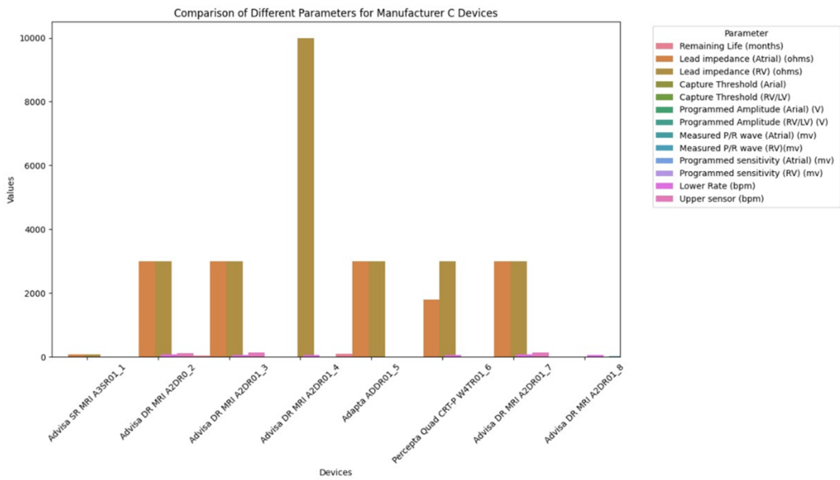

Figure 20 Comparison of different parameters for Manufacturer C devices

6 Discussion

The performance, reliability, and usability of cardiac implantable electronic devices (CIEDs) can be well evaluated on the basis of an analysis of pacemaker interrogation reports of three companies. The reports have structured data, focusing on key aspects such as battery performance, lead diagnostics, pacing modes, arrhythmia monitoring, and usability. However, differences in data presentation and reporting structures reflect distinct clinical decision-making approaches, highlighting the necessity for standardized practices to ensure consistency and optimize patient management [43].

6.1 Battery Performance

Manufacturer C's reporting is better in highlighting voltage trends and forecast analysis so that clinicians can plan and prepare battery replacements. Devices A likes real-time efficiency metrics with true battery status notifications but lacks a predictive function. B focuses more on simple battery life estimation, where efficiency metrics are the priority, possibly at the expense of using it for long-term planning. These variations highlight the need for uniform battery life estimation methodologies across manufacturers to ensure reliability in clinical decision-making [44, 45]. Standardized reporting of device longevity is essential to facilitate accurate comparisons and prevent premature or delayed replacements [46].

6.2 Lead Performance

Lead diagnostics play a crucial role in ensuring effective pacing and minimizing complications. C Devices leads the way in lead performance monitoring with full diagnostics including impedance measurements, sensing thresholds, and pacing thresholds, along with trend graphs to review historically. Device A emphasizes more real-time lead diagnostics with instantaneous alerts for likely problems. Manufacturer B emphasizes long-term stability by using historical lead performance data but gives fewer instantaneous alerts. Integrating both real-time and historical diagnostics into a standardized framework would improve lead monitoring strategies across manufacturers [46, 47].

6.3 Pacing Modes and Arrhythmia Management

The approach to pacing and arrhythmia management varies across manufacturers. C Devices provide in-depth pacing mode and arrhythmia control information through advanced diagnostics and trend analysis of history. Manufacturer A prioritizes real-time arrhythmia detection and pacing mode optimization with prompt clinical action alerts. B Devices prioritizes pacing stability over the long term and arrhythmia trends, but its real-time monitoring capabilities are less robust. These are clinical priority distinctions, wherein A and C Devices are best in real-time data utilization, and B Devices is best for historic data in longitudinally managing patients. These differences underscore the need for interoperable data sharing and harmonization of pacing and arrhythmia diagnostics across different systems to enhance clinical decision-making [48, 49].

6.4 Report Layout and Usability

Variations in report design impact how clinicians interpret and utilize interrogation data. C devices reports provide rich data on pacing modes and arrhythmia control with the assistance of advanced diagnostics and historical trend monitoring. Manufacturer A highlights real-time detection of arrhythmia and pacing mode optimization with timely clinical action alerts. B Devices highlights long-term pacing stability and arrhythmia trends, though its real-time monitoring is weaker. These are differences in clinical priorities, where Devices A and C lead in the utilization of real-time data and B focuses on historical data for longitudinal patient management. These differences in usability suggest that standardizing report structures while preserving critical manufacturer- specific innovations could improve clinician workflow efficiency [50].

6.5 Remote Monitoring and Customization

Remote monitoring solutions further distinguish the three manufacturers. Manufacturer C's CareLink network merges remote monitoring and interrogation reports, providing predictive

analytics and easy data integration. Manufacturer A's Merlin.net system emphasizes simplicity of interface and real-time data transmission optimized. B's LATITUDE system provides remote monitoring optimized with a focus on operational efficiency. C Devices allows for greater levels of customization, with the ability for reports to be specific to clinical needs, while A and B provide more standardized reporting systems. Standardizing remote monitoring protocols while allowing some degree of customization could enhance patient management without sacrificing clinical flexibility [43, 51].

Overall, the interrogation reports are all unique in terms of data presentation, usability, and clinical usefulness. The variance in reporting design and functionality points to the need for standardization of device reporting in order to provide consistency, efficiency in clinician workflow, and optimal patient outcomes. Standardization of these reporting practices should be the goal of future endeavors with the retention of the innovative elements that set each company apart.

7 Conclusion

The research provides a comprehensive comparative evaluation of pacemaker interrogation reports by the leading manufacturers in terms of key features of battery performance, lead status, pacing modes, arrhythmia detection, and reportability. The research focuses on different aspects of device management to benefit clinical decision-making. These differences in reporting formats and diagnostic performance emphasize the potential advantages of adopting standardized reporting practices, which would enhance data consistency, comparability, and clinical utility across manufacturers.

In terms of battery performance, C Devices provides trend analysis and predictive insights, Manufacturer A focuses on real-time efficiency metrics and notifications, B emphasizes straightforward battery life estimations with long-term stability, reflecting distinct priorities. For lead performance, C Devices offers comprehensive diagnostics and historical trends, Manufacturer A delivers real-time alerts, B prioritizes long-term stability with fewer immediate alerts, highlighting the need for balanced monitoring. Regarding pacing modes and arrhythmia management, C provides advanced diagnostics and historical trends, Device A focuses on real- time detection and actionable alerts, and B emphasizes long-term pacing stability and trends, showcasing differing clinical priorities. These variations underscore the importance of integrating diverse functionalities to optimize patient care and outcomes.

Finally, pacemaker selection and its associated interrogation system must be resolved according to the patient's individual clinical needs and the practice environment of the healthcare organization. By leveraging the unique strengths of each device reporting system and demanding higher levels of standardization, clinicians can maximize the efficient utilization of pacemakers and improve cardiac care and patient outcomes. This study focuses on the necessity of collaboration among manufacturers, clinicians, and regulators in creating standard reports that will stimulate innovation.

Conflicts of interest

The authors declare no conflicts of interest.

References

[1] American Heart Association. "Why would I need one?", 2021.
https://www.heart.org

[2] Aquilina O. A brief history of cardiac pacing. Images in paediatric cardiology. 2006, 8(2): 17.
https://pmc.ncbi.nlm.nih.gov/articles/PMC3232561

[3] Shivi A, Shinde RK. Smart Pacemaker: A Review. Cureus. 2022, 14(10).
https://doi.org/10.7759/cureus.30027

[4] Ward C, Henderson S, Metcalfe NH. A short history on pacemakers. International Journal of Cardiology. 2013, 169(4): 244-248.
https://doi.org/10.1016/j.ijcard.2013.08.093

[5] Kalra J, Lightner NJ, Taiar R. (Eds.). Advances in Human Factors and Ergonomics in Healthcare and Medical Devices: Proceedings of the AHFE 2021 Virtual Conference on Human Factors and Ergonomics in Healthcare and Medical Devices, July 25–29, 2021, USA. Springer.
https://doi.org/10.1007/978-3-030-80744-3

[6] Shepard RK, Ellenbogen KA. Leads and longevity: how long will your pacemaker last? Europace. 2008, 11(2): 142-143.
https://doi.org/10.1093/europace/eun359

[7] Maisel WH, Moynahan M, Zuckerman BD, et al. Pacemaker and ICD generator malfunctions: analysis of Food and Drug Administration annual reports. Jama. 2006, 295(16): 1901-1906. https://doi.org/10.1001/jama.295.16.1901

[8] Ferrick AM, Raj SR, Deneke T, et al. 2023 HRS/EHRA/APHRS/LAHRS expert consensus statement on practical management of the remote device clinic. Heart Rhythm. 2023, 20(9): e92-e144. https://doi.org/10.1016/j.hrthm.2023.03.1525

[9] Piccini JP, El-Chami M, Wherry K, et al. Contemporaneous Comparison of Outcomes Among Patients Implanted With a Leadless vs Transvenous Single-Chamber Ventricular Pacemaker. JAMA Cardiology. 2021, 6(10): 1187. https://doi.org/10.1001/jamacardio.2021.2621

[10] Burri H, Senouf D. Remote monitoring and follow-up of pacemakers and implantable cardioverter defibrillators. Europace. 2009, 11(6): 701-709. https://doi.org/10.1093/europace/eup110

[11] Slotwiner D, Varma N, Akar JG, et al. HRS Expert Consensus Statement on remote interrogation and monitoring for cardiovascular implantable electronic devices. Heart Rhythm. 2015, 12(7): e69-e100. https://doi.org/10.1016/j.hrthm.2015.05.008

[12] Shanmugam DK, Anitha SC, Souresh V, et al. Current advancements in the development of bionic organs using regenerative medicine and 3D tissue engineering. Materials Technology. 2023, 38(1). https://doi.org/10.1080/10667857.2023.2242732

[13] Schaldach M. Electrotherapy of the heart: technical aspects in cardiac pacing. Springer Science & Business Media, 2012.

[14] Salih A M. Characterization of in-vivo damage in implantable cardiac devices and the lead residual properties. Wright State University, 2019. https://corescholar.libraries.wright.edu/etd_all

[15] Marras E, Sciarra L, Bocchino M, et al. Pacemaker malfunctions in Danon's disease. Pacing and Clinical Electrophysiology, 2008, 31(1): 125-128. https://doi.org/10.1111/j.1540-8159.2007.00937.x

[16] Atlee JL. Pacemaker Malfunction in Perioperative Settings. In: Atlee, J.L., Gombotz, H., Tscheliessnigg, K.H. (eds) Perioperative Management of Pacemaker Patients. Springer, Berlin, Heidelberg, 1992. https://doi.org/10.1007/978-3-642-76531-5_18

[17] Sabbagh E, Abdelfattah T, Karim M, et al. Causes of Failure to Capture in Pacemakers and Implantable Cardioverter-defibrillators. Journal of Innovations in Cardiac Rhythm Management. 2020, 11(2): 4013-4017. https://doi.org/10.19102/icrm.2020.110207

[18] Goswami T. Investigation of Retrieved Cardiac Devices. Biomedical Journal of Scientific & Technical Research. 2019, 23(4). https://doi.org/10.26717/bjstr.2019.23.003924

[19] Salih A, Goswami T. Residual properties of silicone (MED-4719) lead with leads from retrieved devices. Materials Engineering Research. 2022, 4(1): 236-244. https://doi.org/10.25082/mer.2022.01.005

[20] Mulpuru SK, Madhavan M, McLeod CJ, et al. Cardiac pacemakers: function, troubleshooting, and management: part 1 of a 2-part series. Journal of the American College of Cardiology. 2017, 69(2): 189-210. https://doi.org/10.1016/j.jacc.2016.10.061

[21] Rockland R, Parsonnet V, Myers GH. Failure modes of American pacemakers—in vitro analysis. American Heart Journal. 1972, 83(4): 481-492. https://doi.org/10.1016/0002-8703(72)90039-7

[22] Sabbagh E, Abdelfattah T, Karim M, et al. Causes of Failure to Capture in Pacemakers and Implantable Cardioverter-defibrillators. Journal of Innovations in Cardiac Rhythm Management. 2020, 11(2): 4013-4017. https://doi.org/10.19102/icrm.2020.110207

[23] Willy K, Ellermann C, Reinke F, et al. The Impact of Cardiac Devices on Patients' Quality of Life — A Systematic Review and Meta-Analysis. Journal of Cardiovascular Development and Disease. 2022, 9(8): 257. https://doi.org/10.3390/jcdd9080257

[24] Mulpuru SK, Madhavan M, McLeod CJ, et al. Cardiac pacemakers: function, troubleshooting, and management: part 1 of a 2-part series. Journal of the American College of Cardiology. 2017, 69(2): 189-210. https://doi.org/10.1016/j.jacc.2016.10.061

[25] Mond HG. The Development of Pacemaker Programming: Memories From a Bygone Era. Heart, Lung and Circulation. 2021, 30(2): 233-239. https://doi.org/10.1016/j.hlc.2020.08.006

[26] Paglia E, Carter J. Cardiac Pacemakers. Hospital Medicine Clinics. 2017, 6(3): 374-396. https://doi.org/10.1016/j.ehmc.2017.04.007

[27] Davies G, Siddons H. Prediction of battery depletion in implanted pacemakers. Thorax. 1973, 28(2): 180-182. https://doi.org/10.1136/thx.28.2.180

[28] Davies G, Siddons H. Prediction of battery depletion in implanted pacemakers. Thorax. 1973, 28(2): 180-182. https://doi.org/10.1136/thx.28.2.180

[29] Munawar DA, Mahajan R, Linz D, et al. Predicted longevity of contemporary cardiac implantable electronic devices: A call for industry-wide "standardized" reporting. Heart Rhythm. 2018, 15(12): 1756-1763.
https://doi.org/10.1016/j.hrthm.2018.07.029

[30] Paratz ED, Block TJ, Stub DA, et al. Postmortem Interrogation of Cardiac Implantable Electronic Devices. JACC: Clinical Electrophysiology. 2022, 8(3): 356-366.
https://doi.org/10.1016/j.jacep.2021.10.011

[31] Olabi AG, Abdelghafar AA, Soudan B, et al. Artificial neural network driven prognosis and estimation of Lithium-Ion battery states: Current insights and future perspectives. Ain Shams Engineering Journal. 2024, 15(2): 102429.
https://doi.org/10.1016/j.asej.2023.102429

[32] Katz D, Akiyama T. Pacemaker longevity: the world's longest lasting VVI pacemaker. Annals of Noninvasive Electrocardiology. 2007, 12(3): 223-226.
https://doi.org/10.1111/j.1542-474X.2007.00165.x

[33] Davis J, Thibault B, Mangat I, et al. Canadian Registry of Electronic Device Outcomes (CREDO): The Abbott ICD Premature Battery Depletion Advisory, a Multicentre Cohort Study. CJC Open. 2021, 3(1): 48-53.
https://doi.org/10.1016/j.cjco.2020.09.008

[34] Melman YF, Steinberg BA, Lancaster J, et al. Limitations of manufacturer-recommended remote monitoring in the St. Jude Assurity/Endurity battery recall. HeartRhythm Case Reports. 2021, 7(12): 791-794.
https://doi.org/10.1016/j.hrcr.2021.09.013

[35] Sinha SK, Akinyele B, Spragg DD, et al. Managing cardiac implantable electronic device patients during a health care crisis: Practical guidance. Heart Rhythm O2. 2020, 1(3): 222-226.
https://doi.org/10.1016/j.hroo.2020.05.005

[36] Neuenschwander JF, Peacock WF, Migeed M, et al. Safety and efficiency of emergency department interrogation of cardiac devices. Clinical and Experimental Emergency Medicine. 2016, 3(4): 239-244.
https://doi.org/10.15441/ceem.15.118

[37] D'Angelo RN, Pickett CC. Diagnostic yield of device interrogation in the evaluation of syncope in an elderly population. International Journal of Cardiology. 2017, 236: 164-167.
https://doi.org/10.1016/j.ijcard.2017.02.121

[38] Sobel RM, Donaldson PR, Dhruva N. Pacemaker-mediated tachycardia: Management by pacemaker interrogation/reprogramming in the ED. The American Journal of Emergency Medicine. 2002, 20(4): 336-339.
https://doi.org/10.1053/ajem.2002.33780

[39] Kawase K, Yamagata K, Ishibashi K, et al. Leadless pacemaker interrogation interference after conversion of a left ventricular assist device. HeartRhythm Case Reports. 2023, 9(1): 25-27.
https://doi.org/10.1016/j.hrcr.2022.10.005

[40] Cronin B, Birgersdotter-Green U, Essandoh MK. Perioperative Interrogation of Boston Scientific Cardiovascular Implantable Electronic Devices: A Guide for Anesthesiologists. Journal of Cardiothoracic and Vascular Anesthesia. 2019, 33(4): 1076-1089.
https://doi.org/10.1053/j.jvca.2018.05.005

[41] Burgemeestre GM, Timmer SAJ. Syncope due to pacemaker failure to capture after device transition into Safety Mode. HeartRhythm Case Reports. 2022, 8(7): 482-484.
https://doi.org/10.1016/j.hrcr.2022.04.008

[42] Boriani G, Bertini M, Saporito D, et al. Impact of pacemaker longevity on expected device replacement rates: Results from computer simulations based on a multicenter registry (ESSENTIAL). Clinical Cardiology. 2018, 41(9): 1185-1191.
https://doi.org/10.1002/clc.23003

[43] Varma N, Braunschweig F, Burri H, et al. Remote monitoring of cardiac implantable electronic devices and disease management. Europace. 2023, 25(9).
https://doi.org/10.1093/europace/euad233

[44] Alam MB, Munir MB, Rattan R, et al. Battery longevity in cardiac resynchronization therapy implantable cardioverter defibrillators. Europace. 2013, 16(2): 246-251.
https://doi.org/10.1093/europace/eut301

[45] Censi F, Calcagnini G, Mattei E, et al. Estimate and reporting of longevity for cardiac implantable electronic devices: a proposal for standardized criteria. Expert Review of Medical Devices. 2021, 18(12): 1203-1208.
https://doi.org/10.1080/17434440.2021.2013199

[46] Kusumoto FM, Schoenfeld MH, Wilkoff BL, et al. 2017 HRS expert consensus statement on cardiovascular implantable electronic device lead management and extraction. Heart Rhythm. 2017, 14(12): e503-e551.
https://doi.org/10.1016/j.hrthm.2017.09.001

[47] Karnik AA, Helm RH, Gaskill MD, et al. High impedance alert with safety switching: An unreported hazard of hybrid pacing systems. Journal of Cardiovascular Electrophysiology. 2019, 30(7): 1102-1107.
https://doi.org/10.1111/jce.13941

[48] Diamond J, Varma N, Kramer DB. Making the Most of Cardiac Device Remote Management. Circulation: Arrhythmia and Electrophysiology. 2021, 14(3).
https://doi.org/10.1161/circep.120.009497

[49] Slotwiner DJ, Abraham RL, Al-Khatib SM, et al. HRS White Paper on interoperability of data from cardiac implantable electronic devices (CIEDs). Heart Rhythm. 2019, 16(9): e107-e127. https://doi.org/10.1016/j.hrthm.2019.05.002

[50] Daley C, Coupe A, Allmandinger T, et al. Clinician use of data elements from cardiovascular implantable electronic devices in clinical practice. Cardiovascular Digital Health Journal. 2023, 4(1): 29-38. https://doi.org/10.1016/j.cvdhj.2022.10.007

[51] Slotwiner DJ, Serwer GA, Allred JD, et al. 2024 HRS perspective on advancing workflows for CIED remote monitoring. Heart Rhythm O2. 2024, 5(12): 845-853. https://doi.org/10.1016/j.hroo.2024.09.012

of the test data to its desired target value [6–8], the corresponding algorithm can be performed as following,

$$\begin{cases} u(f)=1,\, f=f_0 \\ u(f)=1-\frac{(|f-f_0|)}{\delta},\, |f-f_0|\leq\delta \\ u(f)=0,\, |f-f_0|>\delta \end{cases} \tag{1}$$

In Eq. (1), $u(f)$ expresses the membership of experimental data f belonging the desired target value f_0 of the attribute; δ is the pre-assigned data for the critical value of distance of f from f_0, at which the value of $u(f)$ decreases to 0.

As to the condition of "desired target being best", since the limit value of membership $u(f)$ of an attribute response f belonging to f_0 is "1" only, *i.e.*, a finite value instead of infinitely large one, which is not exactly consistent with the essence of "the larger the better" type of index. So, it seems improper to take membership $u(f)$ as a beneficial indicator to conduct this optimization problem directly, since in the latter case the value of the attribute response has the possibility to get a value of infinitely large instead of finite one.

Alternatively, a flexible measure could be introduced to use the "complement" η of the membership value $u(f)$ as an indicator to perform the optimization. The definition of the "complement" η of the membership value $u(f)$ is shown by Eq. (2).

$$\eta = 1 - u \tag{2}$$

Obviously, the lower limit value of η is 0, which corresponds to u taking its maximum value of 1. Therefore, the optimization problem of u approaching its maximum value is equivalent to η inclining to its minimum value of 0.

Furthermore, as to robustness assessment, since the inevitability of spreading of a set of test data at the same experimental conditions due to the effects of external uncertain factors, the evaluation of scattering of a set of test data must be taken into account surely [6–8].

In the light of Lin and Tu's discussion [9], the scattering of a set of test data in term of membership of fuzzy theory can be characterized by Eq. (3).

$$s_{\mathrm{u}} = (\bar{\eta}^2 + \sigma_{\mathrm{u}}^2)^{0.5} \tag{3}$$

In Eq. (3), σ_u indicates the standard deviation of membership value u of a set of test data at the same experimental conditions; $\bar{\eta}$is the mean value of "complement" η of the membership value u in the corresponding set, which is an unbeneficial index to join the assessment of the 1^{st} part of partial preferable probability; s_u is in fact the indicator of scattering of a set of test data in term of membership with regard to the desired target value to participate the assessment of the other part of partial preferable probability.

2.2 Assessment of Preferable Probability

Furthermore, the assessment of two parts $P_{\bar{\eta}}$ and $P_{s_{\mathrm{u}}}$ of partial preferable probability can be done by taking both $\bar{\eta}$and s_u of an attribute as unbeneficial type of dual indexes [6–8]. As a result, the partial preferable probability P_{kl} is the product of both two parts $P_{\bar{\eta}}$ and $P_{s_{\mathrm{u}}}$of an attribute.

Subsequently, the overall preferable probability P_k of k^{th} alternative candidate is the product of its all partial preferable probability P_{kl} [6–8].

$$P_k = \prod_{l=1}^{b} P_{kl}, k = 1, 2, ..., a; l = 1, 2, ..., b \tag{4}$$

Finally, the optimal option is the specific alternative candidate that has the largest overall preferable probability.

3 Utilization Examples for Illustration

3.1 Parameter Design of Leaf Spring with Targeted Free Height of 7.6 Inches

Montgomery mentioned the parameter design of leaf spring problem [10], which was once originally discussed by Pignatiello Jr. et al. [11]. Their article studied the application of the parametric effect of five input variables on the free height of truck leaf springs. The parameters included: furnace temperature - I_1; heating time - I_2; transfer time - I_3; hold down time - I_3, and quench oil temperature - I_4. Especially, the quench oil temperature was taken as the noise variable.

Here it is restudied by using fuzzification regulation. The experimental result data are cited in Table 1 [10]. The optimal design aims to option parameters so as to ensure the desired target value of the free height around f_0 = 7.6 inches with possible smaller spreading [10].

Table 1 Experimental results of leaf spring free height

No.	Input parameter				Value of free height in two noise levels, f (Inch)					
	I_1	I_2	I_3	I_4	I_{5+}			I_{5-}		
1	-	-	-	-	7.50	7.25	7.12	7.78	7.78	7.81
2	+	-	-	+	7.88	7.88	7.44	8.15	8.18	7.88
3	-	+	-	+	7.50	7.56	7.50	7.50	7.56	7.50
4	**+**	**+**	**-**	**-**	**7.63**	**7.75**	**7.56**	**7.59**	**7.56**	**7.75**
5	-	-	+	+	7.32	7.44	7.44	7.54	8.00	7.88
6	+	-	+	-	7.56	7.69	7.62	7.69	8.09	8.06
7	-	+	+	-	7.18	7.18	7.25	7.56	7.52	7.44
8	+	+	+	+	7.81	7.50	7.59	7.56	7.81	7.69

As to fuzzification assessment, the membership value u of a free height f belonging to its desired target value f_0 = 7.6 inches needs to be conducted by employing Eq. (1) first in principle. In the assessment, if a pre-assign data of δ is given, for example δ = 0.6 inches, then it derives the evaluation expression of membership belonging to its desired target value of 7.6 inches for this problem according to Eq. (5).

$$\begin{cases} u(f) = 1,\ f = 7.6; \\ u(f) = 1 - \frac{(|f-7.6|)}{0.6},\ |f-7.6| \leq 0.6 \\ u(f) = 0,\ |f-7.6| > 0.6 \end{cases} \tag{5}$$

Consequently, Table 2 represents the membership values u and the corresponding errors of the free height values shown in Table 1.

Table 2 Membership function u and errors of each tested free height

No.	Membership function u								
	I_{5+}			I_{5-}			$\bar{u}$	σ_u	s_u
1	0.8333	0.4167	0.2000	0.7000	0.7000	0.6500	0.5833	0.2117	0.4674
2	0.5333	0.5333	0.7333	0.0833	0.0333	0.5333	0.4083	0.2578	0.6454
3	0.8333	0.9333	0.8333	0.8333	0.9333	0.8333	0.8667	0.0471	0.1414
4	**0.9500**	**0.7500**	**0.9333**	**0.9833**	**0.9333**	**0.7500**	**0.8833**	**0.0957**	**0.1509**
5	0.5333	0.7333	0.7333	0.9000	0.3333	0.5333	0.6278	0.1830	0.4148
6	0.9333	0.8500	0.9667	0.8500	0.1833	0.2333	0.6694	0.3291	0.4664
7	0.3000	0.3000	0.4167	0.9333	0.8667	0.7333	0.5917	0.2624	0.4854
8	0.6500	0.8333	0.9833	0.9333	0.6500	0.8500	0.8167	0.1280	0.2236

Furthermore, the evaluation results for preferable probability are conducted and presented in Table 3, which indicates the alternative candidate No. 4 giving the largest overall preferable probability, therefore optimum option of this optimal problem is the alternative candidate No. 4.

Table 3 Assessment results of preferable probability

No.	$\bar{\eta} = 1 - \bar{\mu}$	s_μ	$P_{\bar{\eta}}$	P_{s_μ}	$P_t \times 10^2$	Rank
1	0.4167	0.4674	0.0937	0.0968	0.9069	6
2	0.5917	0.6454	0.0375	0.0429	0.1606	8
3	0.1333	0.1414	0.1847	0.1956	3.6122	2
4	**0.1167**	**0.1509**	**0.1900**	**0.1927**	**3.6622**	**1**
5	0.3722	0.4148	0.1079	0.1128	1.2172	4
6	0.3306	0.4664	0.1213	0.0971	1.1782	5
7	0.4083	0.4854	0.0963	0.0914	0.8802	7
8	0.1833	0.2236	0.1686	0.1707	2.8781	3

3.2 Robust Design of a Clamping Mechanism Stroking under Orthogonal Experimental Condition

Robust design of a clamping mechanism stroking under orthogonal experimental condition was investigated by Wu et al. [12], the controllable input parameters include, x_1, x_2 and x_3; while the machining errors of x_1, x_2 and x_3 are taken as the noise variables; the stroking's movement region f is the optimal attribute with robustness around its desired target value f_0 of 525.00 mm.

Table 4 cites the data of the design of controllable input parameters and machining errors. Table 5 cites the simulated consequences by using ADAMS technique. The designs $L_4(2^3)$ and $L_9(3^4)$ were used for outer table and inner table of orthogonal experimental condition in Wu's study, individually.

Table 4 Designed levels of input parameters

Level	Controllable variable			Noise variable		
	x_1/mm	x_2/mm	x_3/°	Δx_1/mm	Δx_2/mm	Δx_3/°
1	369	300	95	–0.02	–0.02	–0.10
2	379	311	98	0.02	0.02	0.10
3	389	320	100			

Table 5 Simulated results with $L_4(2^3)$ and $L_9(3^4)$ for outer and inner variables

Variable	Inner table $L_9(3^4)$				Outer table $L_4(2^3)$				No./Variable
					1	2	3	4	
No.	1	2	3	4	1	1	2	2	Δx_1
					1	2	1	2	Δx_2
	x_1	x_2	x_3	ex	1	2	2	1	Δx_3
No.					Consequence, f / mm				
1	1	1	3	1	507.554	508.469	508.313	507.652	
2	**1**	**2**	**2**	**2**	523.847	524.858	**524.688**	**523.947**	
3	1	3	1	3	534.906	536.03	535.845	535.007	
4	2	1	2	3	488.239	489.234	489.087	488.334	
5	2	2	1	1	501.651	502.747	502.589	501.747	
6	2	3	3	2	552.237	553.185	553.015	552.338	
7	3	1	1	2	468.327	469.392	469.253	468.419	
8	3	2	3	3	521.454	522.404	522.253	521.552	
9	3	3	2	1	531.098	532.139	531.979	531.169	

Table 6 presents the membership values u of the stroking movement region f belonging to its desired target value f_0 = 525 mm in case of δ = 57 mm, and their mean value $\bar{u}$.

Table 6 Membership values μ and its mean value $\bar{\mu}$

No.	μ				$\bar{\mu}$
1	0.6939	0.7100	0.7072	0.6956	0.7017
2	0.9798	0.9975	0.9945	0.9815	**0.9883**
3	0.8262	0.8065	0.8097	0.8244	0.8167
4	0.3551	0.3725	0.3699	0.3567	0.3636
5	0.5904	0.6096	0.6068	0.5921	0.5997
6	0.5222	0.5055	0.5085	0.5204	0.5141
7	0.0057	0.0244	0.0220	0.0074	0.0149
8	0.9378	0.9545	0.9518	0.9395	0.9459
9	0.8930	0.8748	0.8776	0.8918	0.8843

Table 7 shows the evaluated results of η, s and values of partial and overall preferable probabilities, which reflect that the alternative candidate No. 2 exhibiting largest overall preferable probability, therefore alternative candidate No. 2 can be the primary selection of this robust design.

Table 8 is the range analysis of this assessment by means of overall preferable probability. The consequences in Table 8 reflect the optimal configuration bing $x_1 1$, $x_2 2$, $x_3 2$, it is exactly the alternative candidate No. 2., and impact order of input variables is $x_2 > x_1 > x_3$.

Table 7 Evaluated results of η, s and partial and overall preferable probabilities

No.	σ_u	$\bar{\eta}=1-\bar{u}$	S_u	$P_{\bar{\eta}}$	P_{s_u}	$P_t \times 10^2$	Rank
1	0.0070	0.2983	0.2984	0.1204	0.1205	1.4505	5
2	**0.0078**	**0.0117**	**0.0140**	**0.1698**	**0.1693**	**2.8758**	**1**
3	0.0087	0.1833	0.1835	0.1403	0.1402	1.9663	4
4	0.0077	0.6364	0.6365	0.0621	0.0623	0.3873	8
5	0.0086	0.4003	0.4004	0.1028	0.1029	1.0584	6
6	0.0072	0.4859	0.4859	0.0881	0.0882	0.7771	7
7	0.0084	0.9851	0.9852	0.0020	0.0024	0.0005	9
8	0.0073	0.0541	0.0546	0.1625	0.1623	2.6385	2
9	0.0082	0.1157	0.1160	0.1519	0.1518	2.3057	3

Table 8 Range analysis of the total preferable probability

Level	x_1	x_2	x_3
1	2.0975	0.6128	1.008
2	**0.7409**	**2.1909**	**1.986**
3	1.6482	1.6830	1.553
Range	1.3566	1.5781	0.9778
Impact	2	1	3
Optimal conf.	1	2	2

4 Conclusion

This study indicates that the combination of PMOO with fuzzification is effective; the introduction of "complement" of the membership value is a proper indicator to perform the assessment of robust design in condition of "desired target being best"; all these procedures consist of the regulation of fuzzification measure reasonably.

Conflicts of interest

The authors declare that they have no conflict of interest.

References

[1] Enea M, Piazza T. Project Selection by Constrained Fuzzy AHP. Fuzzy Optimization and Decision Making. 2004, 3(1): 39-62.
https://doi.org/10.1023/b:fodm.0000013071.63614.3d

[2] Önüt S, Soner Kara S, Efendigil T. A hybrid fuzzy MCDM approach to machine tool selection. Journal of Intelligent Manufacturing. 2008, 19(4): 443-453.
https://doi.org/10.1007/s10845-008-0095-3

[3] Liao TW. A fuzzy multicriteria decision-making method for material selection. Journal of Manufacturing Systems. 1996, 15(1): 1-12.
https://doi.org/10.1016/0278-6125(96)84211-7

[4] Vasant P, Barsoum NN. Fuzzy optimization of units products in mix-product selection problem using fuzzy linear programming approach. Soft Computing. 2005, 10(2): 144-151.
https://doi.org/10.1007/s00500-004-0437-9

[5] Babanli M, Gojayev T. Application of Fuzzy AHP Method to Material Selection Problem. 11th World Conference "Intelligent System for Industrial Automation" (WCIS-2020). Published online 2021: 254-261.
https://doi.org/10.1007/978-3-030-68004-6_33

[6] Zheng M, Yu J. A Probability-based Fuzzy Multi-objective Optimization for Material Selection. Tehnički glasnik. 2024, 18(2): 178-182.
https://doi.org/10.31803/tg-20230515054622

[7] Zheng M, Yu J, Teng H, et al. Probability-Based Multi-Objective Optimization for Material Selection. Springer Nature Singapore, 2024.
https://doi.org/10.1007/978-981-99-3939-8

[8] Zheng M, Yu J. Robust Design and Assessment of Product and Production by Means of Probabilistic Multi-Objective Optimization. Springer Nature Singapore, 2024.
https://doi.org/10.1007/978-981-97-2661-5

[9] Lin DKJ, Tu W. Dual Response Surface Optimization. Journal of Quality Technology. 1995, 27(1): 34-39.
https://doi.org/10.1080/00224065.1995.11979556

[10] Montgomery, D. C. (2017) Design and Analysis of Experiments, 9th Ed. Hoboken, NJ, John Wiley & Sons, Inc.

[11] Pignatiello JJ, Ramberg JS. Discussion. Journal of Quality Technology. 1985, 17(4): 198-206. https://doi.org/10.1080/00224065.1985.11978969

[12] Wu L, Xu Y, Zhao Y, et al. Taguchi robust design for the stroking of a clamping mechanism. Machine Tool & Hydraulics, 2014, 42(5): 85-89.