

Human-Centered Intelligent Monitoring and Control of Industrial Systems:
A Framework for Immersive Cyber-Physical Systems

by

Todd Charter

B.A.Sc., University of British Columbia, 2021

A Thesis Submitted in Partial Fulfillment of the
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MASTER OF APPLIED SCIENCE

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ABSTRACT

This thesis embarks on a comprehensive exploration of modern industrial workplaces, delving into the intricate interplay between humans, machines, and software. Motivated by the imperative to bridge existing gaps in industrial automation, the research aims to contribute practical solutions to address the evolving nature of industrial systems. The objectives encompass unraveling the characteristics of so-called Industry 4.0 and Industry 5.0, understanding the contributions of Manufacturing Execution Systems (MES), Cyber-Physical Systems (CPS), and Artificial Intelligence (AI), and enhancing human-machine collaboration in manufacturing environments.

The thesis unfolds through a literature review, introducing an Intelligent Manufacturing Execution System (IMES) framework and presenting real-world applications of AI. Two compelling use cases demonstrate AI's transformative potential in manufacturing control and monitoring applications, addressing challenges hindering widespread adoption. The study further introduces a novel human-centered Cyber-Physical System framework (HC-CPS), leveraging Extended Reality (XR) interfaces and offering design principles for intuitive and collaborative environments. A tangible implementation of this framework serves as a proof of concept, showcasing feasibility and effectiveness in real-world settings.

The contributions of this work extend beyond conceptual frameworks, with practical insights provided through use cases and implementations. The proposed IMES framework and HC-CPS advance understanding and set the stage for the evolution of intelligent and user-friendly manufacturing systems. The thesis concludes with a prototype Cyber-Physical System featuring a 3D digital twin and demonstrating the integration of extended reality technologies to create immersive and human-centered systems. Overall, this research makes significant strides in advancing manufacturing systems toward next-generation solutions.

PREFACE

The work presented in this thesis was conducted at the Advanced Control and Intelligent Systems (ACIS) Laboratory at the University of Victoria under the supervision of Dr. Homayoun Najjaran. I had the privilege of working in an encouraging and dynamic environment alongside diverse colleagues, fostering an atmosphere of interdisciplinary collaboration that greatly contributed to the conceptualization and writing of this thesis. Several collaboratively written publications further highlight the richness of this collaborative experience. The following list summarizes these publications and their relevance to the thesis presented.

- The inspiration to develop a system for improving the integration of artificial intelligence within industrial applications originated from a survey on intelligent manufacturing execution systems. I contributed to researching state-of-the-art manufacturing systems, reviewing relevant technologies, and analyzing publication data.

[1] A. Shojaeinasab, T. Charter, M. Jalayer, M. Khadivi, O. Ogunfowora, N. Raiyani, M. Yaghoubi, and H. Najjaran, “Intelligent manufacturing execution systems: A systematic review,” *Journal of Manufacturing Systems*, vol. 62, pp. 503–522, 2022.

- The work on machinery condition monitoring provided insight into the data challenges that prevail in real-world industrial environments. I contributed to the development and verification of a data synthesis method to assist in data-driven fault detection and diagnosis when faced with few fault data.

[2] M. Ahang, M. Jalayer, A. Shojaeinasab, O. Ogunfowora, T. Charter, and H. Najjaran, “Synthesizing rolling bearing fault samples in new conditions: A framework based on a modified cgan,” *Sensors*, vol. 22, no. 14, p. 5413, 2022.

- The use of computer vision for quality management further sheds light on data limitations in real-world industrial applications. I contributed to the research and development of a software framework for improving defect detection in composite materials manufactured by automated fibre placement.

[3] A. Ghamisi, T. Charter, L. Ji, M. Rivard, G. Lund, and H. Najjaran, “Anomaly detection in automated fibre placement: learning with data limitations,” *Frontiers in Manufacturing Technology*, vol. 4, p. 1277152, 2024.

- A survey on deep reinforcement learning methods for machine scheduling provided insight into intelligent control and decision-making. I contributed to this work by reviewing machine scheduling environments and prominent reinforcement learning algorithms.

[4] M. Khadivi, T. Charter, M. Yaghoubi, M. Jalayer, M. Ahang, A. Shojaeinasab, and H. Najjaran, “Deep reinforcement learning for machine scheduling: Methodology, the state-of-the-art, and future directions,” *arXiv preprint arXiv:2310.03195*, 2023.

- Further exploring the use of artificial intelligence for condition monitoring, I contributed to a review paper on intelligent condition monitoring in industrial plants. This work sheds light on different methodologies and uncertainty management strategies.

[5] M. Ahang, T. Charter, O. Ogunfowora, M. Khadivi, M. Abbasi, and H. Najjaran, “Intelligent condition monitoring of industrial plants: An overview of methodologies and uncertainty management strategies,” *arXiv preprint arXiv:2401.10266*, 2024.

- A real-world scheduling problem involving human personnel and various machines led to the exploration of mathematical modeling and the interplay be-

tween humans and machines in a production setting. In this work, I developed a data generator to better test and validate scheduling systems.

[6] M. Khadivi, M. Abbasi, T. Charter, and H. Najjaran, “A mathematical model for simultaneous personnel shift planning and unrelated parallel machine scheduling,” arXiv preprint arXiv:2402.15670, 2024.

- Developing a method for machine condition monitoring with incomplete data brought attention to real-world challenges in industrial systems and the need for innovative solutions. In this work I contributed to the development of a machine health monitoring system and its comparison with other approaches.

[7] M. Ahang, M. Abbasi, T. Charter, and H. Najjaran, “Condition monitoring with incomplete data: An integrated variational autoencoder and distance metric framework,” arXiv preprint arXiv:2404.05891, 2024.

- Approaching the topic of human-robot collaboration led to the exploration of extended reality and artificial intelligence as tools to improve communication between humans and machines. My contributions include conceptualizing the human-in-the-loop approach and evaluating the technologies that enable these systems.

[8] Y. Karpichev, T. Charter, J. Hong, A. M. S. Enayati, H. Honari, M. G. Tamizi, and H. Najjaran, “Extended reality for enhanced human-robot collaboration: a human-in-the-loop approach,” arXiv preprint arXiv:2403.14597, 2024.

Through my contributions to the aforementioned publications, I gained valuable experience in diverse AI methodologies and their applications in industry. These projects provided insights that have significantly influenced my understanding of industrial systems and their interacting components: humans, machines, and software.

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I would also like to express my sincere gratitude to all of my colleagues at the Advanced Control and Intelligent Systems (ACIS) Lab. Thank you for the supportive and encouraging atmosphere, the engaging discussions that sparked further innovation, and the joyful social activities that brought us together outside of our research endeavors. Special thanks to my co-authors—Assef, Ardeshir, Jayden, Masoud, Maryam, Maziyar, Mostafa, and Yehor—for their collaboration and shared insights, which were crucial in shaping my research outcomes.

Furthermore, I am immensely grateful for the financial support provided by the Natural Sciences and Engineering Research Council (NSERC) Canada under the Alliance Grant ALLRP 555220 - 20, which was instrumental in funding this research.

Thank you all for your contributions, both big and small, that have made this journey not only possible but also a memorable chapter of my life.

Chapter 1

Introduction

This chapter serves as an entry point into the extensive exploration undertaken in this thesis, providing an in-depth examination of the motivation, research objectives, and organization of the work. In order to provide a meaningful context for the research, this chapter presents an introduction to the innovative technologies that are shaping modern industrial worksites. It also highlights the significant values and concepts that are currently being explored in research. This contextual foundation sets the stage for a nuanced exploration into the intricate roles performed by humans, machines, and software. This exploration not only frames the motivation of the thesis but also plays a fundamental role in shaping the subsequent research questions and objectives.

1.1 Motivation

Modern industrial workplaces operate as intricate ecosystems where the dynamic interplay between humans, machines, and software is indispensable to achieve common goals. However, this complexity introduces challenges that demand innovative solutions. The pursuit of optimal performance necessitates constant efforts to improve efficiency, involving fine-tuning processes to streamline operations, reduce downtime,

and maximize output. Safety is of utmost importance and requires the harmonization of humans and technology to mitigate risks and ensure a secure working environment. The relentless pace of technological advancement, exemplified by Industry 4.0 and the emerging Industry 5.0, underscores the need for a deep understanding of effective technology integration to stay competitive. In the era of Industry 4.0, data-driven systems are invaluable, yet extracting meaningful insights from the vast data generated poses challenges. The proper balance between automation and human control is crucial for the evolution of human-machine interaction. Despite progress in industrial automation, gaps persist in achieving seamless integration. This work is motivated by the imperative to bridge these gaps, offering practical solutions to address the complex and evolving nature of industrial systems.

In response to these challenges, this research aims to present a comprehensive Cyber-Physical System (CPS) framework and an Intelligent Manufacturing Execution System (IMES), complemented by industrial applications of Artificial Intelligence (AI). Addressing the multifaceted dynamics of modern industrial workplaces, this work aspires to contribute to the advancement of efficient, safe, and technologically adept industrial systems.

1.2 Objectives

In the dynamic landscape of modern industry, the intricate interplay between humans, machines, and technology presents both challenges and opportunities. This thesis sets out on a compelling exploration with a series of carefully crafted objectives and research questions. The journey commences by unraveling the defining characteristics of Industry 4.0 and Industry 5.0, casting a spotlight on the transformative technologies that have shaped the industrial terrain. A subsequent deep dive into the roles played

by Manufacturing Execution Systems (MES), Cyber-Physical Systems (CPS), and Artificial Intelligence (AI) unfolds, elucidating their contributions to the advancement of industrial practices. Amidst these complexities, attention shifts towards the domain of human interaction in industrial environments, aiming to uncover ways to enhance collaboration and establish design principles for human-centered CPS. Furthermore, the thesis aims to provide a tangible proof of concept for the proposed framework, addressing challenges in the adoption of Industry 4.0 technologies. The subsequent list articulates the specific research questions that guide this pursuit of knowledge and innovative solutions.

1. What are the defining characteristics of Industry 4.0 and Industry 5.0?
2. How do MES, CPS, and AI contribute to industrial advancements?
3. What challenges exist in adopting Industry 4.0 and associated technologies?
4. How can human-machine collaboration be improved in manufacturing environments towards the concept of Industry 5.0?
5. How can human-centered CPS contribute to the realization and adoption of Industry 4.0 and Industry 5.0?

In addressing these objectives and research questions, this research aims to not only provide valuable insights into the technological landscape but also to offer practical solutions that bridge gaps and contribute to the evolution of efficient, safe, and technologically adept industrial systems.

1.3 Contributions and Organization

The present work makes significant contributions to the field of manufacturing systems, particularly in the context of advancing towards next-generation CPS solutions.

The key contributions are outlined below:

Chapter 2 provides a thorough literature review of modern-day industrial revolutions and their associated technologies, including MES, CPS, and AI. This chapter explores the differences between Industry 4.0 and Industry 5.0, emphasizing their concurrent progression and establishing the importance of human-centered industrial systems. In addition, this review of the literature looks at the challenges industries face in adopting these concepts and technologies.

Building on the MES literature, Chapter 3 introduces a concept framework, termed Intelligent Manufacturing Execution Systems (IMES), which serves as a blueprint for the development of next-generation manufacturing systems. IMES integrates cutting-edge technologies, particularly AI, to enhance the efficiency and intelligence of manufacturing processes.

Chapter 4 of this work delves into the practical applicability of AI in industrial settings through the presentation of two compelling use cases for manufacturing control and monitoring applications. These cases not only demonstrate the tangible benefits of AI but also provide valuable insights into its implementation across diverse manufacturing scenarios, shedding light on the transformative potential of these technologies. Simultaneously, the chapter addresses the challenges and impediments that currently hinder or limit the widespread adoption of AI in real-world industrial scenarios.

In recognition of the pivotal role of human-machine interaction in manufacturing, Chapter 5 introduces a novel conceptualization and implementation of an immersive human-centered CPS (HC-CPS). This model is meticulously designed to enhance the cooperation between humans, machines, and software, aiming to create a more intuitive and collaborative manufacturing environment. The immersive HC-CPS platform is developed for a robotics research lab with a real-time communication network

enabling the synchronization of physical and virtual assets. This practical implementation serves as a proof of concept that demonstrates the feasibility and effectiveness of the proposed framework in a real-world environment.

In essence, this work not only advances conceptual understanding by proposing the IMES framework and the human-centered CPS but also contributes practical insights through use cases and implementation. By addressing the challenges of AI adoption and prioritizing human-machine collaboration, the research sets the stage for the evolution of intelligent and user-friendly manufacturing systems.

Chapter 2

Background

2.1 Modern Industrial Revolutions

Throughout history, the advancement of technology alongside the changing needs of humanity has shaped the industrial landscape and driven many transformations. The first major shift, known as the industrial revolution or the *first* industrial revolution, occurred between the late 18th century and the early 19th century. Driven by the development of water and steam power, this era witnessed a surge in use of machinery and mechanization in factories, improving production and changing the role of workers. The next significant transformation, the second industrial revolution, took place around the start of the 20th century with the increased applications of electricity. Electric motors and other devices induced mass production. In the late 20th century, as computers became prevalent and practical tools, a third industrial revolution unfolded. During this period, computers and robots started being integrated into factories for automation [11, 12].

As the third industrial revolution developed, the increased use of computers and sensors set the stage for yet another transformative era in manufacturing and produc-

tion. The advent of Industry 4.0, recognized as the fourth industrial revolution, began in the 2010s, driven by the integration of Cyber-Physical Systems (CPSs). These systems encompass various technologies, including data collection devices, cloud computing, and AI, collectively contributing to the seamless connectivity of machines, real-time data exchange, and the implementation of smart manufacturing systems. Industry 4.0 not only revolutionized production processes but also initiated an era of heightened efficiency, productivity, and flexibility.

Building on the foundation established by Industry 4.0, the industrial landscape is currently undergoing a concurrent paradigm shift with the introduction of Industry 5.0. This latest revolution emphasizes a holistic approach, highlighting the collaboration between humans and machines. In contrast to its predecessors, Industry 5.0 places a renewed emphasis on the human element, recognizing the indispensable role of human creativity, intuition, and decision-making working together with cutting-edge technologies. As the innovative concepts of Industry 4.0 continue to be adopted and implemented, the societal aspects of Industry 5.0 are gaining recognition from governments, researchers, and practitioners. Navigating the intricacies of Industry 4.0 and exploring the promising horizons of Industry 5.0, it becomes apparent that these industrial transformations are unfolding concurrently, shaped by the complementary interactions between technological advancements and evolving societal needs. Figure 2.1 shows the five industrial revolutions in a timeline of their introduction, including their key features.

2.1.1 Industry 4.0 - The Technology-Driven Industrial Revolution

Industry 4.0 emerged in 2011 as part of the German government's high-tech strategy, officially introduced at the renowned Hannover Fair, one of the largest trade shows

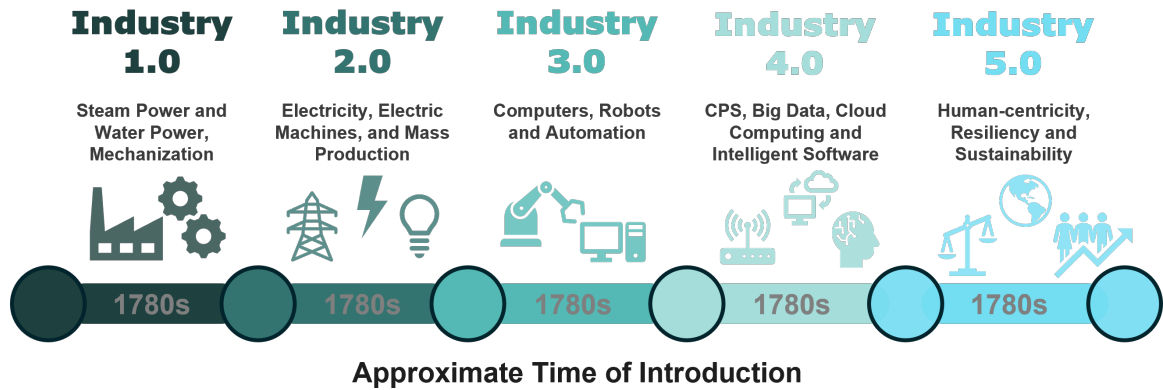


Figure 2.1: A timeline depicting the introduction of each industrial revolution

globally, dedicated to manufacturing and industrial development [12]. Rooted in the principles of CPS, intelligent networking, and the integration of advanced technologies, Industry 4.0 signifies a paradigm shift towards intelligent, interconnected processes and decentralized decision-making in manufacturing. The inception brought together key figures from the German government and industry leaders, marking the onset of a new era in manufacturing characterized by smart factories propelled by digitalization, intelligent agent interactions, and decentralized processes facilitated by the Internet of Things (IoT) and CPSs [12].

Although the concept originated in Germany, Industry 4.0 quickly gained global attention and adoption. Other countries, recognizing the potential benefits, have embraced this technological revolution to enhance their manufacturing capabilities. The results have varied, with improvements in efficiency, productivity, and adaptability to changing market demands observed across different nations [12].

The adoption of Industry 4.0 is propelled by several factors. Technological advances, including the Internet of Things (IoT), CPSs, AI, and big data analytics, are instrumental in driving this shift. The ability to gain a competitive advantage through the exploitation of data, coupled with the evolution of smart manufacturing processes, has fueled the allurement of Industry 4.0 [11].

Currently, Industry 4.0 is a concept that is predominantly explored in research and academia. Lemstra et al. [13] highlight that much of the existing literature is conceptual, emphasizing the need for practical research to validate theoretical postulates. Reviews of Industry 4.0 suggest a high degree of digitalization, requiring a change in workforce skills and presenting both challenges and opportunities in the industrial landscape [13, 11, 12].

In summary, Industry 4.0 represents a transformative era characterized by intelligent networking, advanced technologies, and decentralized decision making. While its roots trace back to Germany, its global adoption signifies a shift towards smart, interconnected manufacturing processes with profound implications for both industry and society.

2.1.2 Industry 5.0 - The Value-Driven Industrial Revolution

Industry 5.0 is a value-driven industrial transformation that seeks to achieve societal goals beyond jobs and growth, placing the focus on globally important aspects such as resiliency, sustainability, and the well-being of humanity. It compliments the concepts of Industry 4.0, in a more interdisciplinary approach rather than having specific technologies as the focal point. The concepts of Industry 5.0 have been introduced and debated in the literature since 2017 with a formal definition proposed by the European Union in 2021 [12].

The initiation of the Industry 5.0 concept took place during two virtual workshops held on the 2nd and 9th of July in 2020, where various stakeholders, including policymakers, researchers, and technology leaders, met to address the limitations of Industry 4.0 [14]. These workshops resulted in the formal definition and conceptualization of Industry 5.0, with an emphasis on the importance of integrating social and environmental priorities into technological innovation. The general outcome highlighted the

need for a transformative approach that goes beyond economic considerations and embraces the values of resiliency, sustainability, and human well-being.

The rationale behind Industry 5.0 stems from the shortcomings of its predecessor, Industry 4.0. While Industry 4.0 focuses on the convergence of physical and virtual worlds through CPSs, it falls short in addressing broader societal concerns. The realization that human involvement is essential in industrial processes prompted the shift towards Industry 5.0. Unlike Industry 4.0, which primarily aimed at efficiency through automation, Industry 5.0 emphasizes human-centric technologies that enhance workers' abilities, ensuring safer and more satisfying work environments.

The definition proposed by the European Union positions Industry 5.0 as a value-driven transformation, centering around human-centricity, ecological benefits, and social considerations. The outcomes of the EU meeting emphasize the need for technologies to align with future societal values, creating a change of mindset from considering workers as a "cost" to viewing them as an "investment." This shift includes the creation of safe and inclusive work environments that prioritize physical and mental health, worker autonomy, dignity, and privacy [12].

Industry 5.0 shares common ground with the Japanese concept of Society 5.0, a concept that envisions societal development following the technological advancements of Industry 4.0. While both concepts prioritize human well-being and societal advancement, they differ in scope and focus. Society 5.0 encompasses broader societal stages, ranging from individual workers and users to the entire society, forming a spectrum of socio-centric values. This aligns with Industry 5.0's emphasis on the inclusion of broader values beyond human-centricity.

Industry 5.0 has garnered attention and reviews due to its distinctive approach of placing societal values at the forefront. The challenges and enablers identified in the literature, such as social heterogeneity, measurement of environmental and social

value generation, interdisciplinary research, and agile innovation policies, highlight the complexities associated with this industrial revolution. Reviews suggest that Industry 5.0, with its focus on sustainability, resiliency, and human well-being, necessitates a careful balance between productivity and substantial investments to realize its objectives [14].

2.2 Cyber-Physical Systems

The advent of Cyber-Physical Systems (CPS) signifies a pivotal advancement in engineering, blending computational capabilities with physical processes. Introduced by Helen Gill at the National Science Foundation in 2006, CPS epitomizes the integration of embedded systems with networked digital technologies, facilitating real-time interaction and control between the physical and virtual worlds [15]. This integration is deeply rooted in cybernetics, a discipline pioneered by Norbert Wiener, which investigates the feedback control systems and communication within and among machines and living beings, setting the foundational principles for CPS [16].

As the main driving technology behind Industry 4.0, Cyber-physical Systems (CPSs) are instrumental in fostering the intelligent integration of digital and physical assets within manufacturing and other industries. Modern data collection, processing, and analysis techniques are contributing to the growth of an ever-expanding data-driven society. Coupled with advancements in computing and communication technology, data-driven systems are changing many aspects of everyday life. CPSs combine many of these advancements to bridge the digital and physical worlds by facilitating real-time monitoring and control of physical systems through digital interfaces. This convergence paves the way for unprecedented levels of automation, efficiency, and adaptability in industrial worksites.

In a CPS, numerous sensors are strategically distributed throughout a physical system to collect real-time data and generate a cyber model of the actual system. These models, commonly referred to as digital twins, offer real-time insights derived from the sensor data collected across the physical system. A digital twin essentially serves as a virtual replica of a physical system, designed to update synchronously with its real-world counterpart. Although the primary purpose of a digital twin is real-time monitoring, it can also be utilized to simulate new scenarios for rapid prototyping and debugging.

Expanding on the concept of digital twins, CPSs introduce an additional layer to the virtual replica, enabling not only real-time monitoring but also real-time control capabilities [17]. In industrial environments, this level of monitoring and control can provide numerous benefits in efficiency, safety, and effective human-machine interaction. CPS unifies and integrates several technological approaches, including big data analysis and AI, enhancing real-time monitoring and control of manufacturing processes [18]. By integrating computation with physical processes to monitor and control them in real-time, CPS offers great potential for the digital transformation of industrial value creation.

2.3 Manufacturing Execution Systems

For industries to realize the potential of CPSs, it's crucial that such technology be designed to integrate with existing systems easily. In the manufacturing industry, the standard software for monitoring, controlling, and managing operations is known as a Manufacturing Execution System (MES). The concept of Manufacturing Execution Systems (MES) was developed in the mid-1990s to supplement the functionalities that Enterprise Resource Planning (ERP) systems lacked, particularly in the domain of

real-time operational management on the manufacturing floor [19]. ERP systems are comprehensive in nature, encompassing modules for production planning, inventory management, demand forecasting, cost accounting, and marketing activities within manufacturing organizations [20]. However, given that ERP frameworks aggregate and synthesize information on a daily, weekly, or monthly basis, they fall short in providing the immediate, detailed responsiveness required for each transaction occurring on the manufacturing floor [21].

To address this problem, the concept of Manufacturing Execution Systems (MES) was introduced to bridge the gap between the manufacturing floor and the ERP layer. Viewed from the top-down perspective of the management hierarchy, MES fuses the initial production planning derived from ERP systems with live data concerning processes, materials, and operations collected from machines, control systems, and personnel on the shop floor. This fusion facilitates the real-time oversight of production activities, spanning from the initiation of orders to the delivery of finished goods. Conversely, from a bottom-up perspective, MES supplies ERP systems with summarized data regarding the execution on the shop floor. For example, it notifies the ERP system about the completion status of orders, thereby affecting the scheduling of subsequent planned orders [9].

Within the scope of the automation pyramid (as illustrated in Figure 2.2), a Manufacturing Execution System (MES) serves as the principal tool for managing production, establishing a two-way connection between the enterprise planning layer and the shop floor's control/automation layer [22]. The MES gathers information about the shop floor's status via actuators and sensors integrated into the Supervisory Control and Data Acquisition (SCADA) system, which includes Distributed Control Systems (DCSs), Programmable Logic Controllers (PLCs), and various intelligent devices. This data is subsequently refined to the level of abstraction required

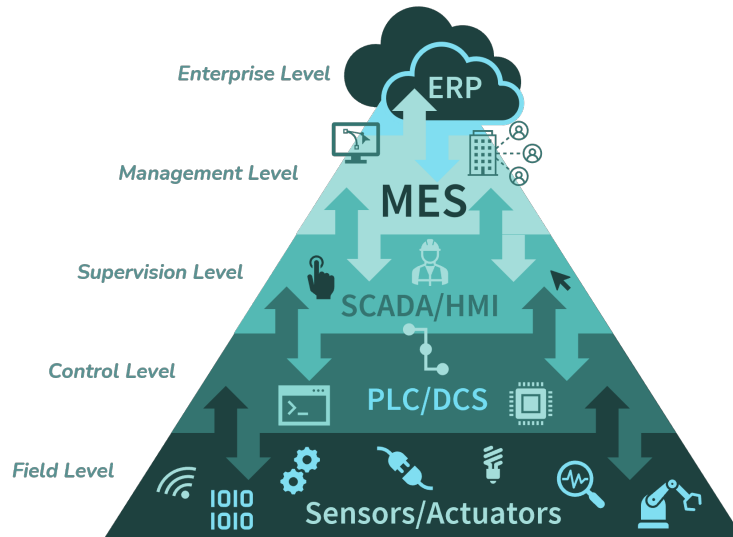


Figure 2.2: Information and management systems for planning and control [9]

by the Enterprise Resource Planning (ERP) system to facilitate decision-making processes [23]. Such refinement is crucial because the SCADA system produces data that is both highly detailed and narrowly focused (for instance, on a particular resource), whereas the ERP system, situated within the enterprise planning layer, necessitates more generalized information to inform its decisions [9]. From the management hierarchy's top-down perspective, the ERP system supplies information on planned orders, detailing product mixes, sizes, and deadlines to the MES. The MES then converts these production objectives (planned orders) into a comprehensive schedule for implementation on the shop floor [24]. Operating from a daily to a real-time basis, the MES translates decisions made on a monthly to daily timeframe at the enterprise planning layer into immediate schedules essential for maintaining control over the shop floor [9].

Figure 2.3 outlines the core functions of the Manufacturing Execution System (MES), which include the collection and simplification of data, precise scheduling of activities, allocation and management of resources, assignment of production tasks

to machinery and personnel, quality assurance of products, and the upkeep of equipment and tools [25]. The adoption of MES within manufacturing organizations leads to significant improvements in key performance indicators (KPIs), notably in the reduction of lead times and costs, the enhancement of product quality, the augmentation of production transparency, and the increase in operational efficiency [19]. Moreover, MES facilitates real-time access to information regarding raw material inventories, equipment malfunctions, and production delays on the manufacturing floor for each entity within the supply chain. This feature supports the Supply Chain Management (SCM) layer in its interaction with the ERP layer, enabling a more effective response to disruptions and unforeseen events [9].



Figure 2.3: The eleven main functionalities of MES

The development of Industry 4.0 aims to infuse manufacturing enterprises with intelligence, adaptability, operational effectiveness, and the capability for predictive production [26]. As illustrated in Figure 2.4, the initial step towards this ambition involves the aggregation and assimilation of data from Manufacturing Execution Systems (MES) alongside other informational systems, the Internet, and manufacturing assets [10]. This data can subsequently be processed and leveraged to enhance intelligence across product design, planning, production processes, and the maintenance of

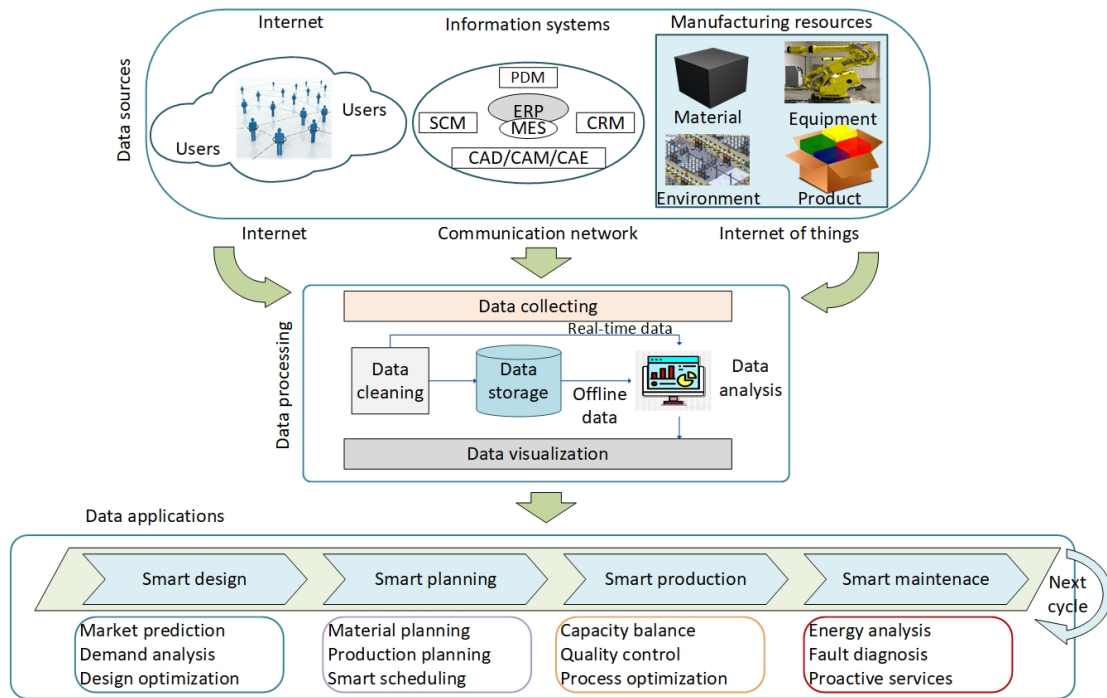


Figure 2.4: The sources, processing, and applications of data in manufacturing enterprises under industry 4.0 context [10]

machinery. Specifically, MES is acknowledged as a pivotal facilitator of the fourth industrial revolution within the manufacturing sector for two principal reasons. Firstly, the intrinsic characteristics of MES lay the groundwork for the application of Industry 4.0 principles. Secondly, through the use of Cyber-Physical Systems (CPSs), MES empowers business operations within ERP and throughout the supply chain to advance in intelligence by providing real-time data from intelligent products and machinery on the production floor [27, 28].

The fusion of AI within Manufacturing Execution Systems (MES) represents a leading edge of research, aiming to evolve current MES to align with the Industry 4.0 paradigm. Production environments, comprising robots, conveyor systems, machinery, and ancillary operations like maintenance, quality assurance, and materials management, strive for the efficient creation of products. Despite their complexity,

these systems are required to function at peak efficiency to maintain a competitive edge in the market by achieving goals related to productivity, quality, and cost, all while ensuring a safe working environment. AI technologies, such as machine learning and deep learning algorithms, can be employed to analyze vast datasets from machines, environmental sensors, control units, and personnel activities. This analysis can uncover patterns that offer vital insights for addressing manufacturing challenges [29, 30]. Applications of AI in MES encompass predictions of productivity, detection of quality anomalies, determination of defect causality, optimization of job scheduling and resource distribution, enhancement of human-robot interaction, implementation of machine vision and robotic manipulation, and the facilitation of predictive maintenance and process control in manufacturing [31].

The essence of Industry 4.0 lies in the use of technology to gather data that drives intelligent action within the physical manufacturing realm. These technological solutions enable manufacturers to boost efficiency and minimize manual labor. The extensive data collected by interconnected machines offers deep insights into various operational facets, which, when analyzed, can enhance operational efficiency. MES software plays a crucial role in the Industry 4.0 shift, providing real-time operational transparency [32]. It aids in reducing manual tasks and enhancing efficiency through digitalization, identifying areas where competitive advantages can be developed.

In this landscape, MES continues to play a critical role in production, focusing on optimizing manufacturing processes and supporting real-time decision-making. Achieving such objectives requires monitoring and confirming the availability of necessary resources and procedures, a task streamlined by deploying an integrated, centralized MES.

2.4 Artificial Intelligence in Industry

Artificial Intelligence has undergone significant evolution since its conceptualization, with notable advancements over the past decade. In recent times, the integration of AI into various aspects of daily life has witnessed exponential growth, and industries have embraced this transformative technology. However, the industrial sector, while acknowledging the advantages AI brings, grapples with inherent risks and challenges [33]. This section explores the contemporary landscape of industrial AI, acknowledging its potential benefits, and addressing concerns surrounding safety, financial risks, and the opacity of AI algorithms.

The adoption of AI in industries is marked by its dependence on copious amounts of quality data. Although AI aims to replicate human intelligence, its true strength lies in automating pattern recognition and comprehension. In real-time control scenarios, AI algorithms augment decision-making processes, demonstrating their efficacy in various industrial applications [33]. In manufacturing AI can enable systems to be self-learning, self-optimizing, and self-regulating, offering added value to products and systems [34]. However, this ability comes at the cost of substantial data requirements, which hinders widespread adoption across industries.

The black-box nature of many AI algorithms complicates matters for industry professionals, impeding their understanding and trust in these systems [33]. While AI exhibits promise in industrial applications, challenges such as data availability, skill shortage, data security, return on investment, and passive mindsets hinder its seamless integration. Recognizing these concerns, efforts are underway to invest in data collection and cleaning processes, training programs, robust security measures, and a culture of innovation [33].

Nonetheless, there are still obstacles that need to be addressed in the field of industrial AI. These challenges include limitations and drawbacks related to data,

such as the availability of large, specific, and well-annotated datasets, as well as the unpredictability of data distribution. Additionally, there are concerns regarding the interpretability of machine learning models, as well as security and privacy issues [34]. These challenges highlight the importance of ongoing research and development in industrial AI, with a focus on transparency, interpretability, and security.

2.4.1 Data Limitations

Although AI has promising potential to improve automation and optimization in many industrial applications, the requirement of sufficient quality data becomes a critical challenge for many industrial systems. Due to the complex nature of industrial environments, data collection, organization, cleaning, and storage pose many hurdles. This challenge is particularly pronounced in systems that have not yet embraced the digitization requirements of Industry 4.0.

Several factors contribute to the complexity of data acquisition in industrial settings. Noise, sensor disruptions, network interruptions, human error, and unstructured data are among the obstacles that impede the seamless flow of data. Even with the advent of modern big data technologies, numerous industrial processes still grapple with data deficiencies. This inadequacy becomes more pronounced as processes evolve over time, making specific data unattainable. Moreover, data from one process configuration may not accurately represent other configurations or working conditions, highlighting the inherent variability in industrial processes and the absence of standard data-sharing practices.

The concerns regarding data collection in industrial settings extend beyond the intricacies of data quality and representation. Many industries face substantial difficulties in the actual collection process. The integration of sensors comes with a high cost, making it a significant investment for companies. Additionally, certain

industrial environments, characterized by elements like dust, heat, and pressure, pose challenges for sensors to operate effectively. The selection of appropriate sensors and the decision-making process regarding their placement are crucial tasks that demand significant time, expertise, and financial resources.

In essence, the composition of challenges, as outlined, underscores a pronounced deficiency in proper data collection across many industrial settings. The inherent complexities and dynamic nature of industrial processes, coupled with the practical challenges of sensor integration, significantly hinder the progression toward harnessing AI in Industry 4.0. The journey is impeded not only by the necessity for robust and well-organized data but also by the considerable dynamism and unpredictability inherent in industrial processes. Operating conditions exacerbate difficulties in both the collection and interpretation of data, with harsh environmental factors adding a layer of costliness to the implementation of proper data collection procedures.

Additionally, the collected data itself is susceptible to various issues, including noise, distribution variations, and disruptions. The dynamic nature of industrial processes introduces changing modes in data distribution, contributing to the complexity of data interpretation. Furthermore, the challenges in data availability extend beyond specific industries, posing widespread difficulties in adopting data-driven technologies across sectors. Addressing these multifaceted challenges is not merely advisable but imperative for unlocking AI's full potential in revolutionizing industrial automation and optimization.

2.4.2 Explainability

AI models have become indispensable tools for enhancing efficiency, prediction performance, and data-driven decision-making in industrial processes [35]. However, the integration of AI is not always straightforward, particularly with respect to in-

interpretability. The inherent complexity of AI models, often treated as black boxes due to their inexplicable internal mechanisms, poses a significant concern. In industrial contexts, where decisions carry tangible consequences, the lack of transparency hinders effective real-world implementation [36].

Explainable AI (XAI) emerges as a potential solution to address the interpretability issues associated with AI and other black-box models. XAI methods aim to provide end-users with transparent and understandable information regarding the internal decision mechanisms of complex AI models. Bridging the gap between sophisticated AI methodologies and human comprehensibility, XAI empowers users with insights into the rationale behind AI-generated outcomes [37].

The field of XAI encompasses various techniques, broadly classified as intrinsic or post-hoc approaches. Intrinsic methods, also known as interpretable AI, focus on designing AI models to be inherently interpretable, employing simpler methods such as linear regression and logic-based rules. Post-hoc methods, on the other hand, apply external tools in parallel to analyze the internal mechanisms of black-box models concerning predicted outputs [38].

Common post-hoc XAI tools include Local Interpretable Model-agnostic Explanations (LIME), which learns local interpretable models around predictions, and Shapley Additive Explanations (SHAP), utilizing game theory concepts to explain model contributions [39, 40].

In the context of condition monitoring for industrial processes, XAI is proving instrumental. Studies like Bhakte et al. [41] introduce XAI-based frameworks tailored for understanding predictions made by deep learning-based Fault Detection and Diagnosis (FDD) models. Leveraging methodologies based on the Shapley value framework and integrated gradients, these approaches enhance user confidence by providing explanations for correct fault identifications and offering valuable insights

when the model identifies faults incorrectly. The integration of XAI into industrial AI models significantly enhances transparency, dependability, and interpretability. This advancement holds profound implications for AI-enabled monitoring and control, improving human understanding, and interaction with industrial AI systems [5].

2.4.3 Causality

Deciphering the complex web of cause-and-effect relationships in industrial settings is critical for making informed decisions and enhancing process efficiency. While Explainable AI (XAI) provides a window into the logic and behavior of intelligent systems, it often overlooks the real-world systems that generate underlying data. In contrast, the study of causality concentrates on uncovering the actual causal dynamics that drive these systems, differentiating from mere statistical correlations [42]. This insight is especially valuable in the realm of industrial operations, where numerous variables, disturbances, and noise can lead to deceptive correlations and mistaken inferences. Thus, the pursuit of causal analysis is essential for better understanding of the complexities of industrial processes.

Causal modeling offers a structured way to map out cause-and-effect relations, typically through the use of Bayesian networks or structural equation models. Such models are usually developed by experts who are deeply familiar with the specific systems and draw on extensive domain knowledge. In situations where direct expert insight is lacking, causal relationships might instead be approximated through randomized control trials and other experimental approaches, though these methods may not always be practical or safe for industrial analysis. This is where causal discovery techniques, like those explored by Vukovic et al. [43], prove invaluable, utilizing statistical algorithms to sift through historical data and deduce causal links within a complex array of variables.

Incorporating causality into AI, a practice known as Causal AI (CAI), enhances the robustness and clarity of predictions made by models [5]. This approach leverages the foundational mechanisms by which data is generated within a system, making CAI models less prone to bias from training data and more adept at navigating new scenarios through the application of causal principles derived from prior data [44]. By focusing on the actual drivers behind anomalies or operational issues, CAI enables the generation of actionable insights, leading to precise and effective intervention strategies. Moreover, CAI techniques are instrumental in minimizing false positives and negatives by effectively differentiating between misleading correlations and genuine causal relationships. Additionally, these techniques are highly suitable for root-cause analysis, a critical component in identifying faults and monitoring system conditions, thereby enhancing diagnostic processes and maintenance protocols.

Recent research showcases CAI's applicability in monitoring industrial processes. For example, Ma et al. [45] developed a monitoring framework focusing on Key Performance Indicators (KPIs) that combines Bayesian fusion and Granger causality to improve fault detection and trace fault pathways. Wu et al. [46] introduced a multi-modal framework for fault analysis using a deep local adaptive network and a causal Bayesian network to examine fault spread. Li et al. [47] implemented a deep learning approach based on spatial sequences, using LSTM models with attention mechanisms for accurate fault prediction and causal factor identification. Arunthavanathan et al. [48] presented a self-updating framework for real-time monitoring that incorporates causality via variable contributions identified through permutation analysis. Furthermore, Bi et al. [49] proposed a causal discovery method using a time-series transformer model to pinpoint causal factors and refine relationships through feature importance analysis. Lastly, Wang et al. [50] applied causality in their temporal registration network to enhance the identification of root causes and fault propagation

paths. These studies highlight the integration of causality into industrial monitoring, paving the way for improved fault detection and diagnostic capabilities.

Chapter 3

Intelligent Manufacturing Execution System (IMES)

The Manufacturing Execution System (MES) constitutes a crucial component within the hierarchy of the automation pyramid, bridging the gap between the upper-tier enterprise resource planning (ERP) layer and the lower-tier control and shop floor operations. However, integrating MES models with the standards of Industry 4.0 has not been sufficiently explored [51]. This study elucidates the influence of emerging technologies and the prevailing trends in Industry 4.0 on the evolution of MES architectures, while also spotlighting the deficiencies and obstacles that hinder the implementation of an effective MES. To tackle these challenges, the text introduces a theoretical framework for an Intelligent Manufacturing Execution System (IMES), depicted in Figure 3.1. The elements of this proposed model are subsequently delineated.

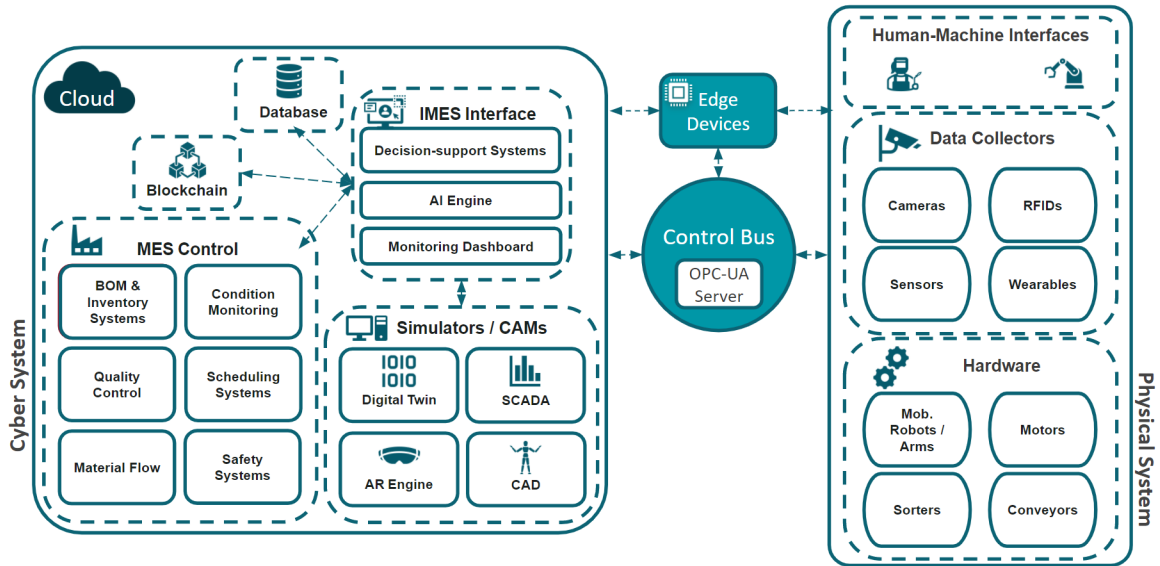


Figure 3.1: The components of the proposed conceptual IMES model

3.1 Interface and Controlling Systems

Device, software, and database interoperability are critical to the operationalization of intelligent manufacturing environments, particularly within the Manufacturing Execution System (MES) domain. For MES software to facilitate real-time decision-making, it must rapidly receive and process status updates from a network of interconnected devices throughout the manufacturing floor. Additionally, it is imperative for the MES to dispatch commands and updates to these devices to oversee and direct production activities efficiently. Achieving this level of interaction necessitates a communication protocol that is both swift and secure, enabling not only device-to-software but also device-to-device exchanges for the coordination of resource availability and operational statuses. Presently, the Open Platform Communication Unified Architecture (OPC UA) stands as the predominant standard in the industry for such purposes [52]. Initially designed for facilitating machine-to-machine dialogue in industrial automation, OPC UA provides a framework for the uniform definition of machine characteristics, including data structures and interfaces, alongside adaptable

security measures [53, 54].

In the context of IMES, edge computing devices are instrumental, serving as platforms for localized AI-driven data processing. These devices, serving as a connector between hardware and the cloud network, execute computational tasks closer to the data source, thereby diminishing the need for transmitting data to cloud services for analysis [55]. While edge devices do not fully replace cloud computing, they can alleviate network strain and reduce latency for AI applications, enhancing service speed and responsiveness over traditional central or cloud-based processing [55]. Nevertheless, cloud computing remains integral to MES functionality, suggesting that combining edge and cloud computing offers the most advantageous solution [56]. Such hybrid systems can relay critical information back to the central MES infrastructure without transmitting every sensor reading, enhancing both operational efficiency and data security.

Given the complexity inherent in IMES architectures, a unified management interface is paramount for ensuring coherence and ease of use. Such a centralized platform for MES administration should support user-centric management while embracing standardized Application Programming Interfaces (APIs) and communication protocols for seamless integration with other enterprise systems [57]. The goal of an MES is to augment human decision-making in manufacturing management, necessitating an interface that is both intuitive and effective. The integration of AI, such as the deployment of AI-powered chatbots for MES user support proposed by Mantravadi et al., exemplifies an innovative approach to enhancing user engagement through interactive and responsive design, facilitating superior information access and management [58]

3.2 Software Systems and AI Modules

The next-generation Manufacturing Execution Systems (MES) are distinguished by their capacity to oversee operations on the shop floor. This oversight capability encompasses managing inventory systems, monitoring conditions, ensuring quality control, scheduling systems, overseeing material flow, and maintaining safety protocols. These subsystems are interconnected with databases, blockchain technology, and OPC-UA servers, enhancing automation and operational efficiency by integrating AI in the form of various software modules [59].

In the outlined IMES framework, it is advised that manufacturers maintain both system and product logs detailing their statuses and characteristics in a dedicated database system [60]. Adopting a blockchain system as a secondary data repository is recommended to bolster data quality, transparency, and permanence [61, 62]. Blockchain technology, known for its robust availability, ease of access, and compatibility with edge computing devices, can mitigate the risk of data-related single points of failure. Its inherent pseudonymity and security features allow it to serve as a reliable storage solution, akin to traditional database management systems (DBMS) [63, 62].

Selecting appropriate DBMS or designing blockchain systems requires careful consideration of each inventory system's specific use cases and requirements [64]. For instance, deep learning applications within MES that classify goods based on product features may necessitate using a relational or column family database, such as Cassandra. Conversely, unsupervised learning methods might be better served by document-based databases like MongoDB, given their flexibility in handling unanticipated class outputs [65, 66].

The proposed IMES framework also includes an automated document control toolbox designed to streamline the review, modification, issuance, and access of doc-

uments. This requires integrating Natural Language Processing (NLP) modules to process document images and developing a cloud-based, decentralized software for enhanced document accessibility [67]. Employing blockchain technology with scripting capabilities can facilitate distributed computation and support advanced document recognition and response systems [68, 69, 70].

Moreover, the new generation MES must address supply chain visibility, offering trackable, transparent, secure, and reliable solutions. Storing production stage records on a consortium or hybrid blockchain enhances this transparency and security, a practice already adopted by several companies [64, 71].

Quality control within these systems integrates with the OPC-UA server and database logs to utilize data from cameras, sensors, and auto-identification technologies. Implementing computer vision for fault detection and anomaly recognition, along with developing digital twins and simulation software for pre-launch testing, can significantly reduce production faults. Extended Reality (XR) technology further contributes to minimizing human error and training employees in routine tasks [72].

Safety systems within IMES leverage a wide array of sensors, including those for temperature, humidity, and air quality, alongside computer vision modules for real-time hazard detection on the production floor [73, 74]. The recent COVID-19 pandemic has also highlighted the importance of automated emergency response protocols in maintaining operational safety [75].

3.3 Connection to Physical Assets

The variety of machinery, devices, and hardware on the shop floor, such as conveyors, sorters, actuators, robots, CNC machines, motors, and rotating equipment, varies significantly across industries and manufacturing sectors. An IMES must be capable

of interfacing with and managing these diverse field devices. This necessitates including IoT connectivity and controller utilization within the IMES, which are identified as critical elements in the Reference Architecture Model for Industry 4.0 (RAMI4.0) [76].

Data collection stands as a fundamental capability of MESs; thus, the latest generation of MESs is expected to efficiently automate the acquisition of data from various sources on the shop floor, including equipment, personnel, materials, and products. This is achieved through the deployment of sensors, RFIDs, various camera systems, and wearable technologies. Incorporating RFID middleware is an important aspect within the IMES architecture, necessitating robust security protocols to safeguard against data breaches [77]. To manage the extensive volume, diversity, and rapid influx of data from physical assets, the envisioned IMES should adopt a cloud-based data management framework, which could encompass solutions like cloud-enabled distributed architectures [78], blockchain-based networks [79], among other innovative data handling strategies [80, 81].

Chapter 4

Industrial Applications of AI

4.1 Introduction: Bridging IMES and AI for Advanced Industrial Applications

In the preceding chapter on IMES, we explored the foundational elements that constitute the backbone of modern manufacturing environments, emphasizing the integration of advanced technologies and Industry 4.0 principles. As we transition from the broad architectural considerations of IMES, this chapter delves into the critical role of AI in transforming CPS to be more dynamic, intelligent, and responsive. The integration of AI indicates a new era in manufacturing efficiency and decision-making. It sets the stage for developing advanced CPSs where intelligent software assists human operators, enhancing their capabilities and providing insights for decision-making.

This chapter focuses on two pivotal applications of AI within industrial contexts, serving as concrete examples of how AI-driven approaches are redefining traditional processes and paving the way for more advanced CPS:

1. **Machine Condition Monitoring with Limited Fault Data:** The first case study illustrates the application of AI in enhancing the reliability and safety of

manufacturing processes through advanced condition monitoring [2]. In environments where fault data is scarce due to the predominance of normal operating conditions, the challenge lies in accurately identifying potential failures to prevent downtime and ensure safety. Through innovative AI techniques, such as generative models, this section demonstrates how synthetic fault data can be created from normal condition data, enabling more robust and accurate fault detection. This approach improves operational efficiency and aligns with the human-centered design philosophy by prioritizing system reliability and worker safety.

- 2. Quality Control with AI-Driven Visual Inspection:** The second case study addresses the crucial aspect of quality control in manufacturing, particularly in processes like Automated Fibre Placement (AFP) used in aerospace manufacturing [3]. Adopting AI-driven visual inspection methods marks a significant leap from manual quality assurance practices, offering a more efficient, reliable, and scalable solution to defect detection. By leveraging deep learning and computer vision, this section explores how AI modules can autonomously identify defects, enhancing the overall quality of the manufacturing process. Such advancements not only contribute to operational excellence but also support the HC-CPS framework by reducing human error and enabling more immersive and intuitive human-machine interactions.

Together, these case studies present the transformative impact of AI in manufacturing, highlighting the shift towards systems that are not only intelligent and efficient but also designed to enhance human-system interaction. As we delve into these applications, the narrative seamlessly bridges the gap between the conceptual framework of IMES and the imminent evolution towards Human-Centered Cyber-Physical Systems, emphasizing the central role of AI in this transition. This discussion illustrates

the practical applications of AI in current industrial settings and foreshadows the future direction of manufacturing systems where workers and technology converge to create more adaptive, responsive, and empowering cyber-physical environments.

4.2 Machine Condition Monitoring with Limited Fault Data

Condition Monitoring (CM) is an essential procedure across many industries, enhancing systems' safety, reliability, and efficiency [1]. It involves analyzing measurable variables to detect significant changes indicative of potential faults in industrial settings. If undetected, these faults and deviations from standard behavior can culminate in production interruptions, breakdowns, or even pose risks to human operators [82].

Rotating machinery, used in many industries, heavily relies on bearings. Astonishingly, 44% of machine faults in manufacturing are attributed to bearing failures [83]. Detecting faults early is paramount for improving production efficiency, curbing costs, and preventing accidents. Researchers and practitioners have invested a lot of effort into developing improved fault detection and diagnosis methods, focusing on two main approaches: model-based and data-driven methods.

While model-based approaches use system models to discern faults, data-driven methods leverage sensor data and AI for fault identification [1]. Deep learning, renowned for processing vast datasets and robustness against noise, particularly shines in intelligent fault detection [84]. Convolutional Neural Networks (CNN), Stacked Auto Encoders, and Deep Belief Networks have demonstrated high accuracy in this domain [85, 86, 87, 88, 89].

However, a common challenge is the scarcity of fault data, given the predominance

of normal operating conditions. Generative algorithms like Variational Autoencoders (VAE) and Generative Adversarial Networks (GAN) come to the fore for creating synthetic fault data [90, 91, 92]. Conditional GANs (CGAN) offer a unique advantage, generating data based on specific conditions [93].

Inspired by image-to-image translation, a novel method is presented in this section for synthesizing bearing fault data from normal condition data using vibration signals. The approach builds upon Pix2Pix, a CGAN-based image translation algorithm by Isola et al. [94]. Unlike typical CGANs, Pix2Pix exhibits a deterministic generator, and dropout layers are incorporated to introduce randomness. The model utilizes U-Net and PatchGAN architectures for its generator and discriminator, respectively [95, 96].

4.2.1 Fault Data Synthesis: The N2F-GAN Approach

As previously noted, industrial environments often face a shortage of fault data while having an abundance of normal operational data. This section presents an innovative approach for synthesizing fault data from normal operational data. Drawing inspiration from image-to-image translation techniques, this method adapts a variant of Conditional Generative Adversarial Networks (CGANs) for conditional data generation tasks. Traditional GANs are designed to generate a fake sample $\tilde{x} = G(z)$ from a random noise vector z . In contrast, CGANs are trained to generate \tilde{x} using both an observed input y and a random noise vector z . This research enhances the CGAN framework to make it applicable for signal-to-signal translation tasks. In the developed method, named N2F-GAN, normal operational data serves as the direct input to the generator, bypassing the need for random noise, akin to the strategy employed in the Pix2Pix model. Figure 4.1 illustrates the distinctions among traditional GANs, CGANs, and the N2F-GAN approach.

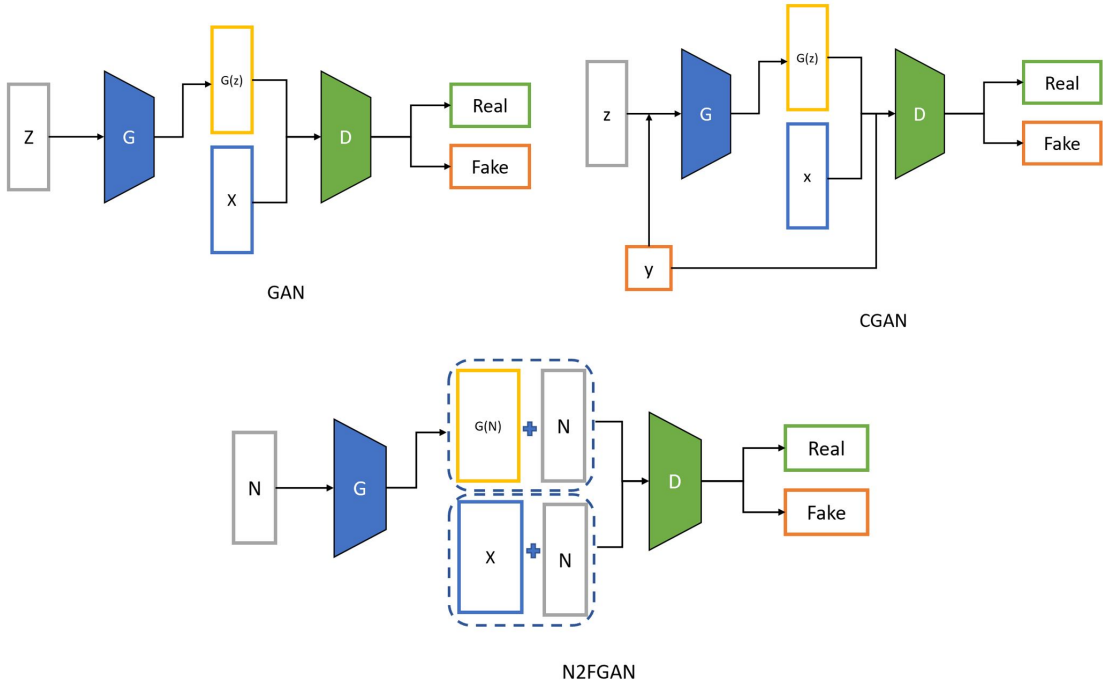


Figure 4.1: A comparison between GAN, CGAN, and the proposed method (N2FGAN)

The generator utilizes an encoder-decoder architecture, where the input undergoes a series of downsampling operations in the encoder phase, followed by an inverse operation in the decoder phase to reconstruct the output. This procedure allows for the extraction of the data's underlying information. The generator's structure comprises both an encoder and a decoder, each containing blocks that include a 1D convolutional layer, followed by Batch Normalization and a Leaky ReLU activation layer for the encoder. In contrast, the decoder's blocks are equipped with Transposed convolution, Batch Normalization, dropout, and ReLU activation layers. This architecture is designed with four blocks each in the encoder and decoder, processing input data vectors of length 512 and translating them into a latent space dimension of 64.

The discriminator functions as a convolutional classifier, incorporating three blocks, each featuring a 1D convolutional layer, Batch Normalization, and a Leaky ReLU activation layer. It evaluates two types of concatenated input pairs: one comprising

the normal operational data alongside the true fault data, designated as real, and the other pairing the normal data with the synthetically generated fault data produced by the generator, labeled as fake.

Objective and Loss Function Definition

The overall loss calculation combines the losses from both the generator and the discriminator. The loss for the generator is computed using sigmoid cross-entropy between the fabricated data and a vector of ones, aiming to enhance the resemblance of the generated output to the actual target data. This similarity is quantified using the L_1 norm, which calculates the mean absolute difference between the generated and target data.

$$\mathcal{L}_{L1}(G) = \mathbb{E}_{x, \tilde{x}, z} [|\tilde{x} - G(x, z)|_1], \quad (4.1)$$

On the other hand, the discriminator's loss is derived from adding the sigmoid cross-entropy loss for the real data paired with a vector of ones and the loss for the fake data paired with a vector of zeros. The optimization goal for the proposed approach is formulated as below, with λ being a predetermined constant valued at 100.

$$G^* = \min_G \max_D V(D, G) + \lambda * \mathcal{L}_{L1}(G), \quad (4.2)$$

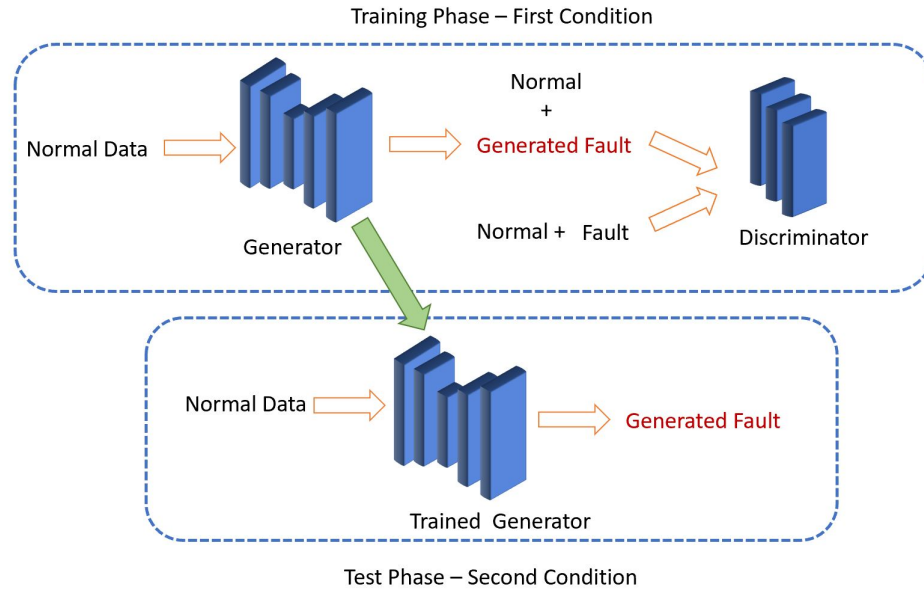


Figure 4.2: The proposed data generation framework (N2F-GAN)

4.2.2 Generating Realistic Fault Samples in New Conditions

The study progresses by deploying N2F-GAN to synthesize novel fault data. Initially, the network is trained using a dataset containing normal and fault instances. Subsequently, the trained generator produces fault data from normal operational data under new conditions where no prior fault examples existed. The model undergoes testing across several real-world scenarios, employing three distinct classifiers to assess the quality of the generated data. Specifically, variations in machinery motor loads and speeds serve as the basis for defining different testing conditions. Comparative analyses of statistical attributes and visual examinations are conducted to evaluate the fidelity of the generated data against the actual samples, with the latter term denoting the original dataset entries and the former the output from the generator. An illustrative summary of the methodological approach is provided in Figure 4.2.

This investigation utilizes the Case Western Reserve University (CWRU) bearing dataset [97] for empirical validation. Data was gathered from a test rig compris-

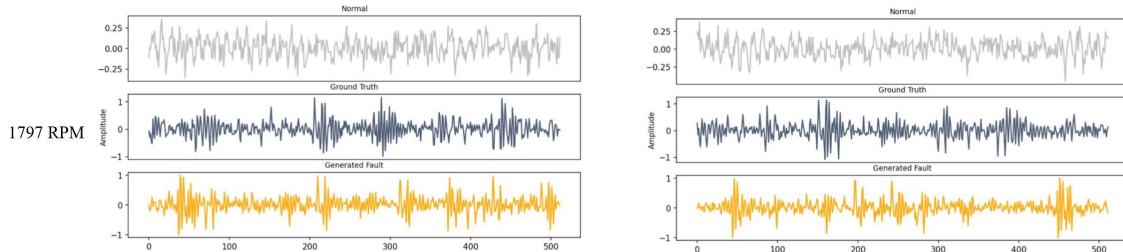


Figure 4.3: Samples of generated fault data in 1797 RPM

ing a Reliance Electric motor, torque transducer/encoder, dynamometer, and control electronics. Measurements were taken at a rate of 12,000 samples per second from both the fan-end and drive-end bearings. Fault conditions were artificially introduced through electro-discharge machining (EDM), with fault sizes varying between 0.007 inches and 0.040 inches across three primary fault types: inner raceway, rolling element, and outer raceway. The outer raceway faults were induced in three orientations to simulate a comprehensive range of fault scenarios, totaling five distinct fault classifications. Vibrational data collection spanned motor loads from 0 to 3 horsepower and speeds ranging from 1730 to 1797 RPM, focusing on the drive-end. Data segmentation into bursts of 200 samples, along with the addition of 100 SNR noise, was implemented to enhance the complexity of data generation.

Utilizing the specified framework, we produce fault data under the initial condition (specifically at 1797 RPM), where both normal and pre-existing fault data are accessible. This generation process employs the Adam optimization algorithm with a learning rate set to 0.0002, conducted across 4000 iterations. The experimentation targets real normal data and inner raceway faults characterized by a 0.007-inch diameter at the 1797 RPM condition. Despite the availability of fault data, the objective is to enrich the dataset with additional fault instances. Visual representations of the normal data, actual fault data (referred to as ground truth), and the newly generated fault data during the training phase are depicted in Figure 4.3.

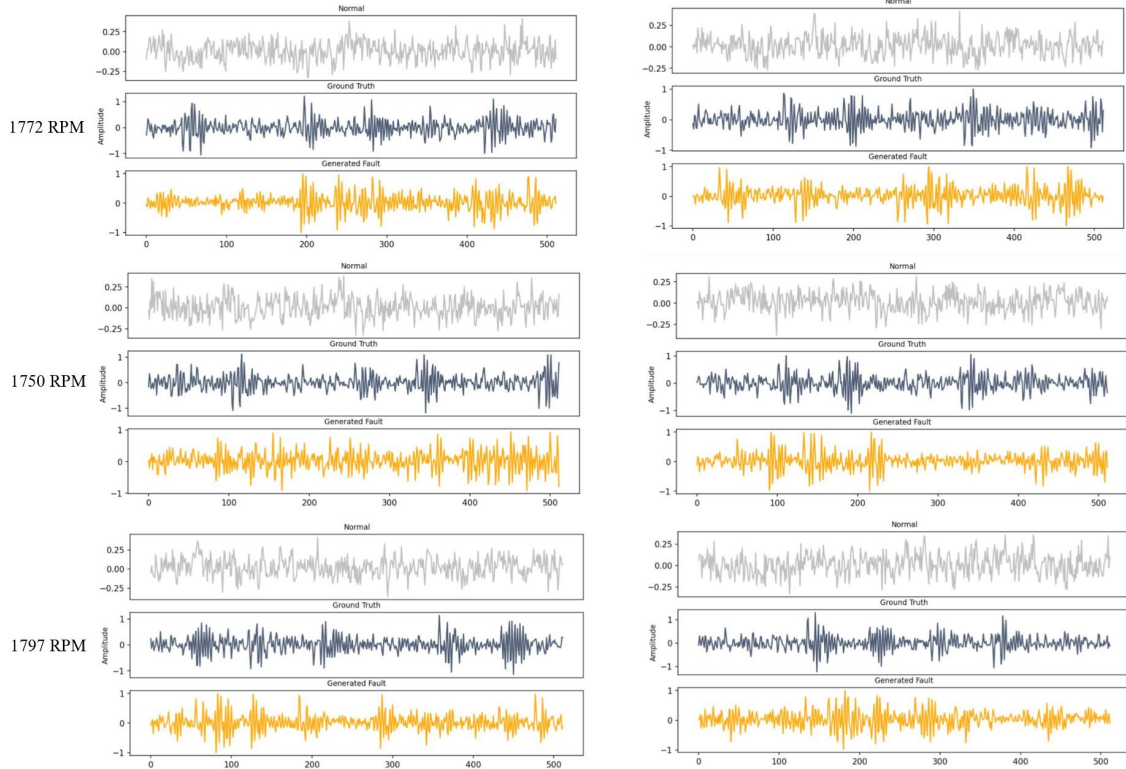


Figure 4.4: Samples of generated fault data in different conditions

The generator, once trained, is employed to create fault data under novel operational scenarios; these scenarios entail varying working speeds, specifically at 1772, 1750, and 1730 RPM. In these scenarios, no existing fault data samples are available in training, yet the generated fault data is tested against actual ground-truth data for validation purposes. The generator receives normal operational data from these new conditions as input, with actual fault data not incorporated into the generation process. Visualizations of the data generated under these diverse conditions by the trained network are provided in Figure 4.4. Although the generator was initially trained at 1797 RPM, this same model was applied to generate data across all the specified conditions.

4.2.3 Assessing Generated Data Quality

Assessing the quality of generated data presents significant challenges. The goal is for the generated samples to mirror the real data under all conditions closely. To verify the quality of the generated data, we employ classifiers based on neural networks and perform a statistical analysis using t-SNE (t-distributed stochastic neighbor embedding) to depict the data distributions. We extract both time and frequency domain features based on work conducted in [98], which are then utilized for t-SNE visualization. The features considered are detailed in Table 4.1, while the 2-component t-SNE visualizations for various conditions are illustrated in Figure 4.5. The distinction between the generated fault data and data from normal conditions is clear, with the generated data closely resembling the ground truth. This similarity indicates that the feature distributions of the generated signals are closely aligned with those of the actual fault features.

Initially, to differentiate between faulty and normal generated data, a Binary LSTM classifier equipped with a Softmax layer is employed as detailed in [99]. This classifier undergoes training using the original dataset. Upon completion of the training phase, the actual instances from the target category are substituted with generated data samples, which are then inputted into the classifier for testing. The dataset for testing comprises various classes, including normal, inner race, ball, centered outer race, orthogonal outer race, and opposite outer race faults, assigned labels from 0 to 5, respectively, with each class containing 480 samples. This procedure was replicated across both binary and multiclass classifiers. The binary classifiers demonstrated a 100% accuracy rate for both identical and novel conditions of generated data, indicating a clear distinction from the normal data. For multiclass classification, three distinct classifiers were deployed: ConvLSTM, CNN, and ConvAE, with their specifications detailed in table 4.2.

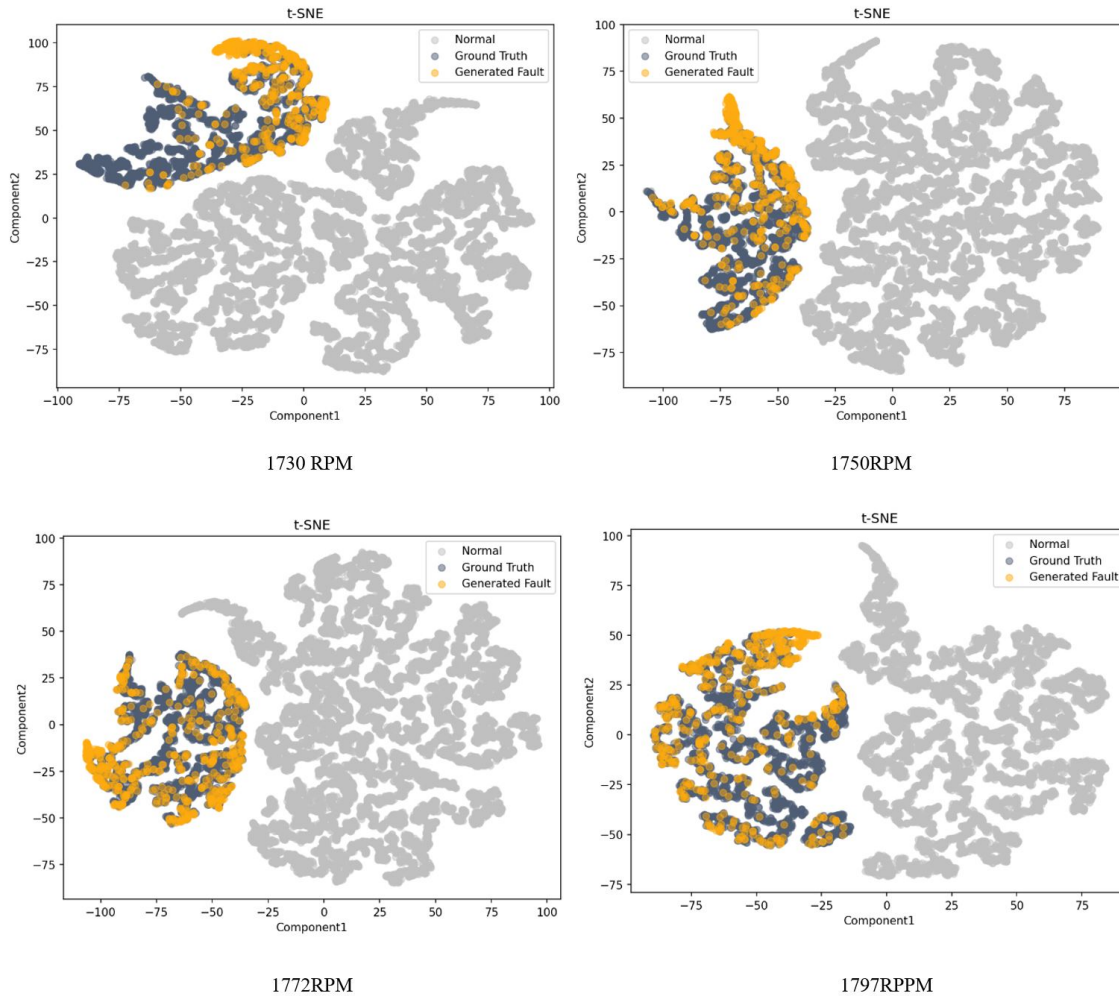


Figure 4.5: A two-dimensional t-SNE visualization of generated data

The efficacy of these multiclass classifiers was equally impressive, consistently exceeding 96% accuracy. The confusion matrices depicting the classifiers' performance under various conditions are presented in Figure 4.6. Moreover, Table 4.3 lists the accuracies of these multiclass classifiers when applied to the generated data.

4.2.4 Implications for Industrial Fault Diagnosis

Within industrial settings, the prevalence of fault data is notably low, whereas data reflecting normal operational conditions is often copious. Machinery operates under a

Table 4.1: Selected features for analysis of generated fault data

Time Domain	Feature	Formula
	Mean	$\bar{x} = \frac{1}{N} \sum_{i=1}^N x(i)$
	Standard Deviation	$\sigma = \sqrt{\frac{1}{N-1} \sum_{i=1}^N (x(i) - \bar{x})^2}$
	Skewness	$\tilde{\mu}_3 = \frac{\sum_{i=1}^N (x(i) - \bar{x})^3}{(N-1) * \sigma^3}$
	Crest Factor	$CF = \frac{\max x(i) }{\sqrt{\frac{1}{N} \sum_{i=1}^N x(i)^2}}$
	Kurtosis	$\kappa = \frac{1}{N} \sum_{i=1}^N x(i) - \max(x(i))^4$
Frequency Domain		
	Mean	$\bar{f} = \frac{1}{N} \sum_{i=1}^N f(i)$
	Standard Deviation	$\sigma_f = \sqrt{\frac{1}{N-1} \sum_{i=1}^N (f(i) - \bar{f})^2}$
	Skewness	$\tilde{\mu}_{3f} = \frac{\sum_{i=1}^N (x(i) - \bar{f})^3}{(N-1) * \sigma_f^3}$
	Crest Factor	$CF_f = \frac{\max f(i) }{\sqrt{\frac{1}{N} \sum_{i=1}^N f(i)^2}}$
	Shannon Entropy	$-\sum_{i=1}^N f(i) \log(f(i))$

diverse array of conditions, including varying loads and speeds, where fault instances are exceedingly rare. This scarcity of fault data constrains the effectiveness of machine learning methodologies, as models trained under these conditions are predisposed to a bias towards normal operational states. The framework proposed herein seeks to mitigate this issue by enriching the dataset with adequately simulated fault data under specific conditions, thereby enhancing the robustness of machine learning models for fault diagnosis, even in the face of previously unencountered fault scenarios.

This study presents an innovative approach to data augmentation for the synthesis of fault data through a modified version of CGAN. This adapted CGAN is designed to learn from both normal and existing fault data under a given condition. Subsequently,

Table 4.2: Architecture descriptions of the classifiers

Framework	Description
ConvLSTM	The architecture consists of two CNN blocks (containing 1D-Convolutional layers, Batch Normalization, ReLU, and Max Pooling), an LSTM block, a Dense layer with Sigmoid activation function, a Dropout, and a SoftMax layer.
CNN	It consists of four CNN blocks (containing one 1D-Convolutional layer, Batch Normalization, ReLU, and Max Pooling layer), A flatten layer, a fully connected layer, and a SoftMax classification layer.
ConvAE	It is a multi-layer network consisting of an encoder and a decoder. Each includes three CNN blocks (containing 1D-Convolutional layers, ReLU and Max Pooling or upsampling), A flatten, a fully connected layer, and a SoftMax classification layer.

Table 4.3: Classifier accuracies for different conditions while the training condition is 1797 RPM

Condition	ConvLSTM classifier	CNN classifier	ConvAE classifier
Test 1797	99.67%	98.34 %	99.33 %
Test 1772	98.83%	98.01 %	96.19 %
Test 1750	99.17%	97.68%	98.67 %
Test 1730	98.34 %	99.01%	97.01 %

the generator component of the network is tasked with producing fault data from normal operation samples for each motor speed lacking associated fault data. The distributions of the generated data are then assessed by comparing them with actual data and the original normal data using t-SNE analysis. The findings indicate that the synthesized fault data faithfully replicates the characteristics of genuine fault data.

Furthermore, the synthesized data is verified through the deployment of three distinct classifiers, trained on a mixture of normal operation and actual fault data

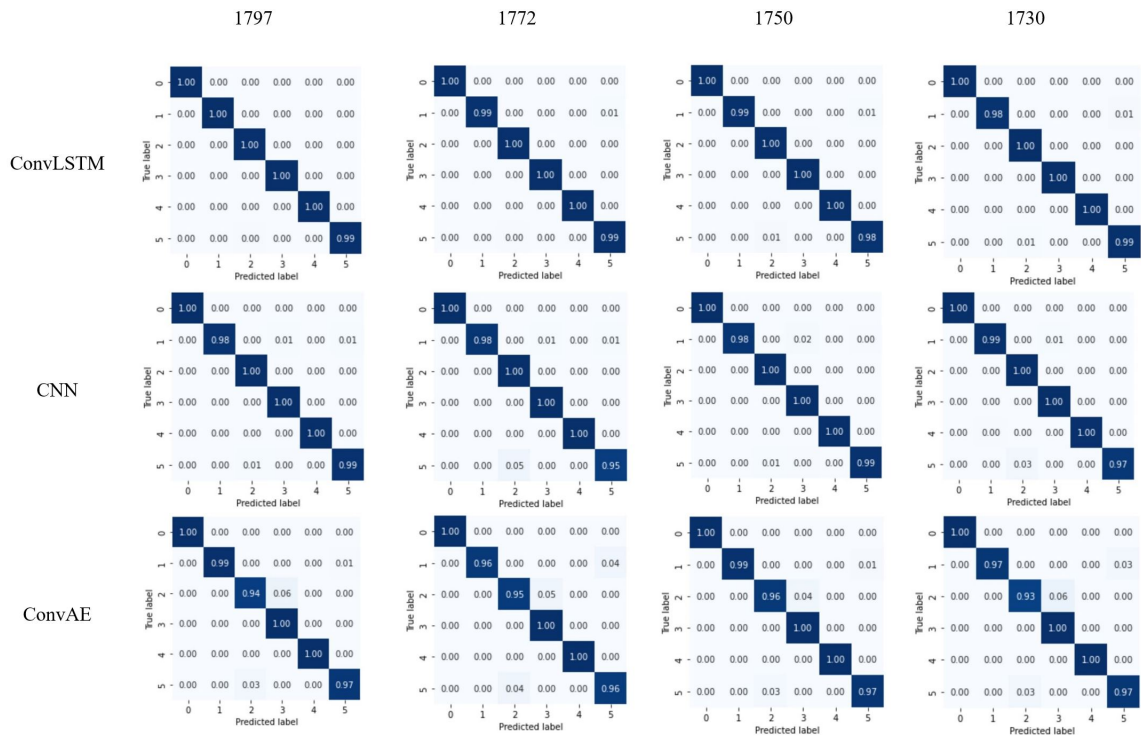


Figure 4.6: Confusion matrices of classifiers tested on generated data in different conditions

samples. During the testing phase, an altered dataset is compiled from the original dataset, with actual fault instances from the specified class replaced by the synthesized faults, which are then evaluated using the pre-trained classifiers. The evaluation was conducted across three different conditions, varying in motor speeds. The outcomes reveal that the artificial faults were accurately identified with a high degree of precision (exceeding 96% accuracy across all tests), underscoring the close resemblance of the synthesized fault data to actual fault occurrences.

Future endeavors will aim to refine the synthesis of signal features over raw vibration samples, enhancing the pertinence and application of generated data. Additionally, developing an efficient hyperparameter tuning framework to expedite the training process of the generator without sacrificing its performance will be crucial. Simplifying the network's complexity to minimize training duration will also be explored.

Furthermore, integrating explainable AI (XAI) principles to elucidate the synthetic data generation methodology will be paramount, ensuring transparency and interpretability in fault diagnosis processes [100]. These advancements, by streamlining the data generation and analysis processes and embedding XAI, not only promise to bolster the efficacy and applicability of fault detection systems but also align with the imperative of integrating human-centered design principles into cyber-physical systems. This approach ensures that technological advancements continue to augment human capabilities, making industrial operations more intuitive, efficient, and aligned with the evolving needs of human operators.

4.3 Quality Control with AI-Driven Visual Inspection

Quality management is another important task in many industries, with defect detection playing a vital role in ensuring the proper condition of parts, equipment, and products. This section introduces an AI module designed for defect detection in Automated Fibre Placement (AFP), an advanced composite manufacturing method for creating strong, lightweight components from strips of reinforced fibers. This method finds widespread use in quality-critical sectors such as aerospace manufacturing. Given the nature of these industries, stringent quality assurance procedures are imperative at every stage of the manufacturing process to identify and rectify defects.

Conventional inspection methods rely on highly skilled human experts who visually inspect each strip of composite fiber, known as tows, before additional layers are applied. This manual inspection process is time-consuming, often taking more than 50% of the manufacturing time[101], highlighting the need for reliable automated inspection methods. Advances in computer vision and deep learning have made vision-

based inspection methods increasingly feasible and reliable. Further development of these techniques holds the potential to enhance the manufacturing industry by improving quality assurance and increasing production rates at lower costs.

The data used in this study comprises depth map images of composite parts collected from an Optical Coherence Tomography (OCT) scanner during the AFP process. While defects are rare in industrial AFP machines, various defect types are deliberately introduced to create a dataset inclusive of these anomalies. A sample from the dataset is illustrated in Figure 4.7, showcasing a depth map scan of a composite part alongside a photographic image of the same component.

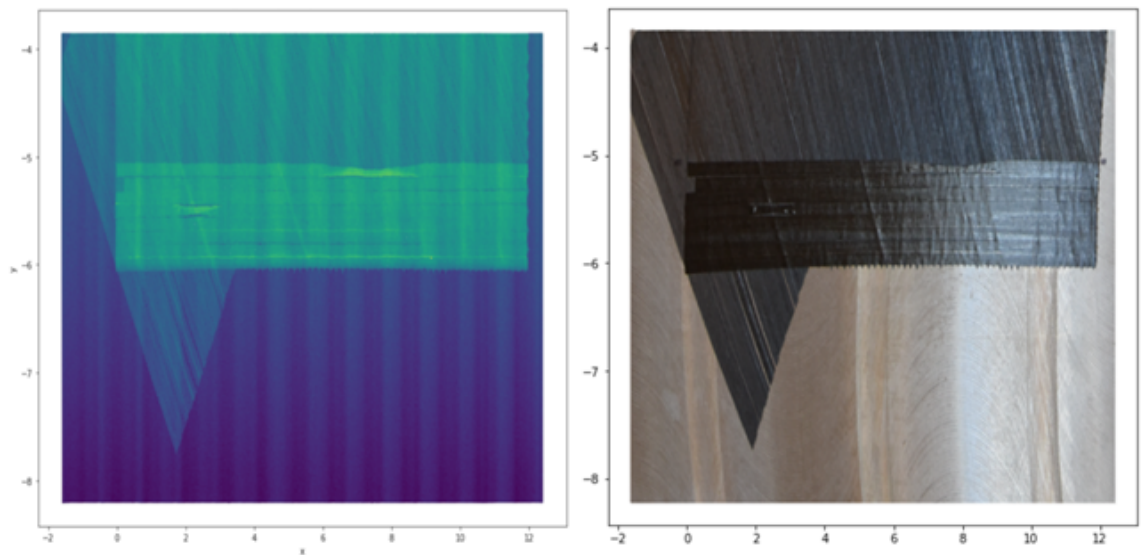


Figure 4.7: Comparing the real image of a composite part and the depth map generated from the same part

There are approximately 20 different defect types in this domain, classified following a standard naming convention as seen in recent literature. Some examples of these defects include gaps, splices, twists, wrinkles, folds, and fuzzballs. Figure 4.8 shows the main defects considered in this work.

Since fiber-based composite manufacturing with AFP is highly dependent on quality, it holds great potential for automated inspection methods. However, the lack of

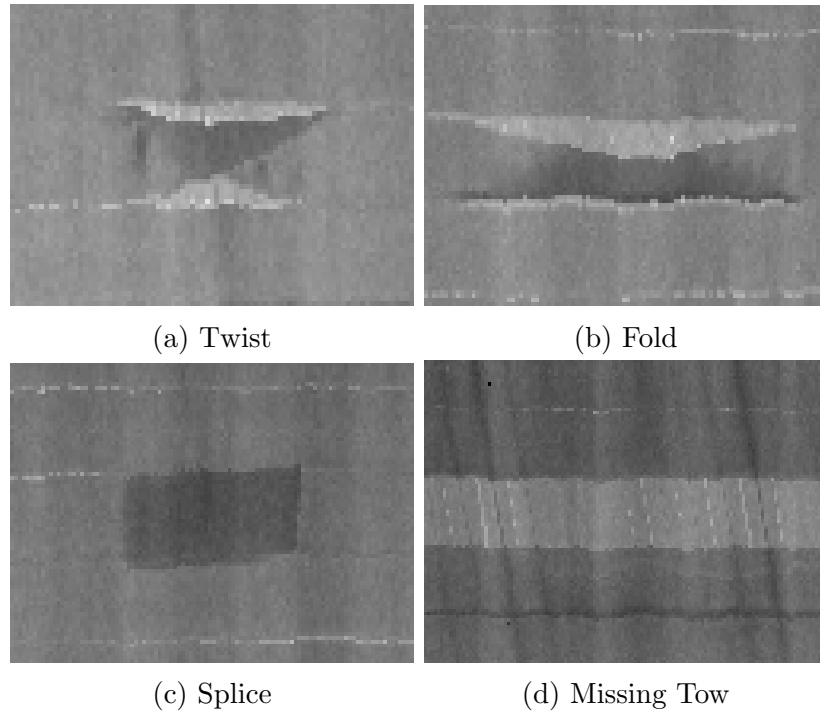


Figure 4.8: Common defect types in AFP

publicly available data in this domain has hindered the development of computer vision applications and limited options for automated inspection in the industry. This work proposes a solution by combining classical computer vision techniques with modern deep learning to improve the current state-of-the-art approaches, providing a method to enhance efficiency in a costly and time-consuming process.

The dataset consists of depth maps from 42 composite surfaces without defects. Creating an efficient end-to-end network for detecting defects with this small sample size is a considerable challenge. To overcome this, the strategy involves capitalizing on the uniformity across the composite tows. By segmenting the scans into smaller, cropped regions, a larger dataset of localized samples is generated. This approach assumes that each segmented portion shares a consistent distribution, based on the premise that sections of defect-free tows would display little to no variation throughout their lengths.

In the data, some preliminary knowledge exists about the structure of the composite tapes. Since the data is collected from a sensor mounted on the AFP machine, all fibre strips appear straight and horizontal in depth map scans. Additionally, the number of tows and their width can be obtained from the as-design data.

Incorporating this knowledge, classical computer vision methods can be used to narrow down the location of interest for identifying defects. This is done by extracting the center lines of each tow, and subsequently analyzing only regions along each tow where defects may be present. A customized Hough transform is introduced to detect these center lines for further data processing. The Hough transform is a feature extraction method commonly used in image processing. In the modified implementation, the transform is used for line detection, limited to a range of angles representative of the tow edges. After detecting the boundaries of the tows, center lines be calculated based on the average of two consecutive horizontal lines bounded within the detected vertical edges.

Utilizing the identified centerlines, local samples are obtained from each depth map scan by employing a square window that traverses the tows to segment cropped areas. The dimension of this window is determined to be the width of the tow plus an additional 50% margin to encompass the tow's boundaries, resulting in a size of 32×32 pixels. This additional 50% margin is deemed ample to include the top and bottom edges of the tows. Opting for a wider margin would inadvertently encapsulate a significant portion of adjacent tows, which contradicts the tow-specific approach advocated in this study.

For this process, the window advances in increments of 8 pixels, ensuring an appropriate overlap among adjacent samples while maintaining their distinctiveness. A selection of these samples is depicted in Figure 4.9. Adopting the same methodology during the inference phase, any window identified with an anomaly is labeled as

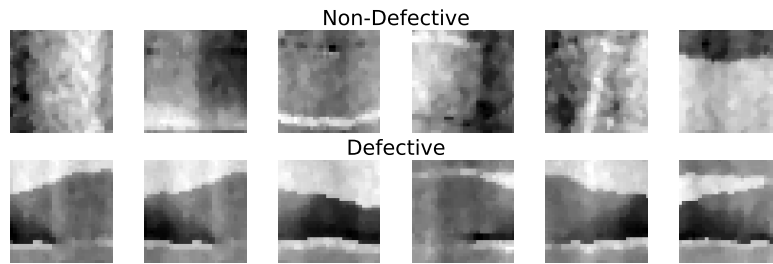


Figure 4.9: A dataset is created from cropped sections of the depth maps, using the sliding window method

containing a defect. Conversely, windows without detected anomalies are considered to exhibit normal tow configurations.

4.3.1 Implementing Anomaly Detection Using a Convolutional Autoencoder

Autoencoders, recognized for their ability to replicate input data, have become powerful mechanisms for identifying anomalies in images, as highlighted in a recent review [102]. These models operate by encoding regular input samples into a compressed latent vector, which is then decoded to recreate the input sample. By comparing the reconstruction with the original input, a measure of reconstruction error is obtained. If an autoencoder encounters an atypical sample, the reconstruction error increases due to the model's unfamiliarity with such data. A threshold is subsequently applied to these errors to ascertain whether a sample is considered normal, with higher errors suggesting the presence of anomalies or defects.

A convolutional autoencoder (CAE) is specifically developed for anomaly detection, featuring symmetric encoder and decoder sections, as depicted in figures 4.10.a and 4.10.b. The training of this model utilizes the mean squared error as the loss function. While the methodology primarily employs continuous-valued anomaly maps for defect identification rather than binary outcomes, binary classification remains in-

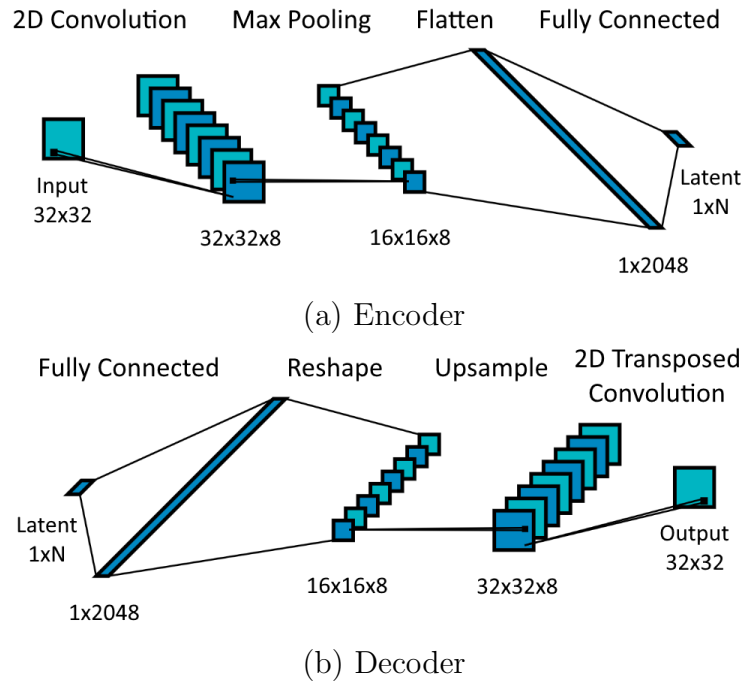


Figure 4.10: A graphic depicting the network structure of the proposed autoencoder including the encoder (a), and the decoder (b)

strumental in assessing the model’s accuracy. This involves setting a threshold for reconstruction errors to categorize samples. The determination of this threshold is facilitated by the use of a Receiver Operating Characteristic (ROC) curve, which contrasts the true positive rate against the false positive rate as the threshold is adjusted. Ideally, the optimal threshold corresponds to a true positive rate of 1 and a false positive rate of 0, represented by the ROC curve’s upper left corner. Therefore, the most suitable threshold is identified from the curve at the point nearest to this corner.

The architecture of the network has been constructed with three varying latent dimensions—2, 16, and 128—to facilitate comparative analysis. Training for each network was conducted using a dataset comprised solely of 27,406 normal samples. The training loss for each autoencoder is illustrated in Figure 4.11. An analysis of the loss trajectories reveals that the capacity for reconstructing inputs enhances as

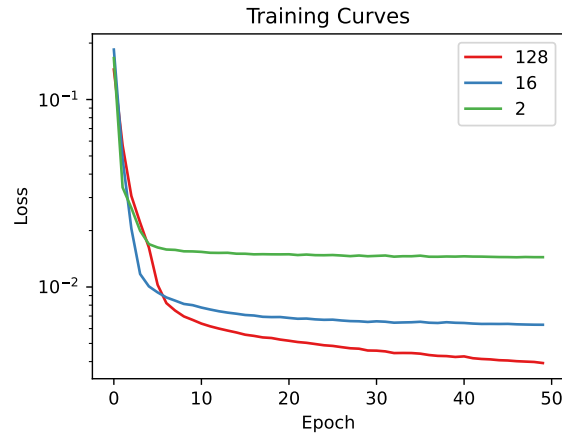


Figure 4.11: The training MSE losses of the three autoencoders are plotted in comparison over 50 epochs

the dimensionality of the latent space increases. Additionally, these curves indicate rapid learning by the models in the initial phases, with marginal gains observed in subsequent epochs.

4.3.2 Evaluation, Insights, and Practical Applications

The reconstructed sample from the autoencoders are displayed in Figure 4.12, with the original samples being randomly chosen from both normal and abnormal categories within the test dataset. These findings indicate that reconstruction quality is notably enhanced when utilizing a larger latent space dimension. Specifically, the autoencoder equipped with a 128-dimensional latent vector accurately reconstructs both normal and abnormal samples. Conversely, the autoencoder with a 16-dimensional latent space demonstrates adequate reconstruction capabilities for normal samples but falls short in accurately reconstructing samples with defects. This discrepancy serves as a beneficial feature for the anomaly detection method. Meanwhile, the autoencoder configured with a mere 2-dimensional latent space struggles to effectively reconstruct any type of sample.

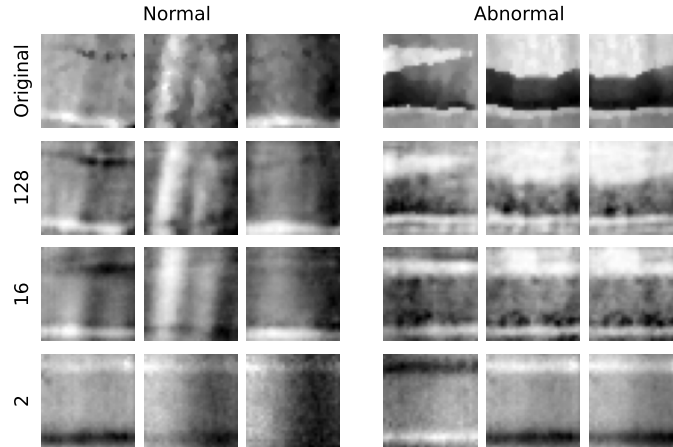


Figure 4.12: The resulting reconstructions from the autoencoders with various latent sizes are compared for both normal and abnormal test samples

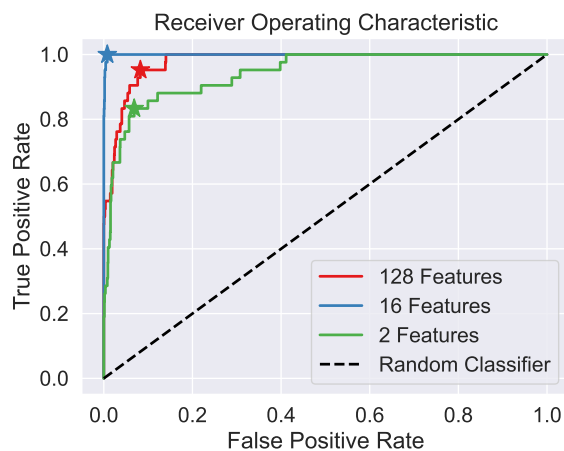


Figure 4.13: ROC curves of the test set are plotted for the three autoencoder classifiers

Figure 4.13 presents the ROC curves for the trio of autoencoders, with the optimal threshold points highlighted by stars. These findings further illustrate that there isn't a direct correlation between the ability to reconstruct and classify accurately. Interestingly, the models with 2-dimensional and 128-dimensional latent spaces display inferior classification efficacy compared to the 16-dimensional model. The autoencoder that employs a 16-dimensional latent space emerges as the top performer, striking a balance with a high true positive rate and a minimal false positive rate.

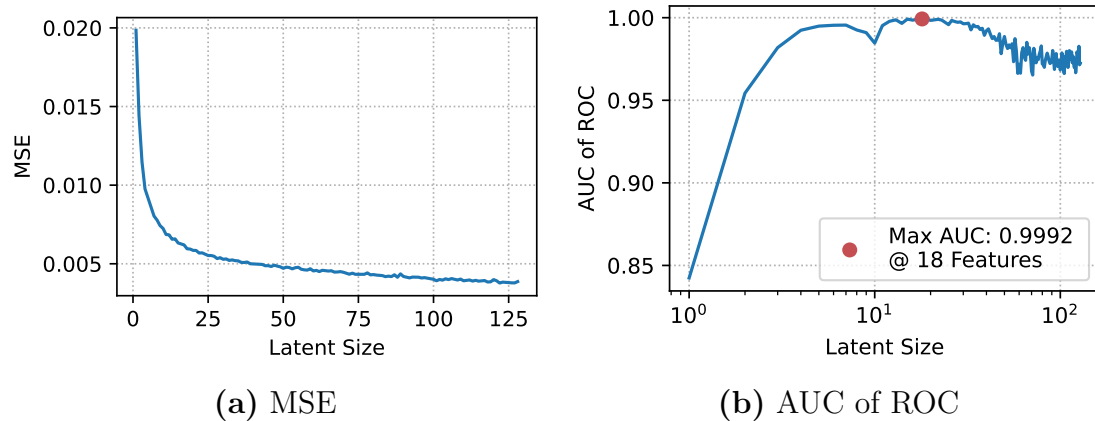


Figure 4.14: MSE and AUC of ROC are plotted for autoencoder models with latent dimensions varied from 1 to 128.

Figure 4.14 illustrates how the size of the latent vector influences the model's performance. 4.14.a indicates that increasing the size of the latent dimensions tends to result in reduced reconstruction errors. Nonetheless, achieving the most accurate classification does not hinge on minimizing reconstruction error; rather, an optimal level of reconstruction that enhances classification outcomes is preferred. In 4.14.b, the optimal latent dimension size is determined by identifying the lowest Area Under the Curve (AUC) value of the ROC curve across varying latent dimension sizes.

Figure 4.15 displays the confusion matrix for classifications made using the ideal latent dimension size. The low values off the main diagonal indicate a high accuracy in correctly classifying samples as either normal or abnormal.

Figure 4.16 showcases the effectiveness of the anomaly detection method on a 2-dimensional depth map, where each point's color reflects the normalized mean squared error (MSE) from reconstructing a small window around that point using the anomaly detector. Notably, regions with defects exhibit a higher concentration of points with increased MSE values. This pattern aids in distinguishing defective areas by overlooking isolated anomalies. The generated anomaly map serves as a direct tool for human inspectors to spot potential anomalies in parts of the composite material. Further-

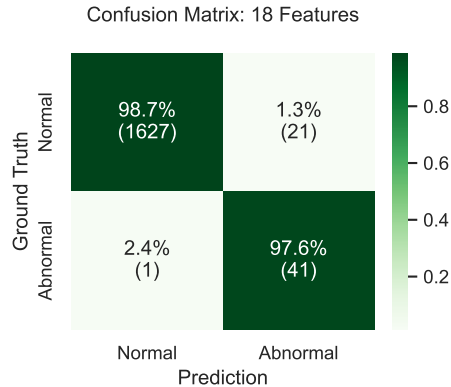


Figure 4.15: The confusion matrix demonstrates the evaluation of the best model

more, this map can undergo additional analysis, such as blob detection techniques, to pinpoint the precise locations of these anomalous regions.

Figure 4.17 demonstrates the procedure for identifying defects within the anomaly map. The height of each curve indicates the mean squared error (MSE) value for a single tow (as denoted by color in the preceding figure). The arrows pinpoint the blobs identified through the application of the Derivative of Gaussians technique. This method successfully detects only those segments where there is a sustained stretch of elevated MSE values. The precise locations of these identified regions can be isolated and highlighted as points of interest for inspection personnel or automated inspection frameworks.

Overall, the proposed anomaly detection method provides a tool to assist human inspectors in identifying areas of interest and streamlining the quality control process. The detected anomalies and corresponding anomaly maps generated with this method can augment human capabilities in quality control processes. These anomaly maps not only streamline the detection of defects in manufacturing components but can also enhance the operational efficiency of human inspectors. By highlighting areas of potential anomalies, inspectors can focus their expertise where it's most needed, reducing inspection times and improving the accuracy of defect de-

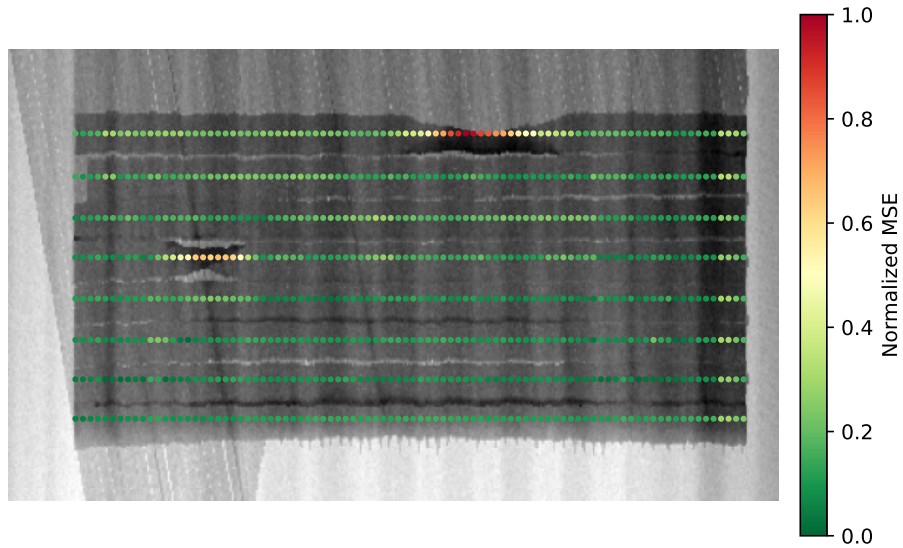


Figure 4.16: An anomaly map is generated from the MSE of individual cropped windows

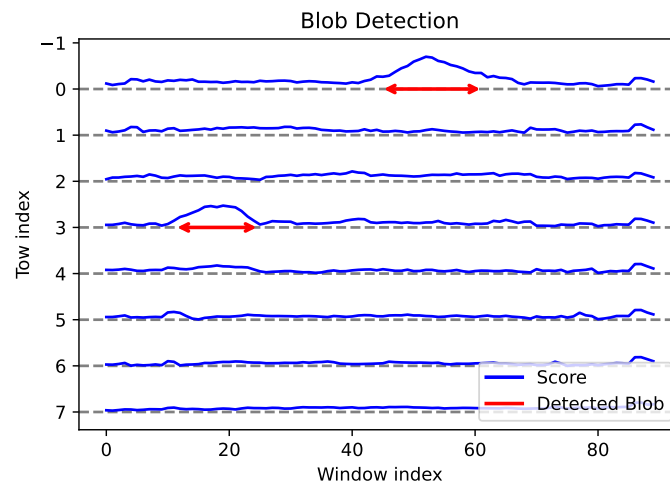


Figure 4.17: Anomaly scores are visualized as 1D signals for blob detection

tection. This synergy between AI tools and human expertise exemplifies the essence of Human-centered Cyber-Physical Systems (HC-CPS), where technology is leveraged to amplify human potential rather than replace it. Further work in this field should explore the integration of visualization tools and extended reality interfaces to help guide human inspectors in real-time. As we transition into the next chapter, we delve deeper into HC-CPS, exploring how this harmonious integration of human skills with cyber-physical systems can be further optimized and applied across various industrial domains, bringing a new era of intelligent and human-centric manufacturing processes.

Chapter 5

Human-centered Cyber-Physical System (HC-CPS)

5.1 Introduction: Embracing Human-centered Design in CPS

Transitioning from the IMES framework and AI case studies detailed in previous chapters, this chapter presents the concept of a Human-Centered Cyber-Physical System (HC-CPS) that blends the innovative values of Industry 5.0 with the foundational technologies of Industry 4.0. Moving beyond the manufacturing-centric IMES framework, the HC-CPS concept is adaptable across a wide range of industries, prioritizing universal design principles over sector-specific standards. This approach aims to explore the intricate interplay between hardware, software, and wetware, illustrating how these components can harmoniously create a system that is not only technologically advanced but also accommodates human users and societal values.

A key component of this proposed HC-CPS framework is its emphasis on immersive interaction between humans, machines, and software. It integrates a real-time

rendering engine, facilitating dynamic user interaction with machinery and real-time data visualization through Extended Reality (XR) interfaces. Additionally, the framework highlights robust cloud integration for seamless remote connectivity and efficient large-scale data processing. Drawing inspiration from the IMES model and existent CPS frameworks, this human-centered approach aims to establish a medium for immersive collaboration and comprehensive remote monitoring. Figure 5.1 illustrates the overarching HC-CPS framework, based on the IMES model, depicting a network of interconnected components and computational systems, with a suite of software interfaces offering secure, remote access across diverse devices.

The concept of a digital twin represents a vital component of the CPS, stretching from basic data collection and analysis to the creation of elaborate 3D simulation environments that mirror the real-world system in its entirety. By leveraging collected data, the framework supports the application of both AI-driven analytics and model-based monitoring strategies developed by domain experts. Such approaches may include the use of numerical simulations to assess and forecast the impact of system modifications. Utilizing resources like Computer-Aided Design (CAD) models, 3D simulation environments can provide realistic visualizations [1].

Central to a human-centered design philosophy is the capacity for scale realization and the accurate rendition of the system within a realistic framework. To achieve this, the HC-CPS framework can incorporate a variety of simulation platforms and physics engines capable of generating environments that range from basic geometric representations to highly detailed, lifelike simulations. This multifaceted approach highlights the framework's approach to enhancing human-machine interaction and ensuring the adaptability of CPS to the evolving demands of Industry 5.0.

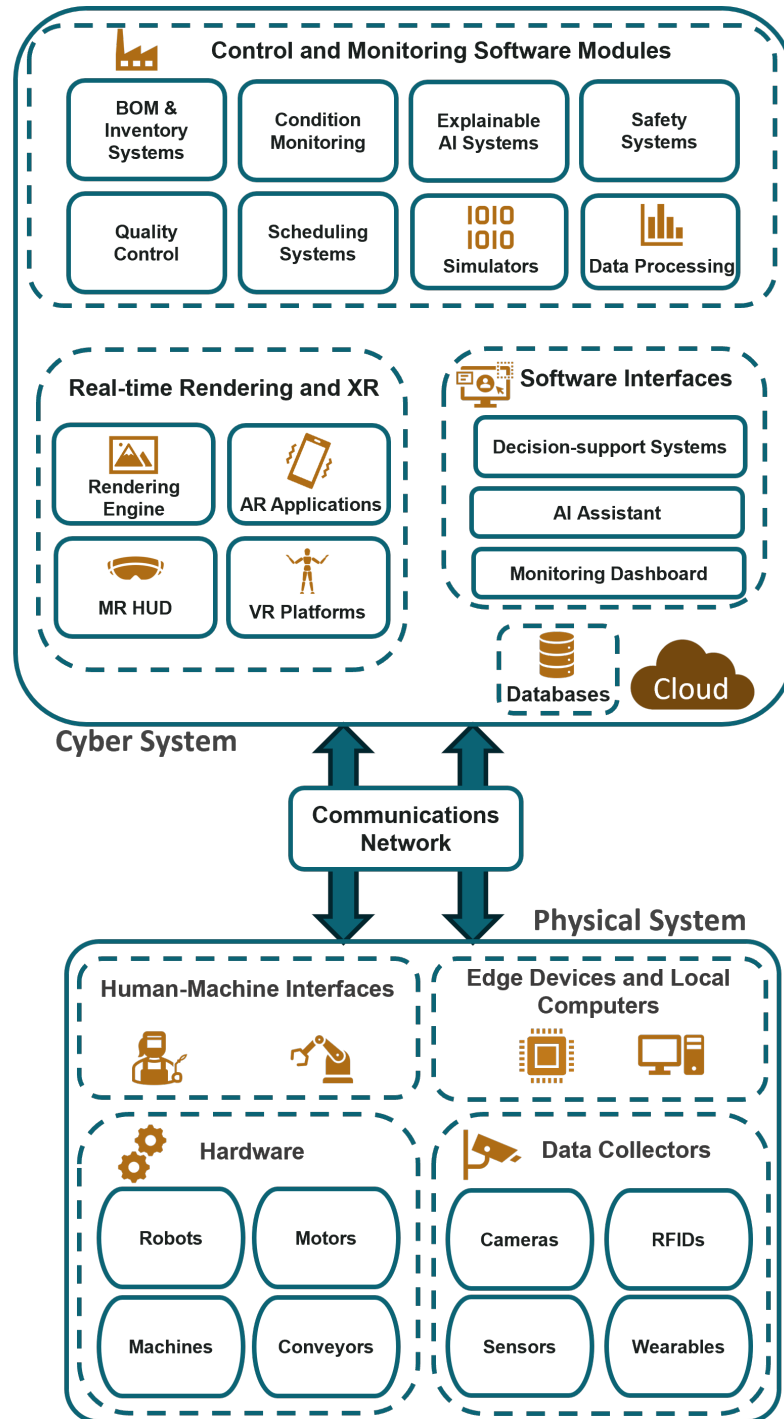


Figure 5.1: The proposed Human-Centered Cyber-Physical System (HC-CPS)

5.2 Conceptual Overview: Defining HC-CPS

The emergence of Human-centered Cyber-Physical Systems (HC-CPS) signifies a pivotal shift toward the seamless integration of technology with human elements, a core aspiration of Industry 5.0. This evolution embodies a deliberate effort to synchronize hardware, sophisticated communication networks, software components, and human interaction mechanisms into a unified system, thereby enhancing human capabilities and promoting well-being within industrial settings. Central to HC-CPS is a comprehensive framework that melds various technological and human elements. This integration includes traditional human-machine interfaces (HMIs), software dashboards/applications, and, notably, extended reality (XR) technologies, which collectively aim to create an intuitive and immersive experience for the user. Delving deeper into the HC-CPS framework, three main components emerge as foundational pillars: Hardware, Software, and Wetware.

- **Hardware:** This encompasses the physical devices and sensors that interact with the real world, capturing data and executing actions. The selection and design of hardware in HC-CPS should prioritize user safety, ergonomics, and accessibility.
- **Software:** Software in HC-CPS serves as the brain of the system, processing data, making decisions, and facilitating human-machine interactions through intuitive dashboards and applications. The emphasis on adaptability, personalization, and explainability in software design is crucial for aligning with human-centered principles.
- **Wetware (Human Element):** Wetware refers to human users, their cognitive and physical capabilities, and their interactions with the system. Understanding

and designing for human behavior, needs, and limitations is paramount in HC-CPS.

The integration of these components within the HC-CPS framework emphasizes a commitment to creating systems that are not only technologically advanced but also designed to support human needs and collaboration among individual users, teams, and organizations. The goal is to foster environments where technology acts as an extension of human capabilities, enhancing rather than replacing human effort and contributing to a sustainable and equitable future.

5.2.1 Hardware Evolution: Towards Human-centered Interactions

The scope of Human-centered Cyber-Physical Systems (HC-CPS) is large and varied, comprising a wide array of hardware components from sensors and actuators to sophisticated machines and robots. These elements are the foundation of CPS, enabling the seamless integration of physical processes with digital oversight and control. As we venture further into the era of Industry 5.0, the design and evolution of these hardware components are increasingly influenced by human-oriented design principles, aiming to enhance the intuitive interaction between humans and machines [103]. This section explores the diversity of hardware in HC-CPS, emphasizing advancements that facilitate human-centered interactions.

Sensors, the primary tools for data acquisition in HC-CPS, serve as the critical link between the physical world and digital systems. Recent advancements in sensor technology have led to the development of more accurate, efficient, and reliable sensors [104]. These improvements have significantly enhanced the responsiveness of CPS to human inputs and environmental changes, facilitating more nuanced and effective human-machine interactions [105, 106].

The spectrum of tools and machines in HC-CPS ranges from stationary equipment to dynamic entities such as mobile robots and aerial drones. These components have been reimaged to support tasks alongside humans, emphasizing safety and effectiveness.

HMIs are instrumental in enabling seamless interaction between humans and Cyber-Physical Systems (CPS). The advent of Extended Reality (XR) technologies, which include Virtual Reality (VR), Augmented Reality (AR), and Mixed Reality (MR), has transformed the landscape of HMIs. By providing immersive experiences, XR technologies significantly improve comprehension, management, and training in CPS environments, thereby promoting a more natural and efficient collaboration between humans and machines.

Looking ahead, the continuous evolution of hardware in HC-CPS is essential in meeting the growing demands for systems that are not only technologically advanced but also inherently aligned with human needs. Interdisciplinary research and collaboration will be vital in exploring new frontiers in sensor technology, robotics, and human-machine interfaces, including the expanding role of XR in creating immersive and intuitive user experiences.

5.2.2 Software Integration: Bridging Humans and Systems

Software serves as the glue adhering the individual components of HC-CPS, orchestrating the interaction between hardware devices and human operators. It interprets sensor data, implements decision-making algorithms, and provides intuitive interfaces for user interaction, thereby playing an essential role in aligning cyber-physical systems with human needs and expectations. The integration of software in HC-CPS not only enhances system functionality but also elevates the user experience, making complex operations accessible and understandable to a broad user base [107]. The

advancement of software technologies has enabled the development of interfaces that are more intuitive, adaptable, and personalized. These interfaces can leverage AI to tailor user experiences, thereby significantly improving interaction efficiency and satisfaction. By analyzing user behavior and preferences, software systems can adapt in real-time, providing personalized feedback and guidance that enhance the overall usability of HC-CPS [108, 109].

Software in HC-CPS acts as a bridge, merging the physical operations of hardware with the cognitive processes of human operators. This bridging is particularly crucial in systems incorporating Extended Reality (XR) technologies, where software algorithms render immersive environments that seamlessly integrate with the physical world. These technologies create a unified experience, blurring the boundaries between digital and physical realms and enhancing system intuitiveness and responsiveness.

Developing software for HC-CPS presents numerous challenges, including real-time data processing, system security, and user interface design. Innovations in software development practices, driven by open-source collaborations and agile methodologies, are pivotal in addressing these challenges. Continuous integration and deployment models, along with user feedback loops, play critical roles in refining software solutions, ensuring they meet the dynamic requirements of HC-CPS.

Looking forward, the landscape of software development in HC-CPS is poised for transformative changes, with emerging technologies such as quantum computing and advanced AI algorithms promising to revolutionize system capabilities. These advancements are expected to further enhance adaptability, security, and alignment with human-centric design principles, driving the next generation of cyber-physical systems toward even more seamless integration between humans and technology.

5.2.3 Wetware Considerations: Prioritizing Human Elements

In the context of Human-centered Cyber-Physical Systems (HC-CPS), wetware—referring to the human component—is the central focus. This concept encapsulates not only the users and operators but also the broader spectrum of individuals impacted by the system. Recognizing and addressing human needs, behaviors, and limitations are essential for designing systems that are not only technologically advanced but also catered towards enhancing human capabilities and promoting societal well-being. This holistic approach is the key focus of Industry 5.0, which is to enhance human potential through technology.

Ergonomics plays a critical role in HC-CPS by ensuring that both physical interfaces and digital interactions are designed with human capabilities and limitations in mind. This encompasses the ergonomic design of hardware, such as control devices and wearable technology, as well as software interfaces that facilitate intuitive navigation and interaction. By prioritizing ergonomics, systems can reduce user strain, lower error rates, and significantly improve user satisfaction and efficiency. Furthermore, cognitive load management within HC-CPS is crucial for maintaining user engagement and preventing information overload. Designing interfaces that align with human cognitive processes—by presenting information in clear, manageable segments and utilizing intuitive design elements—can significantly enhance user comprehension and system usability. Strategies for simplifying complex data visualizations and streamlining user workflows are essential components of reducing cognitive strain.

As we look to the future, the integration of wetware considerations in HC-CPS is set to evolve with advancements in adaptive interfaces, AI-driven personalization, and ergonomic designs. These emerging trends promise further to refine the alignment between technology and human needs, enhancing the intuitiveness, safety, and overall efficacy of cyber-physical systems. Continuous research into understanding the human

aspect of system interaction will remain crucial for advancing human-centered design practices.

5.3 Implementation Strategies

5.3.1 Human Interaction

Various interaction methods are designed to accommodate diverse tasks and objectives within industrial systems. Human-to-human interaction emphasizes safety in collaboration, transparency, and the use of appropriate mediums, such as 3D representations, to ensure a comprehensive understanding of complex systems. Safety is also a critical factor to consider for human-to-machine interaction, including disaster avoidance and warning systems coupled with the design of comprehensive and intuitive control interfaces [110]. These interfaces should facilitate quick and adaptive responses to dynamic environments. At the same time, human-software interaction is critical, necessitating consideration for standardization and human-centered design. To ensure intuitiveness and ease of use, a computer application should serve as the main interface that adheres to globally adopted input standards. Considering a web-based design could be beneficial for scalability, ensuring operational compatibility across various devices. While the main interface should offer basic capabilities to users, specialized software modules might necessitate distinct interfaces with hand-held devices or wearables. This design approach aims to optimize human interaction across different facets of the CPS.

Given the critical role that AI systems play in monitoring and controlling tasks in the CPS, it is essential to take into account human involvement. Collaborative interaction between humans and AI modules is paramount, necessitating careful consideration to ensure that AI-powered decision support systems deliver information

that is interpretable, accurate, and trustworthy. A human-centered CPS necessitates a dedicated software module for comprehending AI, encompassing XAI algorithms, causal analysis, uncertainty quantification, and other informative metrics. Moreover, the increasing prominence of generative AI introduces a growing sphere of human interaction, wherein AI serves as tools for tasks like information retrieval, reporting assistance, and design prototyping [111]. Despite their utility, these generative AI tools require meticulous consideration in their design due to the potential for misleading and inaccurate outcomes. To improve the reliability of generative AI, methods such as Retrieval-Augmented Generation are employed, underlining the imperative to thoroughly scrutinize and refine the dynamics of human engagement with these advanced AI technologies [112].

5.3.2 Real-time Rendering

Real-time rendering engines, exemplified by Unity3D, Unreal Engine, and NVIDIA's Isaac Sim, play a pivotal role in the development of CPSs and the creation of digital twins [113]. These engines, designed for crafting dynamic 3D visual representations, find versatile utility in constructing realistic virtual worlds that form the basis of digital twins within CPSs. In particular, Unity3D stands out for its advanced XR integration and supportive development community, making it a preferred choice for the presented CPS implementation. The real-time rendering process, which involves rendering scenes on the fly, allows the generation of high-fidelity visual effects with efficient resource utilization. Despite their proficiency in visual presentations, real-time rendering engines may have limitations in tasks such as numerical analysis, physics simulations, and device connectivity within the broader CPS framework [113]. Nevertheless, the collaborative efforts of researchers and developers in the Unity3D community have led to the creation of numerous extensions, packages, and plug-ins,

enhancing the engine's capabilities and enabling its seamless integration with robotics and AI applications. In summary, real-time rendering engines serve as indispensable tools for shaping realistic digital environments essential for immersive human interaction.

5.3.3 Immersive Technologies for Advanced User Interaction

To facilitate seamless interaction among humans, machines, and software, enabling real-time monitoring and control of industrial systems, an immersive CPS framework is proposed. This framework incorporates a real-time rendering engine, allowing users to interact with machines and visualize data through Extended Reality (XR) interfaces. It also includes cloud integration, allowing remote connections and facilitating large data processing. Based on the IMES model and existing CPS models, the proposed CPS framework focuses on human-centered design, providing a platform for immersive collaboration and remote monitoring.

The evolution and integration of Extended Reality (XR) technologies into Human-centered Cyber-Physical Systems (HC-CPS) can enable more engaging, intuitive, and immersive human-system interactions. These technologies enable users to interact with physical and virtual environments in an immersive manner through devices like phones, tablets, or headsets. XR forms a spectrum incorporating varying levels of the physical and digital worlds, including Augmented Reality (AR), Mixed Reality (MR), and Virtual Reality (VR). Figure 5.2 depicts the spectrum between fully physical systems and completely digital systems. AR enables users to interact with and view digital components that are overlaid on physical environments. MR, on the other hand, begins to incorporate interaction and control with physical components in addition to digital visualizations. Finally, VR is completely immersive, enabling the user to interact with a fully digital environment.

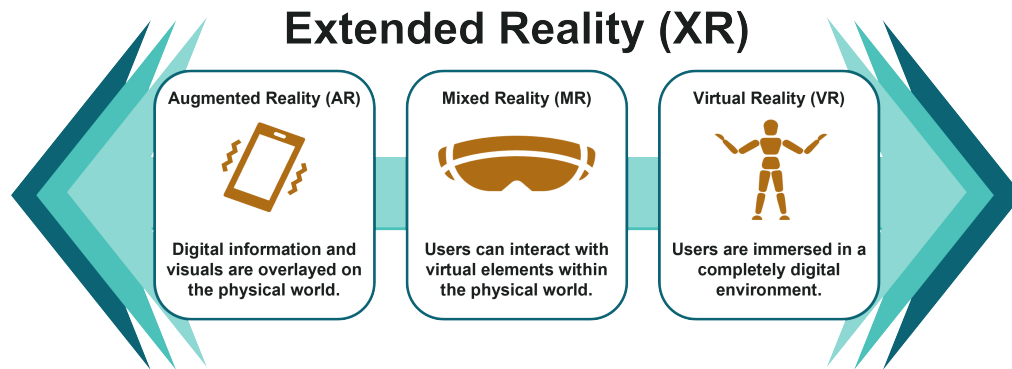


Figure 5.2: A graphic depicting the spectrum of XR, including AR, MR, and VR

Embracing XR technologies within HC-CPS signifies a conceptual leap in the way humans interact with and control their environment, moving beyond traditional interfaces to more integrated and dynamic user experiences. This evolution promises not only to enhance the efficiency and naturalness of human-computer interactions but also to open new possibilities for application across diverse sectors, including healthcare, education, manufacturing, and entertainment. As we continue to explore the potential of XR, ongoing innovation, research, and collaborative efforts will be essential in realizing its full potential within HC-CPS, envisioning a future where the convergence of digital and physical worlds enriches society and industry alike.

5.4 Implementation Examples

5.4.1 Virtual Production Line

With a focus on virtual reality applications, a simple manufacturing production line system is developed to provide an immersive teaching and training environment. The production line, shown in figure 5.3, includes three industrial tables positioned in a U shape around a robotic arm on a linear actuator. With the linear actuator, the robotic arm can move back and forth to reach all areas of the tables. In a real-

world manufacturing environment, a setup like this could include different production systems placed throughout the tables, such as drilling, welding, or painting stations. Many manufacturers produce varying, but similar products that require different combinations of production machines. The centrally placed robotic arm enables parts to be exchanged at the different stations in any desired order or combination. This simulated environment could also provide a testing platform for scheduling solutions.

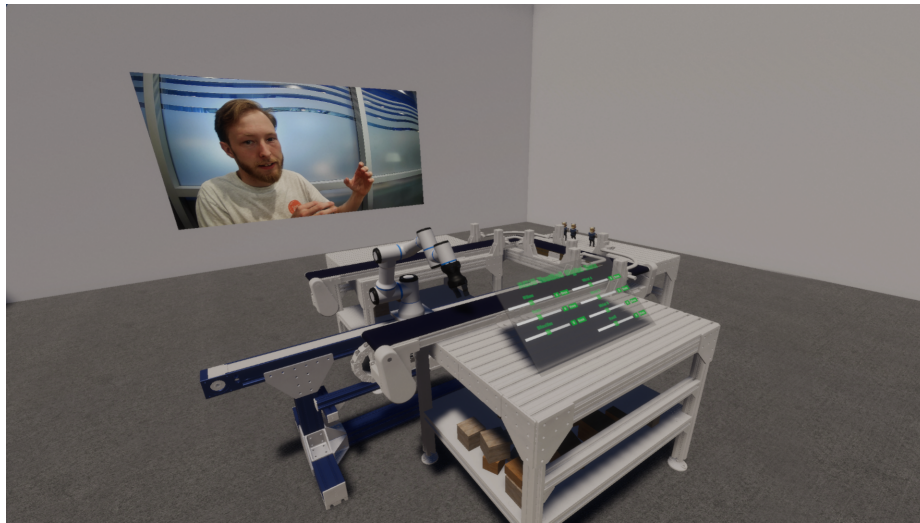


Figure 5.3: A rendering of the digital manufacturing production line

As mentioned above, the primary purpose of this developed system is to serve as a teaching and learning platform, applicable for onboarding new employees or in an academic setting. In the digital room, a virtual monitor is placed, allowing users to watch video demonstrations or engage in video calls with experts from anywhere in the world. In addition, virtual interfaces allow users to receive information and interact with individual equipment. Realistic digital environments like this not only offer a safer alternative to training on real equipment but also mitigate downtime and production losses associated with training on actual production systems.

5.4.2 Virtualization of the ACIS Lab

To fully realize the potential of the proposed CPS, a physical system is imperative. Taking advantage of the Advanced Control and Intelligent Systems Laboratory (ACIS Lab) at the University of Victoria, a digital counterpart is designed where robots and their sensors are analogous to the machines that would be present in factories, mining sites, or other industrial environments. A 3D model is created by meticulously measuring and modeling all aspects of the lab. Additionally, some pre-developed 3D models of the equipment and robots are obtained from the original manufacturers and imported into the digital environment. When the real-time sensor data are connected to update the digital model synchronously with the real world, a Digital Twin is achieved. Figure 5.4 presents the physical laboratory in comparison to its digital twin.

Designing a realistic 3D environment is a challenging task that requires meticulous detail of many different objects and components. Oftentimes, it's advantageous to design each sub-component individually and then combine them to create the more intricate component. Unity3D, like many other rendering engines, follows this design approach by incorporating a prefab system that allows modeled items to be adapted and reused easily. Taking advantage of Unity's prefab system, many of the objects within the ACIS lab are designed as prefabs (Figure 5.5) that can be easily replicated throughout the digital twin environment. As a prefab, the modeled items can be easily edited and adjusted within the scene, having all sub-components contained within a single parenting element. Many of the prefabs created for the ACIS lab digital twin include nested prefabs of smaller components combined to form the overall object.



(a) A photo of the physical ACIS Lab



(b) The ACIS Lab digital twin

Figure 5.4: The ACIS lab digital twin is created to match the physical ACIS lab as a 1:1 real scale copy

Digital Assets

In addition to the pre-built models created, many more common objects are freely available from online resources. Unity's asset store is one resource that provides access to many different types of assets useful for a variety of different applications and projects. For the ACIS digital twin, some models are imported from external

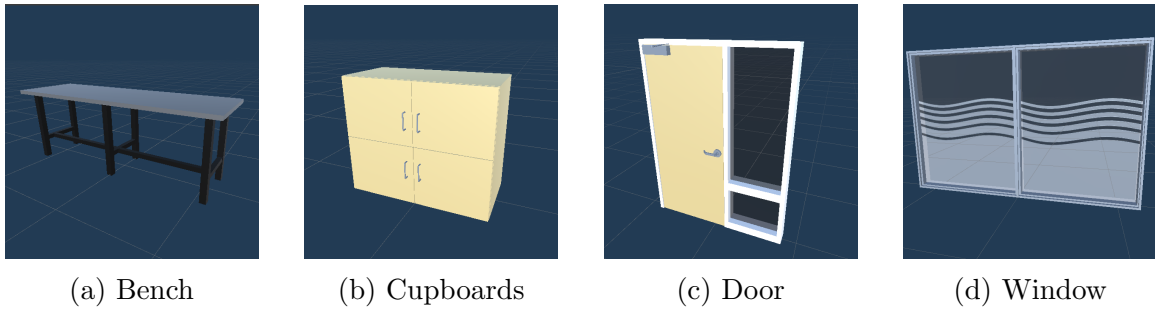


Figure 5.5: Some designed prefabs within the ACIS lab digital twin

sources, Shown in figure 5.6. Two models from the asset store, the chair (5.6a) and the computer monitor (5.6d) are used to represent similar objects within the physical lab. Other objects that are not available in the Unity asset store often have CAD files available from their manufacturers. Unfortunately, Unity does not support CAD files naively, but other software such as Blender, AutoCAD, and CAD Exchanger can be used to convert CAD files into Unity-compatible formats. In the ACIS lab digital twin, the CAD files for the Jackal (5.6b) and Kinova 5.6c robots are converted and used in the Unity environment.

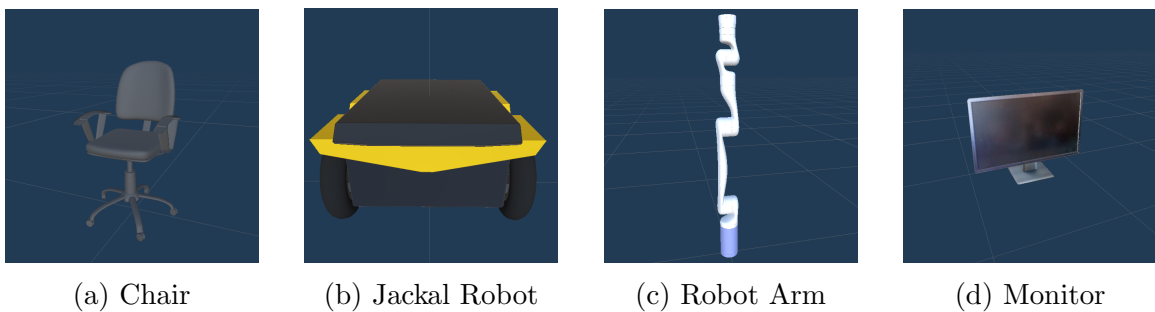


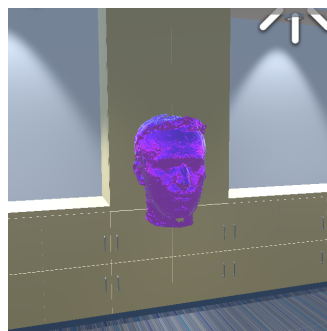
Figure 5.6: Models imported into the ACIS lab digital twin

When assets are not readily available, it can be quite difficult and time-consuming to design them. In this case, there are many different methods to accelerate the design process, depending on the level of detail required. One solution is to scan physical objects with 3D registration software to obtain their 3D models. In the ACIS digital twin, three objects are scanned to create their 3D model, shown in

Figure 5.7. Two different techniques are used as demonstrations. A function generator (5.7a) and an animal sculpture (5.7c) are converted to 3D assets using a close-range photogrammetry method from multiple 2D images of the objects. On the other hand, the human head (5.7b), is scanned using a 3D depth camera to create multiple meshes from different views. These meshes are combined manually to create the object file, with fine-tuning from a human expert. Scanning objects this way is a good method to obtain a 3D model quickly, but it can often miss fine details. Because of this, a developer should consider the pros and cons of designing the assets digitally versus using a 3D scanning method.



(a) Function Generator



(b) Human Head



(c) Animal Sculpture

Figure 5.7: Real-world objects scanned and converted to digital assets for importing into the ACIS lab digital twin

Virtual Reality

For a more realistic view of the ACIS lab digital twin, a virtual reality (VR) implementation is developed to immerse the user. In this application, the HTC Vive Pro VR devices are considered. The HTC Vive Pro includes a VR headset, handheld motion controllers, and base stations to track the devices. This setup works using infrared light projected from the base stations and captured by numerous IR sensors on the devices to localize and track the devices.

Unity provides certain packages and plug-ins to work with VR (and XR) devices.

XR is still an emerging field, and support for specific devices and applications is quite limited and not standardized. OpenXR is an open-source platform that acts as an intermediary between rendering engines and device-specific plug-ins. OpenXR is revolutionizing the XR industry by enabling developers to use a one-size-fits-all package for many different XR devices and applications. This makes it easier to develop XR applications compatible with various headsets and devices, as the developers only have to consider the single OpenXR interface rather than all of the device-specific functions. For this reason, OpenXR is the main package used to integrate XR features in the ACIS lab simulation. The OpenXR package comes with a pre-built interaction profile for the HTC Vive headset and controllers, enabling easy plug-and-play development.

Tracking

A key component of digital twin technology is that the physical and virtual environments are in sync with each other and digital assets should accurately mimic their physical counterpart. In general, this is achieved with many different sensors on the physical system that send signals to update the virtual environment in real-time. For the ACIS digital twin, this concept is incorporated with the use of XR tracking devices. The HTC Vive system has separate tracker devices that work similarly to the headset and controllers, with the base stations tracking the motion properties of each device.

These trackers can be attached to physical objects to provide the digital twin with updated position information of the objects in real time. An example object is shown in Figure 5.8, where a tracker is placed on top of a cardboard box in the center. In the ACIS digital twin, the tracker device is attached to a virtual cube object using C# scripts to update the cube object based on the tracker's information. This

enables the digital cube to move and interact synchronously with the physical box as it is manipulated in the real world. Trackers are also attached to other objects in the ACIS lab digital twin including humans and equipment. In a work environment, similar technology could be integrated into worker's clothing, or tools and equipment, providing necessary tracking details for potential safety and monitoring applications.

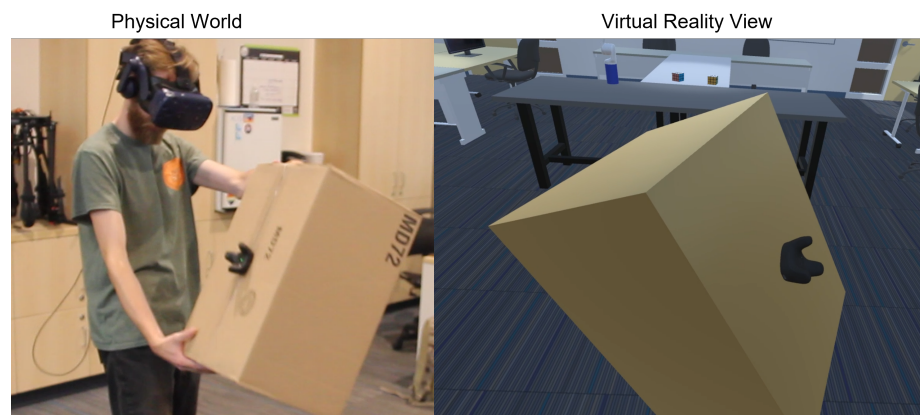


Figure 5.8: A tracker is mounted to a physical box that is replicated in the digital twin environment

Communications Network

The ACIS Lab CPS is built using the Robot Operating System (ROS), a set of software libraries and tools designed for real-time robotics applications. The ROS network enables robots to communicate synchronously with each other, sending and receiving sensor readings, processed data, and control commands. The ROS platform is currently available in two main variants known as ROS1 and ROS2. ROS1 operates as a centralized communication network that requires a master computer to keep track of all activities on the network and facilitate the transfer of data. ROS2 is a decentralized implementation of ROS, which enables each connected device to communicate with one another independently without the need for a centralized master computer. The decentralized approach with peer-to-peer communications provides

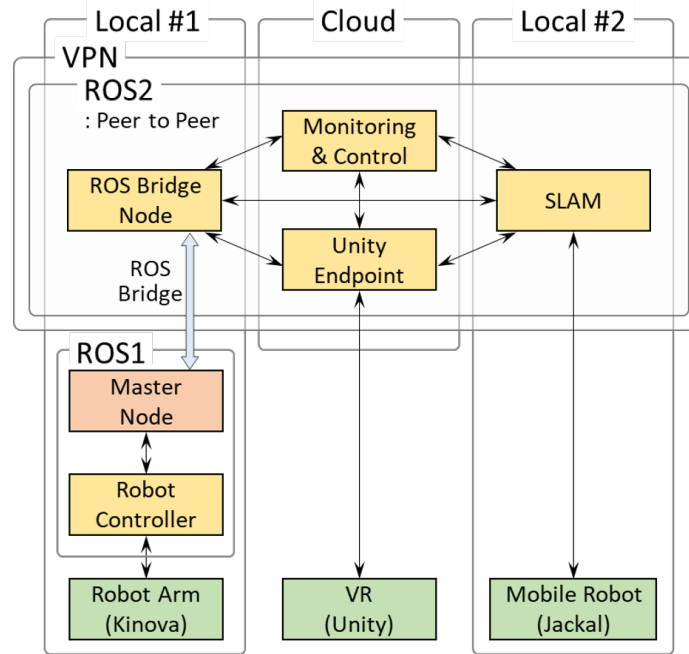


Figure 5.9: The architecture of the implemented cloud-based ROS network

added robustness since the network is not dependent on any one device or computer. However, ROS2 is not yet fully supported by many devices and software. Therefore, the CPS developed is designed to use both ROS1 and ROS2 in combination to achieve a more flexible and robust system. Figure 5.9 shows the core components of the cloud-based ROS implementation.

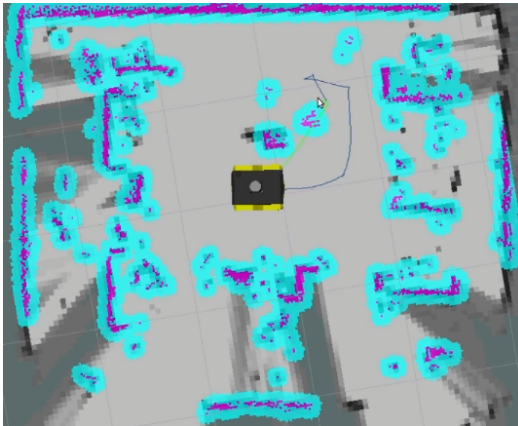
Connected Devices

Three different types of robots are incorporated in the ACIS CPS, including stationary robotic arms, a ground-based mobile robot, and an aerial drone. The robots are connected to the ROS network, providing a direct link for sharing data with the rendering engine, software modules, and other devices. This enables the digital twin to update the robots without the need for additional tracking devices. Furthermore, the robots can share specific information to promote multi-robot collaboration and complex interactions. In this use case, one of the robotic arms has a wrist-mounted

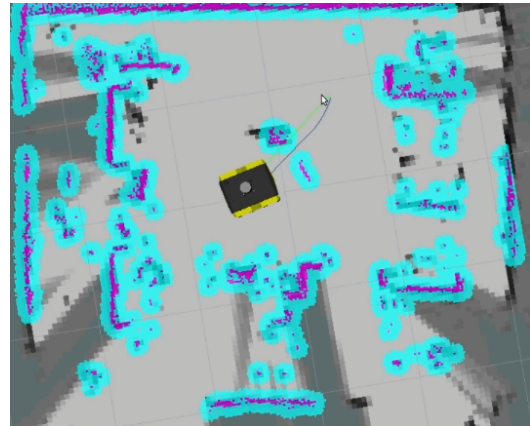
camera that provides essential perception information for identifying grasping locations and planning maneuvers. Through the ROS network, both robot arms can harness this information to perform collaborative tasks. To further demonstrate this seamless data sharing, a control sequence is implemented to enable the aerial drone and the mobile robot to work in combination. The robots can follow each other and make use of their different advantages by sharing data. For example, obstacles that may occlude the mobile robot's perception can be navigated by the drone to provide more information for the mobile robot's path planning system and vice versa. In addition to the multi-robot collaboration, a human operator can use the XR interfaces to control and command the robots remotely. This concept is advantageous for the safe operation of machines in dangerous environments.

The mobile robot is equipped with an edge device capable of processing the raw data collected from the robot's sensors. This allows the mobile robot to act independently from other systems on the network, while still sharing the essential data. Using information from its depth cameras, lidar, and IMU, the robot performs simultaneous localization and mapping (SLAM) in order to perceive its surroundings and identify obstacles. Depending on the task, the robot can receive goal point coordinates from a remote human operator and plan a path to reach the desired point using the popular bidirectional-RRT path planning algorithm. The mapping information and planned paths are shared over the network to provide information to other systems within the CPS. As the robot navigates its surroundings, the path-planning algorithm continuously updates to ensure obstacle avoidance in dynamic environments. This enables the robot to act autonomously while receiving high-level commands from a human operator or task-planning software module. The mapping and path planning is demonstrated in Fig. 5.10, showcasing the robot's ability to adapt to dynamic obstacles. This information is also available to the rendering engine in order to show the

robot's planned movements in the digital twin. This concept can provide additional information to XR users, enabling a heightened level of human-robot interaction, where the human can perceive the robot's intent.



(a) The robot begins by planning a path to the desired goalpoint



(b) The map is dynamically updated and a new path is acquired to avoid moving obstacles

Figure 5.10: A visualization of the mapping and path planning for the mobile robot

In summary, the interconnected devices within the ACIS CPS exemplify the seamless integration of robotics, artificial intelligence, and human-machine interfaces, illustrating a dynamic and adaptive system capable of addressing complex operational challenges. The collaboration between diverse robotic systems, supported by the ROS network and enhanced through XR technologies, showcases the practical realization of advanced cyber-physical systems. Such integrations not only facilitate increased operational efficiency and safety but also highlight the pivotal role of human-centered design in the evolution of industrial systems.

5.5 Navigating Future Challenges and Opportunities

Navigating the dynamic landscape of HC-CPS presents a unique blend of challenges and opportunities. As we delve deeper into integrating advanced technologies such as XR, AI, and IoT into these systems, the potential for transformative change across industries is immense. However, realizing this potential necessitates addressing several critical challenges while simultaneously seizing emerging opportunities to foster innovation and enhance human-technology interaction. The main challenges in implementing the proposed HC-CPS model are described below:

1. **Interoperability and Standards:** A key challenge lies in ensuring seamless interoperability among the diverse components of HC-CPS. Developing and adhering to universal standards is essential for facilitating communication and integration across different platforms, devices, and technologies.
2. **Data Privacy and Security:** As these systems increasingly rely on the collection and analysis of vast amounts of data, safeguarding privacy and ensuring robust security measures become paramount [1]. Addressing vulnerabilities and protecting against cyber threats is crucial for maintaining trust and reliability.
3. **User-Centric Design:** Crafting systems that are genuinely user-centered requires a deep understanding of human needs, behaviors, and limitations. Designing intuitive and accessible interfaces that cater to a broad user base, including those with disabilities, is a significant challenge that demands innovative solutions. This requires an interdisciplinary approach, combining the technical aspects of computer science and engineering with focuses of social sciences such as psychology and sociology [114, 115].

4. **Ethical Considerations:** The integration of AI and autonomous decision-making processes raises ethical questions concerning accountability, transparency, and the potential displacement of human workers [116]. Navigating these ethical dilemmas is essential for ensuring that HC-CPS contribute positively to society and further research should be conducted in this regard.

As researchers continue to break new ground on this front, navigating and addressing the complexities associated with the adoption of HC-CPS, new opportunities will come to light. Below summarizes some of the emerging opportunities and research fronts in this domain and exemplified within this thesis:

1. **Enhanced Human-Machine Collaboration:** HC-CPS opens avenues for more intuitive and productive collaborations between humans and machines. By leveraging XR and AI, these systems can augment human capabilities, making complex tasks more manageable and enabling workers to achieve higher levels of precision and efficiency.
2. **Remote Work and Training:** The use of XR technologies in HC-CPS enables the creation of immersive training environments and facilitates remote work possibilities. This can dramatically reduce training costs, improve safety, and allow for flexibility in work arrangements, broadening access to employment opportunities [1, 117].
3. **Predictive Maintenance and Quality Control:** Integrating AI for predictive analytics in HC-CPS can revolutionize maintenance practices and quality control processes. By anticipating failures and identifying defects early, industries can significantly reduce downtime, enhance product quality, and optimize operational efficiency [1, 5, 3].

4. Sustainable Practices and Resilience: HC-CPS offers the potential to streamline operations and reduce resource wastage, contributing to more sustainable industrial practices. Furthermore, the adaptability and resilience of these systems can help industries better respond to changing market demands and unforeseen challenges.

As we navigate the future of HC-CPS, a concerted effort among researchers, technologists, industry stakeholders, and policymakers is vital. Collaborative innovation, coupled with a steadfast commitment to addressing the social and ethical implications of these technologies, will be key to unlocking their full potential. Embracing a human-centered approach in the design and implementation of cyber-physical systems holds the promise of creating more inclusive, efficient, and sustainable solutions that not only meet the needs of today but also pave the way for a brighter, technology-enabled future.

Chapter 6

Concluding Remarks

Considering the complex interactions of humans, machines, and software within industrial worksites, the work presented in this thesis introduces a human-centered cyber-physical system with practical applications for monitoring and controlling industrial systems. Furthermore, it explores the concepts of Industry 4.0 and Industry 5.0 in regard to their concurrent development, enabling technologies, and societal values. In the domain of manufacturing, a thorough investigation of the state-of-the-art Manufacturing Execution Systems (MESs) is conducted to identify how industry 4.0 enabling technologies can be realized. Eleven key MES functionalities are identified, and a taxonomy is proposed to classify the intelligence levels required to reach an industry 4.0-ready MES. Based on these functionalities and intelligence levels, a conceptual framework is proposed for an Intelligent Manufacturing Execution System (IMES). The IMES framework incorporates industry standards, enabling manufacturers to implement state-of-the-art procedures and systems like the proposed CPS more easily.

In addition to the proposed IMES and CPS models, this work implements two industrial applications using artificial intelligence for improved monitoring and control

capabilities. Deep learning models are developed for machine condition monitoring and defect detection tasks. Both condition monitoring and defect detection are challenging tasks for data-driven models due to the unavailability of adequate fault and defect data in real industrial systems. Circumventing this data limitation, the presented condition monitoring approach uses a synthetic data generation method to provide realistic fault data in different operating conditions. For defect detection, an anomaly detection method is presented that requires only normal data samples. Overall, these case studies showcase the utility of AI in industrial applications and highlight the benefit of integrating AI modules in industrial management software.

Building on the IMES and CPS models, a prototype CPS is realized, featuring a 3D digital twin of the ACIS Research Lab for real-time synchronization between physical and digital assets. With a specific focus on human interaction and extended reality technologies, the CPS incorporates design challenges and development strategies, exemplified through an XR-enabled digital twin of the ACIS laboratory using the Unity3D game engine. This immersive experience in virtual reality, complemented by tracker devices and robot sensors connecting digital and physical worlds, allows users to interact with physical objects in a simulated environment. Noteworthy attention is given to human perception elements, with the virtual environment designed to scale. Furthermore, significant obstacles and new research directions in the context of HC-CPS are presented and discussed. Overall, this work demonstrates the implementation and use cases of cutting-edge technologies that enhance cyber-physical systems and facilitate the creation of human-centered systems.

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