Development of a Cyber Physical Production System Framework for Smart Manufacturing Analytics and Management

THESIS

Submitted in partial fulfilment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

by

RISHI KUMAR

Under the Supervision of

Prof. KULDIP SINGH SANGWAN

Prof. CHRISTOPH HERRMANN

Department of Mechanical Engineering

BITS Pilani
Pilani | Dubai | Goa | Hyderabad

BIRLA INSTITUTE OF TECHNOLOGY & SCIENCE
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Dedicated

To All Mighty God; epitome of hope

To my Research Mentors – Prof. Kuldip Singh Sangwan & Prof. Christoph Herrmann; epitome of empowerment

To my Father – Shri Nand Kishore Keshri; epitome of responsibility

To my Mother – Smt. Shobha Devi; epitome of sacrifice

To my Wife – Kamini Kumari; epitome of companionship

To my Daughters – Manvi & Jasika; epitome of affection

To all my Teachers, family members, co-authors, and friends; epitome of support

Birla Institute of Technology & Science, Pilani
Pilani Campus

CERTIFICATE

This is to certify that the thesis entitled **"Development of a Cyber Physical Production System Framework for Smart Manufacturing Analytics and Management"** submitted by **Rishi Kumar,** ID. No. **2018PHXF0035P** for award of Ph.D. degree of the institute embodies original work done by him under our supervision.

Signature (Supervisor): K.S. Sangwan 25/01/'24

PROF. (DR.) KULDIP SINGH SANGWAN

Shri B. K. Birla and Shrimati Sarala Birla Chair Professor

Senior Professor

Department of Mechanical Engineering

BITS Pilani, Pilani campus, Rajasthan, India

Signature (Co-supervisor): C. Herrmann

PROF. DR.-ING. CHRISTOPH HERRMANN

Chair of Sustainable Manufacturing and Life Cycle Engineering

Institute of Machine Tools and Production Technology

Technische Universität, Braunschweig, Germany

Director, Fraunhofer Institute for Surface Engineering and Thin Films IST, Braunschweig, Germany

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ABSTRACT

Cyber physical production system (CPPS) is a key enabling technology of Industry 4.0 for online monitoring, prediction, visualization, simulation, optimization, *etc.* Its implementation has enhanced the management capabilities and performance of traditional manufacturing systems to meet several engineering requirements at unit, system, and system of systems levels. A generic in-depth understanding of the multidisciplinary concepts of CPPS is required for quick adoption of CPPS by the industries. Therefore, this thesis aims at providing a generic CPPS framework and validates it for a 3D printer, a CNC machining center and a learning factory.

The thesis provides theoretical and practical contributions to the existing body of knowledge on CPPS for smart manufacturing analytics and management. It provides a systematic literature review on CPPS to provide an in-depth understanding of the multidisciplinary concepts for developing a generic CPPS framework for smart manufacturing analytics and management. A large number of elements and sub-elements are developed for the four phases of the CPPS framework. The selection of the elements and sub-elements depends upon the requirement of the system and the objectives of the CPPS for the system.

The proposed CPPS framework for smart 3D printing analytics and management transforms a conventional 3D printer into a smart 3D printer by integrating cost-effective solutions using low-cost sensors, devices, actuators, and open-source software. A three-layer architecture is proposed for cloud, fog, and edge computing implementation in 3D printing, wherein these three computing technologies do not compete rather complement one another. Data-driven descriptive, prognostic, and prescriptive analytics are presented for predicting energy distribution during various 3D printing stages, live estimation of environmental impacts for the 3D printed products, monitoring the nozzle health, and prescribing optimal printing parameters depending on the managerial requirements.

A CPPS framework for smart tool health analytics and management is proposed and implemented for a milling process to enable smart management capabilities of online monitoring of cutting tool degradation, detecting anomalous behaviour, predicting tool life of cutting tool, and prescribing optimum cutting parameters depending on the managerial requirements.

A CPPS framework for an existing learning factory is proposed by integrating it with inexpensive radio-frequency identification (RFID) and machine vision (MV) systems to facilitate smart functionalities of live monitoring, visualization, traceability & tracking, and feedback & control. A live dashboard is developed to monitor energy demand, track & trace the workpiece in real-time and provide real-time feedback. The study allows for the development of transversal competencies for the workforce, industrial engineers, and engineering students to effectively handle the complexity and future challenges of Industry 4.0.

The study would serve as a reference in providing researchers and practitioners with valuable insights, knowledge updates, and decision support in selecting CPPS elements and sub-elements according to their impacts and required efforts. It will also assist in understanding the maturity status, guiding future developments by addressing the important needs, and advancing the knowledge, management capabilities, and potential of traditional manufacturing. Finally, the proposed CPPS solutions developed with inexpensive hardware and open-source software would help micro, small, and medium enterprises (MSMEs) to realize the Industry 4.0 benefits of increased productivity, reliability, and product quality at a reasonable cost.

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LIST OF ABBREVIATIONS AND SYMBOLS

Abbreviation/Symbol	Description
3D	Three-Dimensional
5G	Fifth Generation
ABS	Acrylonitrile Butadiene Styrene
AGV	Automated Guided Vehicle
AI	Artificial Intelligence
AISI	American Iron and Steel Institute
AM	Additive Manufacturing
ANN	Artificial Neural Network
ANOVA	Analysis of Variance
API	Application Programming Interface
APT	Active Power Threshold
AR	Augmented Reality
AUC	Area Under the ROC Curve
AWS	Amazon Web Services
BCPS	Blockchain enabled Cyber Physical System
BiLSTM	Bidirectional Long Short Term Memory
BPNN	Back Propagation Neural Network
BT	Bed Temperature
CAD	Computer Aided Design
CDATT	Cross Domain Adaptation Network based on Attention Mechanism
CNN	Convolutional Neural Network
CPPS	Cyber Physical Production System
CPS	Cyber Physical System
CRM	Customer Relationship Management
CS	Computer Science
CSI	Camera Serial Interface
CSV	Comma Separated Values
d	Axial Depth of Cut

Abbreviation/Symbol	Description
DFA	Desirability Function Approach
DOE	Design of Experiments
DSS	Decision Support System
ERP	Enterprise Resource Planning
ET	Extruder Temperature
f	Feed
FDM	Fused Deposition Modeling
FPR	False Positive Rate
GA	Genetic Algorithm
G-Code	Geometric Code
GHG	Green House Gases
GMM	Gaussian Mixture Model
GPS	Global Positioning System
GRU	Gate Recurrent Units
GUI	Graphic User Interface
GWP	Global Warming Potential
HMI	Human Machine Interface
HMM	Hidden Markov Model
HRC	Hardness Rockwell C
HTTP	Hypertext Transfer Protocol
HVAC	Heating Ventilation and Air Conditioning
I2C	Inter Integrated Circuit
IALF	International Association of Learning Factories
ICT	Information and Communications Technology
IDE	Integrated Development Environment
IIoT	Industrial Internet of Things
IIRA	Industrial Internet Reference Architecture
IoT	Internet of Things
IP	Internet Protocol
IT	Information Technology

Abbreviation/Symbol	Description
KBS	Knowledge Based System
KNN	K-Nearest Neighbour
KPI	Key Performance Indicator
LCA	Life Cycle Assessment
LCD	Liquid Crystal Display
LH	Layer Height
LOF	Local Outlier Factor
LS-SVM	Least Squares Support Vector Machine
LSTM	Long Short Term Memory
LTE	Long-Term Evolution
M2M	Machine to Machine
MES	Manufacturing Execution System
ML	Machine Learning
MPS	Modular Production System
MQTT	Message Queuing Telemetry Transport
MR	Mixed Reality
MRR	Material Removal Rate
MSME	Micro Small and Medium Enterprise
MTBF	Mean Time Between Failures
MTTR	Mean Time To Repair
MV	Machine Vision
NASSCOM	National Association of Software and Service Companies
NFC	Near Field Communication
NI DAQ	National Instrumentation Data Acquisition
NIST	National Institute of Standards and Technology
NM-ICPS	National Mission on Interdisciplinary Cyber Physical Systems
NSGA	Non-dominated Sorting Genetic Algorithm
OEE	Overall Equipment Effectiveness
OPC UA	Open Platform Communications United Architecture
PC	Personal Computer

Abbreviation/Symbol	**Description**
PCA	Principal Component Analysis
PETG	Polyethylene Terephthalate Glycol
PLA	Polylactic Acid
PLC	Programmable Logic Controller
PLM	Product Lifecycle Management
PM	Particulate Matter
PMS	Printer Management Software
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PT	Print Time
PTL	Predicted Tool Life
PW	Product Weight
R_a	Average Surface Roughness
RAM	Random Access Memory
RAMI	Reference Architectural Model Industrie 4.0
RFID	Radio Frequency Identification
RH	Relative Humidity
RMSE	Root Mean Square Error
RNN	Recurrent Neural Network
ROC	Receiver Operating Characteristic
RSM	Response Surface Methodhology
RTLS	Real-time Locating System
RUL	Remaining Useful Life
SAMARTH	Smart Advanced Manufacturing and Rapid Transformation Hub
SCF	Specific Carbon Footprint
SDG	Sustainable Development Goal
SME	Small and Midsize Enterprise
SPI	Serial Peripheral Interface
SQL	Structured Query Language
SSD	Single Shot Detector

Abbreviation/Symbol	Description
SVC	Support Vector Classifier
SVM	Support Vector Machine
SVR	Support Vector Regression
TCP	Transmission Control Protocol
THE	Times Higher Education
TPR	True Positive Rate
UART	Universal Asynchronous Receiver Transmitter
UNIDO	United Nations Industrial Development Organization
UNSW	University of New South Wales
US	United States
USD	United States Dollar
v	Cutting Speed
VOC	Volatile Organic Compound
VPN	Virtual Private Network
VR	Virtual Reality
XDK	Xbox Development Kit

CHAPTER 1

INTRODUCTION

1.1 INDUSTRY 4.0

The historical impacts of industrial revolutions are substantial and continue to shape modern patterns of residence, leisure activities, and political dialogue through advances in manufacturing techniques and organizational structures (Stearns, 2021).

The advent of steam engine in the late 18^{th} century sparked the first industrial revolution. It automated physically demanding and repetitive tasks, leading to increased productivity, reduced production expenses, improved living conditions, and fostered urban development. The second industrial revolution occurred in the late 19^{th} century with the introduction of linear assembly lines. The assembly lines were powered by electricity generated from oil and gas, which enabled mass production and led to significant efficiency improvements. In the 1970s, the third industrial revolution began with the incorporation of electronics, information technology, and communication technology into manufacturing processes. This integration facilitated automation and engineering advancement, resulting in enhanced productivity (UNIDO, 2017).

The rising demand for customised, connected, intelligent, and sustainable products, along with the rapid development of Internet of Things (IoT), cyber physical systems (CPS), and artificial intelligence (AI) technologies led to the emergence of fourth industrial revolution (Moghaddam *et al.*, 2018). It is commonly known as Industry 4.0, a term coined by the German government in the year 2011 as part of its high-tech strategy 2020 action plan to establish Germany as a manufacturing industry leader (L. Xu *et al.*, 2018). The fourth industrial revolution is also referred to as digital manufacturing or smart manufacturing. It has led to the convergence of the physical and virtual worlds in the form of cyber-physical systems, where the computational components cooperate with the physical processes, utilizing and providing data analytics services on the internet (Monostori *et al.*, 2016). It monitors and synchronizes information between physical and cyber systems for improving efficiency, collaboration, and resilience (Lee *et al.*, 2015), and cooperate intelligently to achieve optimal manufacturing processes, manage disruptions, and adapt to changing circumstances (Rojas & Rauch, 2019).

Industry 4.0 has transitioned from being a future trend to a present reality. It currently holds a prominent position in the strategic and research priorities of numerous enterprises (Xu *et al.*, 2018). It has significant potential for addressing customer needs, enhancing decision-making flexibility, increasing resource efficiency, generating value through new services, adapting to demographic changes in the workforce, promoting work-life balance, and sustaining competitiveness in a high-wage economy (Kagermann *et al.*, 2013). Figure 1.1 depicts a timeline of significant industrial developments during the four industrial revolutions.

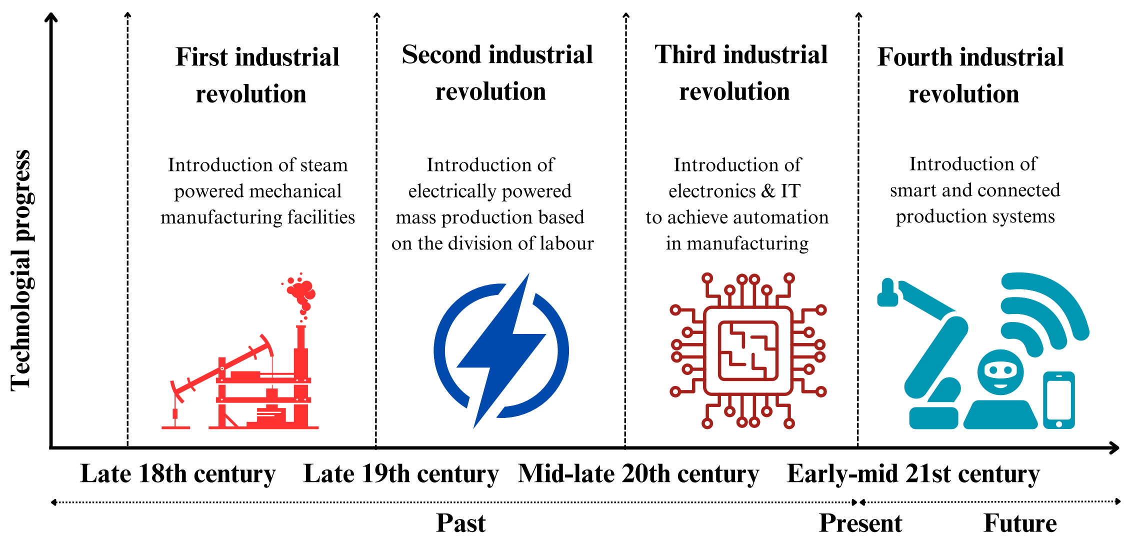


Figure 1.1 A timeline of significant industrial developments during the four industrial revolutions, adapted from UNIDO (2017), Kagermann *et al.* (2013)

The successful implementation of Industry 4.0 transformation necessitates the incorporation of twelve fundamental technologies (García & García, 2019). These technologies include sensors & actuators, RFID & RTLS, mobile technologies, communication & networking, cyber physical systems, additive manufacturing, virtualization technologies (VR & AR), cloud, simulation, data analytics & AI, adaptive robotics, and cybersecurity. Figure 1.2 shows the capabilities of these technologies.

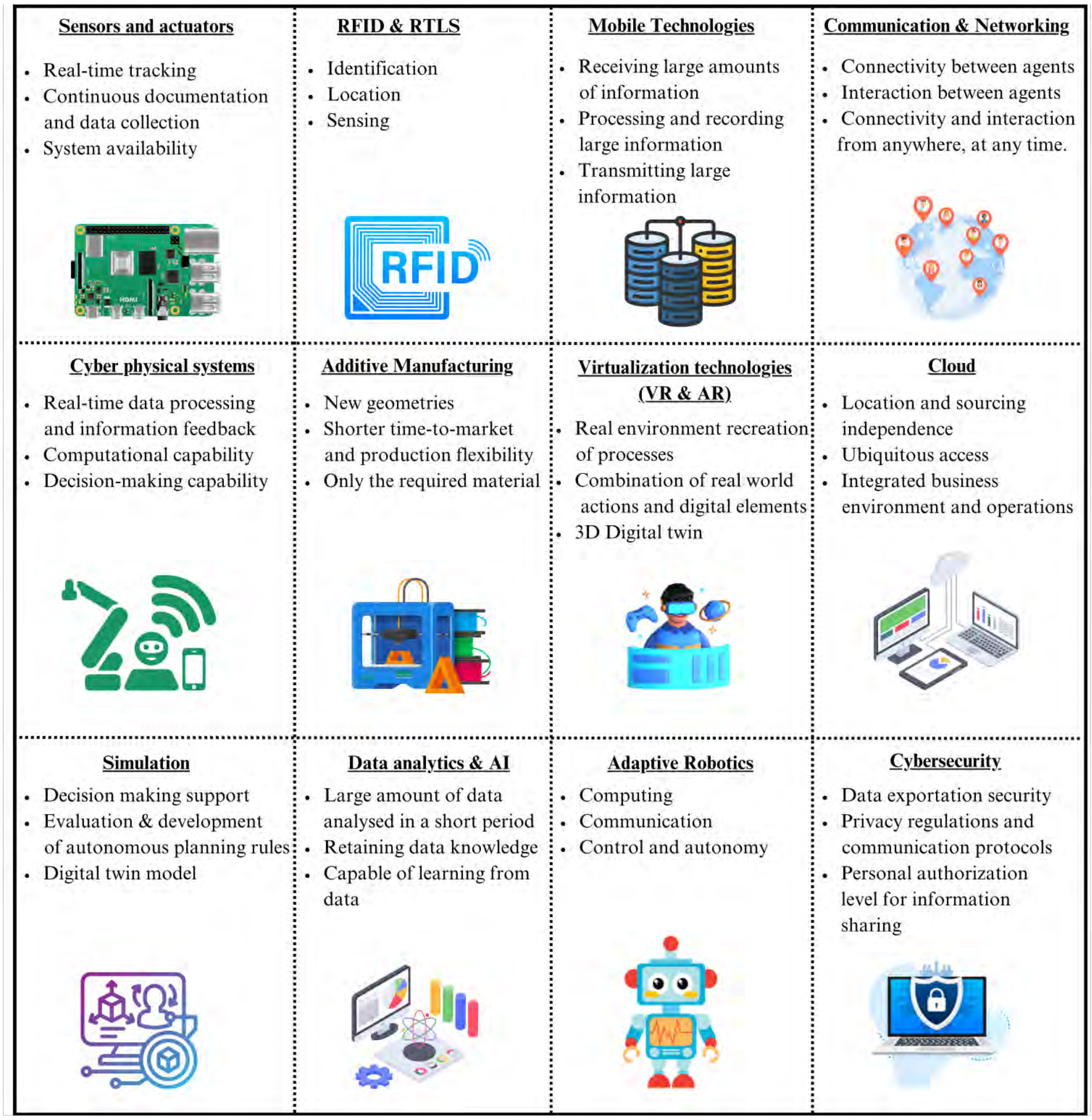


Figure 1.2 Key Industry 4.0 technologies and their capabilities, adapted from García & García (2019)

1.2 CYBER PHYSICAL PRODUCTION SYSTEM

The cyber physical system (CPS) refers to the fusion of the physical world with the virtual world, enabling powerful computation, collaborative communication, and advanced analytics (Morgan & O'Donnell, 2018). In the manufacturing domain, CPS is described as a cyber physical production system (CPPS). CPPS is regarded as one of the fundamental components of the development endeavour leading to smart manufacturing and industry 4.0 (Ahmed *et al.*, 2021). CPPS has the potential to enhance the capabilities of a production system threefold (Lins & Oliveira, 2020). It facilitates innovation, automation, enhanced customer responsiveness, and intelligent systems (Suvarna *et al.*, 2021). It also enables online monitoring, simulation, prediction, and optimization of manufacturing operations, which is essential for improving the flexibility and efficiency of a manufacturing system (Ding *et al.*, 2019).

A cyber world is a virtual representation of the corresponding physical system. It can be either a digital twin or data-driven with varying modelling and computational capabilities (Thiede *et al.*, 2016). Modelling and simulation can be performed using data mining or machine learning techniques (Rogall *et al.*, 2022). Overall, CPPS approach allows integration of various hardware/software, data acquisition, data analytics, dashboards, feedback, and control actions. It also enables real-time capability, modularity, reconfigurability, and scalability (Lins *et al.*, 2020).

The advancements in innovative and cost-effective sensors, microcontrollers, networking, data storage options, *etc.* are driving the deployment of CPPS in industry. The digital applications are generating a huge amount of data from the production systems, and this data has become a commodity of significant value in manufacturing. The potential for data-driven applications to provide manufacturing companies with competitive advantages is becoming increasingly apparent (Kusiak, 2022). This data, which is metaphorized as oil of the 18th century remains an untapped asset lacking systematic uses (Wired, 2018). However, the advancement in the big data analysis or data analytics during the last decade is enabling the manufacturing industry to analyse the past and the present data for identifying potential bottlenecks, detecting anomalies, predicting maintenance events, getting valuable insights to optimize the production systems in real-time. However, the industry is getting only little benefits expected of data analytics, and only a small number of industries are using data analytics to reap its benefits. Therefore, there is a great potential for the manufacturing industries to use data analytics for betterment of processes, sustainability, and profits. Also, there is a huge unexplored business potential for young entrepreneurs and researchers to initiate data acquisition and data analytics start-ups.

Data analytics and machine learning help researchers to mine or discover meaningful correlations, patterns, and trends by blending different technologies and techniques such as pattern recognition, statistics, and mathematics (Larose, 2005). Predictive analytics has several benefits in the manufacturing industry such as minimizing scrap, preventing tool failure, alerting quality issues, factory safety, and remote maintenance of tools. Prognostic analytics assesses tool/equipment health and predicts the remaining useful life (RUL) (Weiss *et al.*, 2015). Prescriptive analytics prescribes the best mode, route, manner or move to operate the systems for improving the agility and value creation. Smart and intelligent decisions based on prescriptive analytics can automate the decision-making of a system concerning its design, planning, scheduling, controlling, and operations using a mix of optimisation, heuristics, machine learning, and cyber physical systems (Menezes *et al.*, 2019).

Generally, CPPS can significantly enhance economic and environmental performance in manufacturing (Thiede, 2018). It promotes self-awareness and self-prediction at the unit/component/process level. At the system level, it enables self-configuration and maintenance, ensures minimal production downtime, and provides factory management with efficient production planning and inventory management (Lee *et al.*, 2015). At the system of systems level, a smart service platform facilitates interconnection and interoperability between multiple system level CPPSs. This allows collaborative application optimization with multiple stakeholders, such as personalized customizations, intelligent design, and remote maintenance. Consequently, the design process is shortened, decreasing time and related expenses (Qi *et al.*, 2018). In the case of smart production logistics, it has resulted in operational benefits of improved delivery, decreased makespan time and energy consumption (Flores-García *et al.*, 2023).

The recent use of CPPS has demonstrated its potential for improving performance of additive manufacturing, subtractive manufacturing, battery production (Schlichter *et al.*, 2022), 3D printing (Wiese *et al.*, 2021), resistance spot welding (Ahmed *et al.* 2021), CNC machine tool (Pantazis *et al.*, 2023), HVAC (Vogt *et al.*, 2022), *etc.*

CPPS has been the subject of numerous review studies, including narrative, systematic, state-of-the-art, and critical literature review. However, these studies are scattered and need to provide a comprehensive understanding of CPPS from a generic perspective. The existing literature does not provide a holistic understanding of the multidisciplinary concepts of CPPS, resembling the parable of 'The Blind Men and an Elephant'. A generic CPPS framework for smart manufacturing analytics and management, impact & effort requirements for CPPS adoption, and a concept map specifically for CPPS is missing in the literature.

Most of the conventional manufacturing equipment are yet to be Industry 4.0 compliant and lacks intelligent functionalities. At present, it is economically impossible from Indian MSMEs' perspective that these equipment will be replaced with the Industry 4.0 compliant equipment before the end of life of these equipment. The enhancement of the smart functionalities of the traditional manufacturing equipment by using inexpensive sensors, actuators, and open-source software is a viable solution to achieve the Industry 4.0 benefits of increased productivity, reliability, and product quality for the Indian MSMEs.

1.3 RESEARCH MOTIVATION

The French novelist, Marcel Proust, famously stated that "The real voyage of discovery consists not in seeking new landscapes, but in having new eyes". This statement remains relevant today, particularly in the context of cyber physical production systems, which offer enhanced visibility to anticipate future events and enable timely decision-making.

In one of studies, Monostori *et al.* (2016) reviewed the potential of cyber physical systems in manufacturing, including their economic potentials. The review concluded that the digitization of the manufacturing industry will have significant economic and organizational effects, with intelligent and connected products bringing about significant changes in value creation and the competitive landscape. These innovations have the potential to significantly boost productivity, and enhance the functionality and performance of products. Furthermore, according to a report published by McKinsey Global Institute, CPPS is projected to yield substantial cost savings of 900 billion to 2.3 trillion USD by 2025, based on the assumption that nearly every manufacturing facility (80 – 100%) will be digitalized by that time (Manyika *et al.*, 2015).

The Indian manufacturing sector is transforming due to Industry 4.0. It has shifted from a production-centric to a customer-centric approach to meet the demand for affordable and customized products. This development increases the need for flexible and responsive manufacturing. Industry 4.0 is significant for India because it has the potential to increase the manufacturing sector's competitiveness, flexibility, and responsiveness to customer demands (Parhi *et al.*, 2022). By 2025, more than two-thirds of Indian manufacturers are expected to embrace digital transformation, which is crucial in achieving India's manufacturing GDP target of 25% (NASSCOM, 2022).

The Indian government has recognized the significant potential of cyber-physical systems in various sectors such as services, manufacturing, agriculture, water management, energy management, traffic management, healthcare, environment, infrastructure, geo-information systems, security, financial systems, and crime prevention. This has resulted in the establishment of a national mission on interdisciplinary cyber-physical systems (NM-ICPS) aimed at ensuring future security through the development of basic research and infrastructure, manpower, and skills. Furthermore, the "smart and advanced manufacturing rapid transformation hub (SAMARTH)" project by Government of India has been initiated to promote Industry 4.0 technologies by 2025, specifically in the manufacturing sector (Parhi *et al.*, 2022).

Despite these efforts, Indian industries still face numerous challenges in leveraging the full potential of Industry 4.0. Employees lack the necessary skills (analytical, data security, data management, *etc.*) to implement Industry 4.0 technologies, resulting in a significant skills gap. Small and medium-sized enterprises are hesitant to implement Industry 4.0 due to the lack of funds, the unpredictability of the investment, and the impact on their bottom line (Singhal, 2021).

The current work is motivated by the need to address these challenges faced by Indian manufacturing industries. This research demonstrates that CPPSs can be developed using low-cost technologies like low-cost sensors, devices, open-source software to harness the potentials of Industry 4.0 and enable competency development to bridge skill gaps by facilitating teaching, training, and experiential learning on a didactic platform.

1.4 OBJECTIVES OF THE STUDY

The objectives of this study are as follows:

- Development of a generic CPPS framework for smart manufacturing analytics and management considering possible elements and sub-elements.
- Development of a CPPS framework for smart 3D printing analytics and management based on data-driven analytics techniques and integrated computing technologies.
- Development of a CPPS framework for smart tool health analytics and management for a CNC milling center.
- Development of a CPPS framework for a learning factory to facilitate teaching, training, and experiential learning.

1.5 RESEARCH METHODOLOGY

The research methodology adopted in this study to achieve the above-mentioned objectives is shown in figure 1.3.

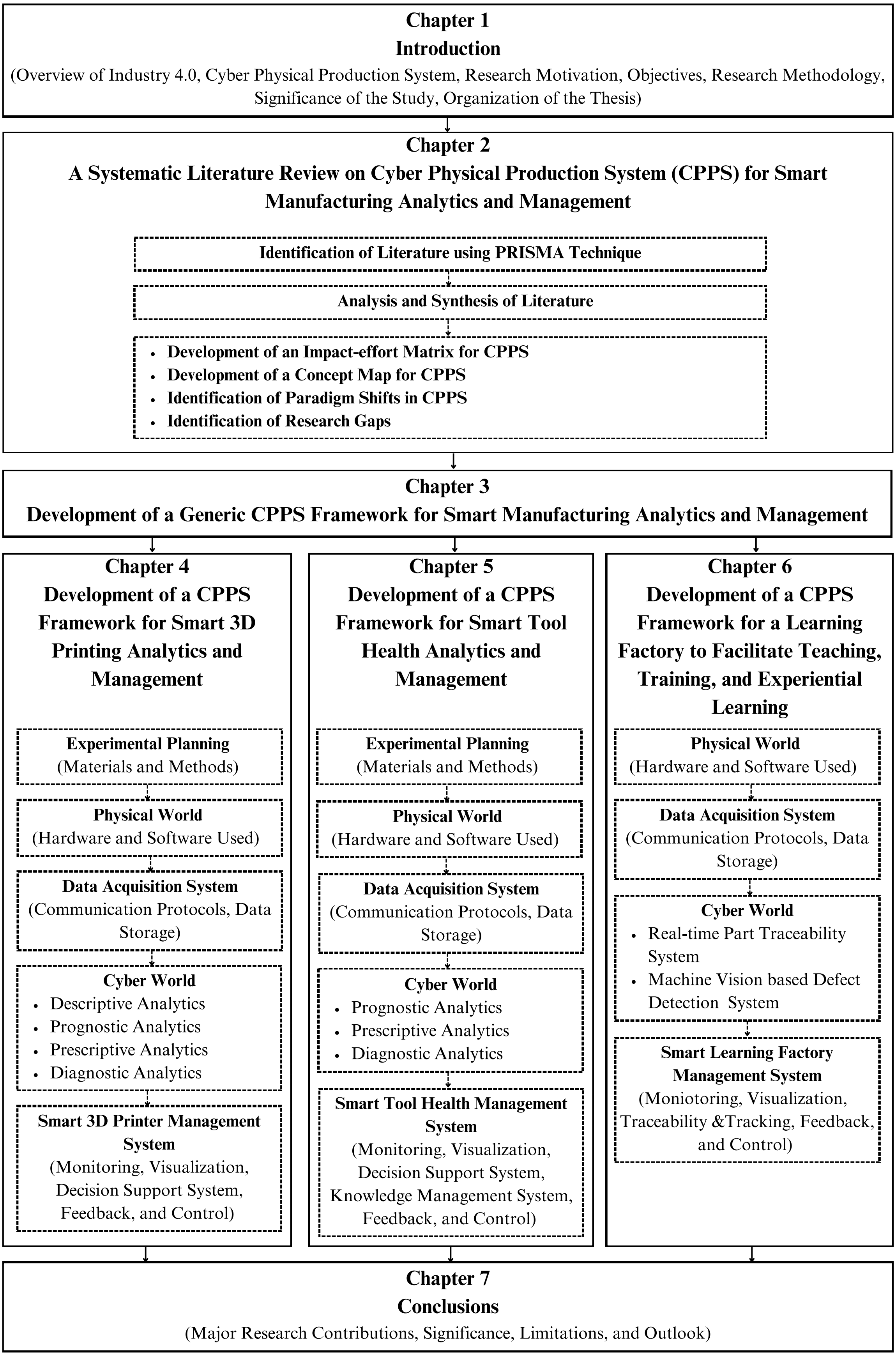


Figure 1.3 Research methodology to achieve the thesis objectives

1.6 SIGNIFICANCE OF THE STUDY

The present work adds value to the body of knowledge of cyber physical production system through systematic literature review that would serve as a reference in providing researchers and practitioners with valuable insights, knowledge updates, and decision support in selecting CPPS elements and sub-elements according to their impacts and required efforts. It will assist in understanding the maturity status; guiding future developments by addressing the important needs; and advancing the knowledge and management capabilities.

The present work utilizes the potential of Industry 4.0 (CPPS and enabling technologies, such as advancements in innovative and cost-effective sensors, microcontrollers, networking, data storage, cloud, fog, edge computing, *etc.*) to facilitate smart functionalities in a conventional manufacturing system. As a result, this could be instrumental in enhancing the management capabilities of a conventional manufacturing system and achieving the Industry 4.0 benefits of increased productivity, reliability, and product quality at a reasonable price.

The significance of this research lies not only in its ability to predict variables, but also in its ability to prescribe optimal solutions using prescriptive analytics that enable recommendation of optimal process parameters.

This research also allows for the development of transversal competencies for workforce, industrial engineers, and engineering students, allowing them to effectively handle the complexity and future challenges of Industry 4.0.

1.7 ORGANIZATION OF THE THESIS

The thesis is organized in seven chapters. Chapter 1 presents an introduction of the thesis. Chapter 2 presents a systematic literature review of 164 articles focusing on cyber physical production system for smart manufacturing analytics and management. It discovers interrelationships among various meaningful information/concepts and provides an in-depth understanding of the multidisciplinary concepts of CPPS. Chapter 3 proposes a generic CPPS framework. Chapter 4 proposes a CPPS framework for smart 3D printing analytics and management, wherein a conventional 3D printer is transformed into a smart 3D printer by integrating cost-effective solutions (low-cost smart sensors, devices, actuators, and open-source software) to enable smart management capabilities of online monitoring, data acquisition, visualization, control, and analytics. Chapter 5 proposes a CPPS framework for smart tool health analytics and management. A CNC milling center is integrated with smart sensors and devices to enable smart management capabilities of online monitoring, data acquisition, visualization, control, and analytics. Chapter 6 proposes a CPPS framework for a learning factory, where an existing learning factory infrastructure is integrated with inexpensive RFID and MV systems. Chapter 7 presents summary of the main contributions, acknowledging limitations, discussing significance, and providing an outlook for future research.

CHAPTER 2

A SYSTEMATIC LITERATURE REVIEW ON CYBER PHYSICAL PRODUCTION SYSTEM

This chapter presents a systematic literature review on cyber physical production system. The study aims to provide an in-depth, clear, and concise understanding of multidisciplinary concepts of CPPS through proper classification and clustering of its knowledge and information, analyzing the engineering needs/requirements, discovering interrelationships among meaningful information/concepts, and visualizing the paradigm shifts.

2.1 INTRODUCTION

The importance of a literature review lies in presenting a logically argued case founded on a comprehensive understanding of the current state of knowledge about a topic of study (Machi & McEvoy, 2021). It is classified into eight types, namely; systematic, state-of-the-art, narrative, realistic, rapid, conceptual, expert, and critical (Sangwa & Sangwan, 2018). A systematic literature review employs narrative and subjective methods to synthesize the findings of selected studies after searching, identifying, evaluating, and abstracting data (Paré *et al.*, 2015). Table 2.1 summarizes the existing literature review papers in the context of CPPS. The analysis of existing reviews reveals that researchers have primarily focused on narrative and systematic reviews, with less emphasis on state-of-the-art and critical literature reviews. During the initial phase of CPPS's development, from the year 2010 – 2015, only narrative reviews were conducted. Since 2016, most researchers have conducted systematic reviews, followed by narrative reviews.

Table 2.1 Summary of the existing literature review on CPPS

Author	**Sub-type**	**Scientific contribution**
Monostori L. (2014)	Narrative	The origin of CPPS; the interaction (parallel development and mutual influence) between CS, ICT, and manufacturing; and CPPS's expectations & challenges were discussed.
Schmidt *et al.* (2015)	Narrative	The integration approach and its types in CPPS were investigated and categorized according to the degree of integration.
Wang *et al.* (2015)	Narrative	The status, recent developments, definitions, characteristics, drivers, barriers and initiatives, applications, and prospects of CPPS were reviewed.
Monostori *et al.* (2016)	Narrative	In addition to the earlier work of Monostori L. (2014), case studies of CPPS were presented, the economic potentials of CPPS were highlighted, and a three-step model was presented to assist companies in developing their own Industry 4.0 vision and roadmap.
Hehenberger *et al.* (2016)	Narrative	The transition from mechatronics to CPS and cloud based (IoT) systems is described; CPPS is explained using case studies; and design, modelling, simulation, and integration were discussed.
Trappey *et al.* (2016)	Systematic	The patent portfolios and international standards pertaining to the 5C's CPS architecture proposed by Lee *et al.* (2015) were reviewed.
Jiang *et al.* (2018)	Narrative	The application of CPPS in monitoring, fault diagnosis, and control was reviewed, along with the practical requirements, challenges, and future research directions.
Moghaddam *et al.* (2018)	Critical	The characteristics of several reference architectures, including RAMI 4.0, IIRA, IBM Industry 4.0, and NIST Smart Manufacturing, were examined. Additionally, strategies that companies can use to modify their current architectural designs to comply with these characteristics were investigated.
Tilbury DM (2019)	Narrative	Architectures, digital twins and simulation, cyber security, and possible future research directions for CPPS, such as mass customization and energy-efficient manufacturing were discussed.
Vater *et al.* (2019)	Narrative	The main components of prescriptive analytics and its needs in smart manufacturing for shopfloor production control were reviewed.
Cardin O. (2019)	Narrative	A framework was proposed to analyse current developments and categorize the developments and applications of CPPS with the support of various illustrative examples.
Rojas *et al.* (2019)	Systematic	A systematic literature review was conducted to investigate recent developments in CPPS, with an emphasis on the importance of connectivity and control systems in manufacturing.
Rossit *et al.* (2019)	Narrative	The impacts of CPPS on scheduling in addressing fundamental issues and higher-level production planning tasks were reviewed.
Sinha *et al.* (2020)	Narrative	The architectures, anticipated features, challenges, and socio-economic impact of CPPS, and its required technologies and management skills, were reviewed and discussed.
Nota *et al.* (2020)	Systematic	Technologies such as CPPS, OEE analysis, and IoT were reviewed for improving energy efficiency. A method to quantify energy losses during batch processes was also proposed.

Table 2.1 Summary of the existing literature review on CPPS (contd…)

Author	**Sub-type**	**Scientific contribution**
Liu *et al.* (2021)	Systematic	A framework for the digitalization and servitization of machine tools was proposed. Topics such as enabling technologies, methodologies, standards, architectures, applications, major research issues, challenges, and future research directions were also discussed.
Rojas *et al.* (2021)	Systematic	The literature review focused on the implementation of CPPS in SMEs with an emphasis on identifying the challenges and future research directions.
Andronie *et al.* (2021)	Systematic	The literature review on CPPS focused primarily on AI-based decision-making algorithms, IoT sensing networks, and deep learning-enhanced smart process management.
X. Wu *et al.,* (2020)	Systematic	The review was focused on the concept development and engineering development stages of CPPS. The findings of the literature review analysis were used to propose a concept map that outlined the themes of existing research.
Danelon *et al.* (2021)	State-of-the-art	A bibliometric analysis of literature focused on CPPS from 2008 to 2019 was conducted to highlight the research trends.
Andronie *et al.* (2021)	Systematic	The purpose of the review was to assess the capabilities of CPPS in achieving sustainable smart manufacturing through data- and service-driven product lifecycle management.
Suvarna *et al.* (2021)	Narrative	A comprehensive view of the CPPS's role in transforming three key and essential drivers, namely data-driven manufacturing, decentralized manufacturing, and integrated blockchains for data security, was presented.
Castillo *et al.* (2022)	Systematic	The review investigated the role of CPPS in enabling smart capabilities like anomaly detection and decision support in the context of FDM 3D printers.
Habib *et al.* (2022)	Narrative	CPS's role in smart manufacturing was reviewed, including technologies, architectures, applications, future scope, and implementation challenges.
Webert *et al.* (2022)	Narrative	The role of CPPS in smart manufacturing, including its features, technologies, architectures, applications, future scope, and implementation challenges, was reviewed.
Fernandes *et al.* (2022)	Systematic	The application of metaheuristic algorithms in CPPS context to address dynamic scheduling issues and achieve energy-efficient scheduling in shop floor operations was reviewed.

The widely used cyber physical system concept map (Berkeley, 2012) has been developed for larger audiences having several applications in sectors including communication, consumer, energy, infrastructure, health care, manufacturing, military, physical security, robotics, smart buildings, and transportation sectors. The concept map is not well suited for the manufacturing domain. A few researchers have attempted to develop a concept map/ontology for CPPS. The scope of the concept map by X. Wu *et al.* (2020) is narrow and limited as it is mainly focused towards CPPS's research topics. Similarly, Wang *et al.* (2016) proposed a concept map consisting of holons, agents and function blocks for CPPS implementation in a decentralized/cloud environment. Trappey *et al.* (2016) presented an ontology based on the 5C's (connection, conversion, cyber, cognition, configuration) of CPS architecture proposed by Lee *et al.* (2015).

Impact effort analysis of CPPS's elements can be highly useful for researchers or practitioners in decision making, *e.g.*, selecting CPPS elements as per the impacts and efforts needed, *e.g.*, skill, machine, time & money. This can also be useful in virtual commissioning or evaluating the elements of CPPS before the actual set-up. However, to the best of author's knowledge, there is no literature in the context of CPPS impact-effort matrix to help the practitioner.

Content analysis helps to gain useful insights and enhances the understanding of a research domain through a broader and more condensed description of a phenomenon (Moldavska *et al.,* 2017). There has been hardly any attempt to classify data, autonomy, analytics, modelling techniques, enabling technologies, significance of implementing CPPS, and applications considering all three hierarchy levels.

Although researchers have outlined several challenges in their studies, there is hardly any literature where these challenges have been identified at element/component levels of the CPPS framework.

Similarly, researchers have outlined several future research directions in their studies. However, a paradigm for CPPS showing its maturity levels over the past, at present and in future is still missing in the literature.

Scientometric analysis is a powerful tool to explore the scope and trend of any research domain and the first step for extracting and validating the most relevant data from a large database (Castillo *et al.*, 2022). In the context of CPPS, scientometric analysis in terms of research type classification and sustainability development goals are missing in the literature. The present study aims to bridge the identified research gaps. This is achieved through the following objectives:

- To conduct an up-to-date systematic literature review from a holistic perspective of CPPS, considering all three hierarchy levels; namely unit, system, and system of systems
- To conduct scientometric analysis in terms of research methodology classification, timeline distribution, geographical distribution, source analysis, SDGs analysis, keyword co-occurrence analysis, co-authorship among countries, and author and co-citation analysis
- To perform descriptive analytics for classifying data types, autonomy, analytics, modelling techniques, enabling technologies, significance analysis, and applications considering the three hierarchy levels of CPPS
- To identify challenges at each element/component of the CPPS framework
- To analyze the engineering needs/requirements at the unit, system, and system of systems levels.
- To develop impacts-efforts matrix of CPPS elements based on the interpretation of the review analysis results that would provide decision support for the realization of a CPPS in their use cases
- To propose a paradigm for CPPS showing its maturity levels over the past, at present, and outline future research directions
- To develop a concept map for CPPS that is well-suited for a researcher or practitioner working in the manufacturing domain

2.2 RESEARCH METHODOLOGY

Figure 2.1 shows the research methodology for conducting the systematic literature review. This consists of four main steps, namely research planning, development of a database for literature review using the PRISMA technique, data analysis and synthesis, and outcome of scientometric and content analyses.

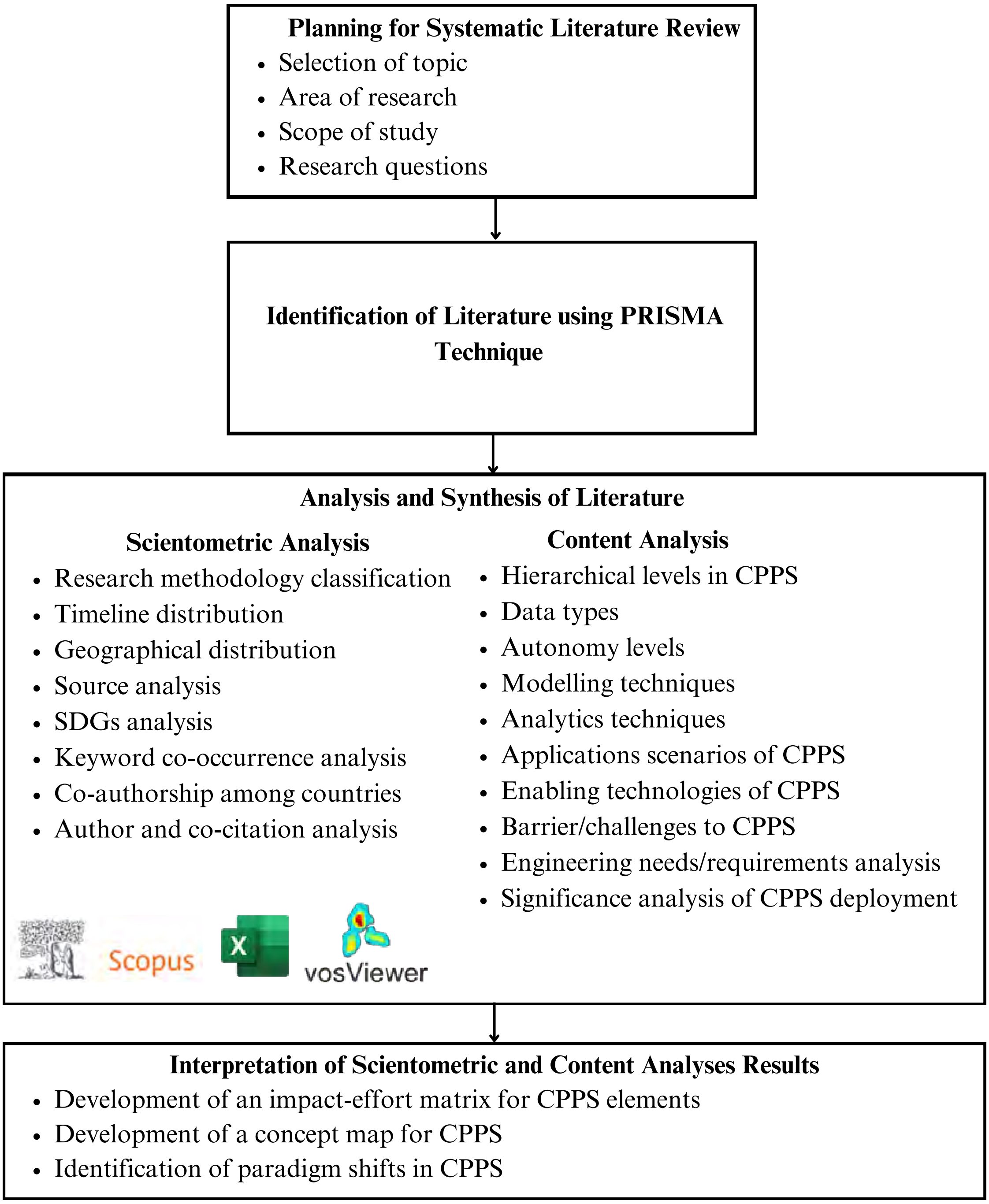


Figure 2.1 Research methodology for the systematic literature review

2.2.1 Planning for Systematic Literature Review

The research planning step consists of selecting the topic, defining the area of research, the scope of the study, and framing research questions. The area of research for the systematic literature review is cyber physical production system for smart manufacturing analytics and management. The scope of the work is limited to cyber physical production systems application in the manufacturing domain. Research questions framed to be investigated in the literature to address the objectives of the present study are as follows:

- What is the current status, trends, and research focus on CPPS?
- What are the potentials, characteristics (*e.g.,* data types, autonomy, analytics, modelling techniques, *etc.*), architectures, frameworks, enabling technologies, and application areas for CPPS implementation?
- What are the major sustainability development goals that can be achieved through CPPS implementation?
- What engineering requirements can be fulfilled by implementing CPPS in a smart manufacturing management system?
- How are the elements of CPPS correlated with the engineering needs/requirements from hierarchy levels and external stakeholders' perspectives?
- What are the major challenges and future research directions in the context of CPPS?
- How are hierarchical levels, autonomy, analytics, modelling techniques, enabling technologies, and applications classified in a CPPS?
- What impact do the elements of CPPS have, and what effort is required for their implementation?
- How to develop a concept map for a better understanding of the interrelationships among different elements and information in a CPPS?

2.2.2 Identification of Literature using PRISMA Technique

Database for literature review is developed using the preferred reporting items for systematic reviews and meta-analyses (PRISMA) technique. It is an evidence-based minimum set of items for reporting in systematic reviews and meta-analyses. It is widely used by researchers to improve the reporting of systematic reviews and meta-analyses (Moher *et al.*, 2009). Figure 2.2 shows the four phases of the PRISMA flow diagram used for developing the database.

In the identification phase, records are identified from databases. In the present study, two databases, namely Scopus and Web of Science, were used to search for literature using the search term "Cyber Physical Production System" in article title, abstract, and keywords. The selected range is up to December 31, 2022, and only English-language articles were considered. The source type included journals, conference proceedings, book chapters, journal editorials, *etc.* The second phase is screening, where duplicates are removed. In the first stage of exclusion, articles were excluded that are out of scope and provided insufficient details. In the second stage of exclusion, articles were excluded based on the thorough examination of the whole paper. The fourth phase involves the inclusion of additional records identified through the snowballing method along with the selected articles after the exclusion phase.

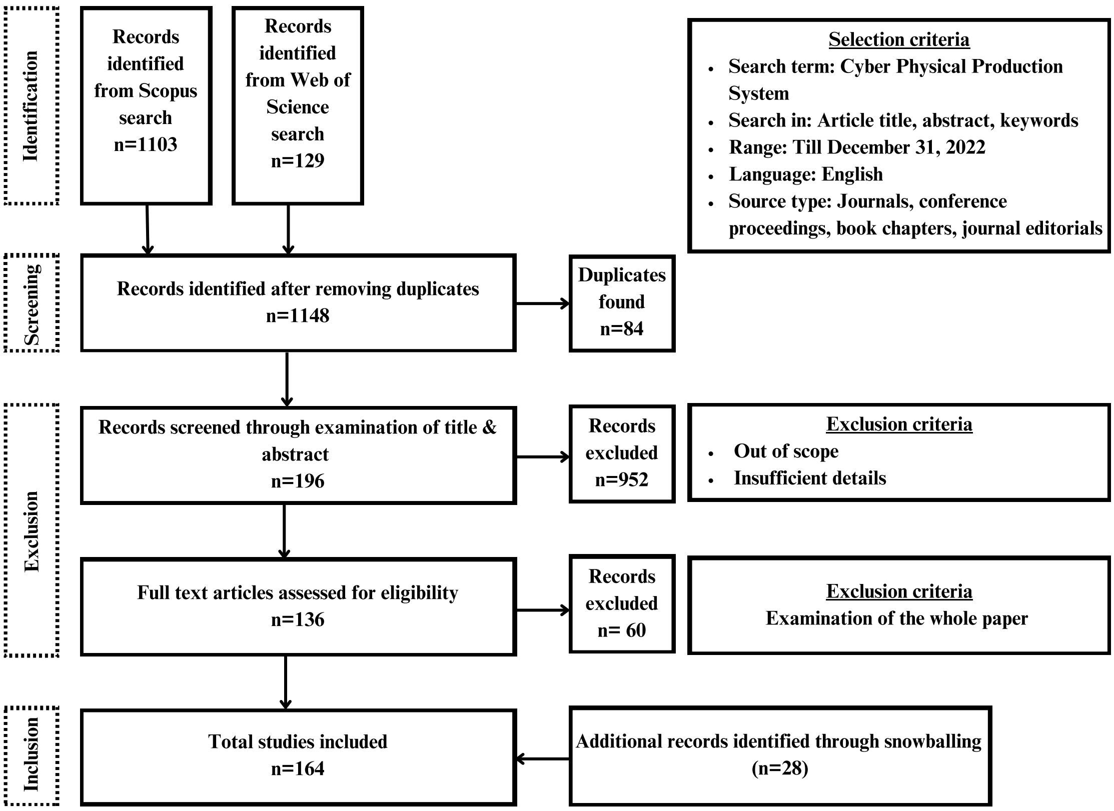


Figure 2.2 Literature review using the PRISMA technique

2.2.3 Analysis and Synthesis of Literature

Data analysis and synthesis for the systematic literature review were conducted using scientometric and content analyses of quantitative and qualitative data, respectively.

Scientometric analysis is a powerful tool to explore the scope and trend of any research domain and the first step to extract and validate the most relevant data from a large database (Castillo *et al.*, 2022). In the present work, scientometric analysis was conducted to get an overview of the latest trends by analyzing various perspectives, namely research methodology classification, timeline distribution, geographical distribution, source analysis, SDGs analysis, keyword co-occurrence analysis, co-authorship among countries, and author and co-citation analysis.

Content analysis helps to gain useful insights and enhances the understanding of a research domain through a broader and more condensed description of a phenomenon (Moldavska & Welo, 2017). In the present work, literature contents were analyzed for classifying/grouping various concepts of CPPS such as hierarchical levels, data types, autonomy, analytics, modelling techniques, and enabling technologies; and analyzing applications areas, barriers/challenges, engineering needs/requirements, and significance.

2.2.4 Interpretation of Scientometric and Content Analyses Results

Interpretations of data analysis and synthesis results help to understand concepts in a clear and concise perspective; discover interrelationships among meaningful information/concepts; and visualize the paradigm shift of a research domain. In the present work, results obtained through data analysis and synthesis were interpreted to propose a concept map, analyze the impact-efforts for the CPPS's elements, provide a paradigm diagram to visualize the shift in research directions, and identify research gaps.

2.3 SCIENTOMETRIC ANALYSIS

This section discusses the results obtained using scientometric analysis, namely research methodology classification, timeline distribution, geographical distribution, source analysis, SDGs analysis, keyword co-occurrence analysis, co-authorship among countries, and author and co-citation analysis.

2.3.1 Research Methodology Classification

The research methodology adopted for the selected articles is broadly classified into seven types, namely conceptual, descriptive, pragmatic, empirical, editorial, report, and literature review. Research methodology is classified as pragmatic, when it deals with practical problems (Okpoti & Jeong, 2021). It is further classified into real, simulation, prototypical, and exemplary based on the production environment. According to Machi *et al.* (2021). "a literature review is a written document that presents a logically argued case founded on a comprehensive understanding of the current state of knowledge about a topic of study". It is further classified into eight types, namely systematic, state of the art, narrative, realistic, rapid, conceptual, expert, and critical (Sangwa & Sangwan, 2018). A brief description of each type and sub-type of research methodology is shown in Table 2.2.

Table 2.2 Research methodologies used in CPPS literature

Type	Subtype/environment	Feature/ focus
Conceptual		Describes fundamental concepts of CPPS.
Descriptive		Describes fundamental concepts of CPPS and proposes a framework/architecture.
Pragmatic	Real	Real-world manufacturing problem is solved along with conceptual/descriptive study
	Simulation	The simulation environment is used to develop a manufacturing problem.
	Prototypical	The manufacturing problem is solved using prototypical implementation along with a conceptual/descriptive study.
	Exemplary	Illustrative or exemplary data are used to describe or solve manufacturing problems along with conceptual/ descriptive study.
Empirical		Data for the study has been taken from existing databases, reviews, case studies, taxonomy, or typological approaches.
Editorial		An opinion or viewpoint expressed by a member of the editorial board or any senior researcher or expert in a journal.

Table 2.2 Research methodologies used in CPPS literature (contd…)

Type	**Subtype/environment**	**Feature/ focus**
Report		An informative document produced by a company or non-profit organisation to highlight features of a solution, product, or service.
Literature review	Systematic	Provides meta-analysis and synthesis of the selected literature.
	State-of-the-art	Concentrates primarily on current research on the selected topic.
	Narrative	Summarizes the information about the methods and results.
	Realistic	Used to synthesize individual studies and produce a generalized theory.
	Rapid	Systematic assessment of the existing findings on the selected topic.
	Conceptual	Provides a theoretical literature review of existing theories and interrelationships among them.
	Expert	Review done by experts of the subject or field.
	Critical	Provides a higher degree of analysis and synthesis of the selected topic.

Figure 2.3 shows the article published in each type of methodology. Figure 2.3 indicates that most of the researchers have used pragmatic, conceptual, and descriptive methodologies.

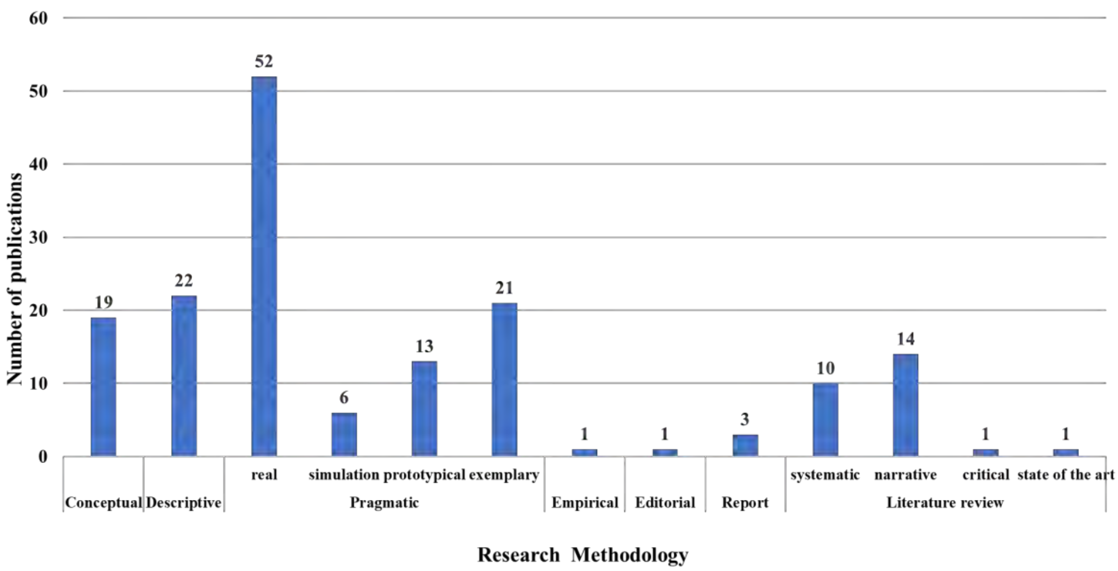


Figure 2.3 Publication distribution versus research methodologies

The reason for the large number of pragmatic studies may be that the many authors have used case studies in real situation to demonstrate the CPPS adoption for enhancing potentials and functionalities (*e.g.,* online monitoring, prediction, visualization, simulation, optimization, automation, *etc.*) of traditional manufacturing systems in an Industry 4.0 environment.

2.3.2 Timeline Distribution

Figure 2.4 shows the distribution of the literature along the timeline from the year 2010 to 2022 in chronological order. The first article was published by Rajkumar *et al.* (2010), where the importance of CPS for enhancing interaction and controlling the physical world in the manufacturing domain was provided along with other domains such as transportation, healthcare, agriculture, energy, defense, aerospace, and buildings. More than one-third of articles were published in the last two years, showing the importance of the topic. There was a sudden drop in articles in the year 2020. This decline can be attributed to the COVID-19 pandemic.

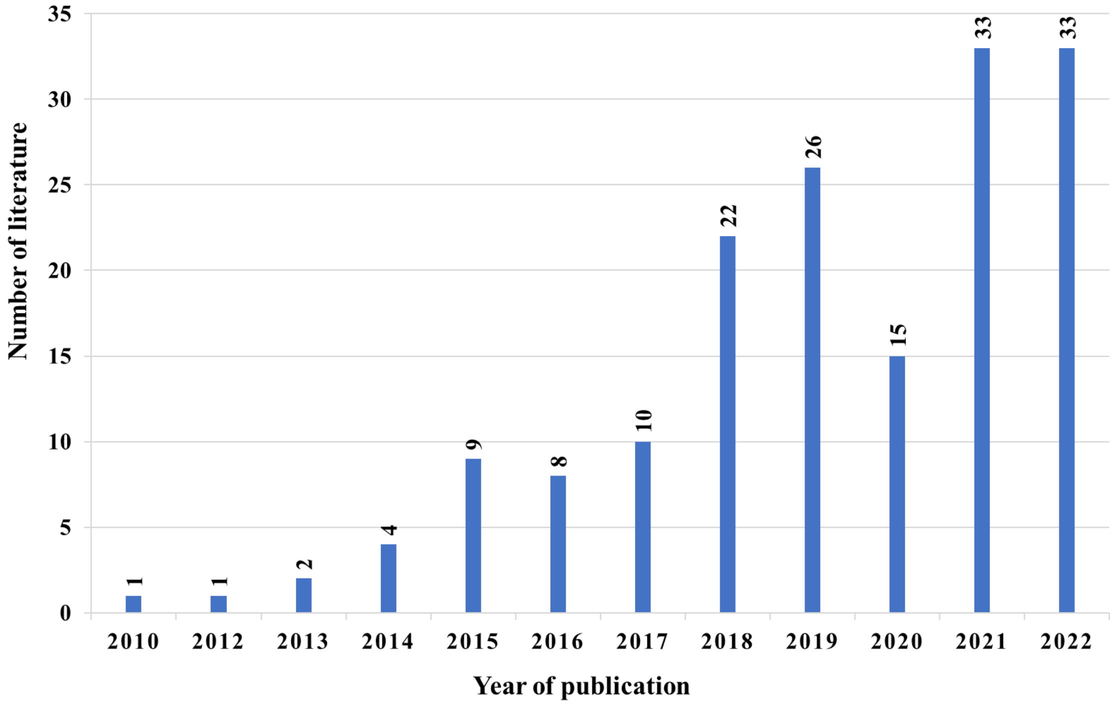


Figure 2.4 Timeline distribution

2.3.3 Geographical Distribution of Literature

Figure 2.5 shows the geographical distribution of literature as per its source. It can be observed that Germany is the leading country, followed by China and the United States, which are equally placed. France, Italy, Austria, and India are placed at fourth, fifth, sixth, and seventh positions, respectively. The geographical distribution of literature on the world map is graphically visualized in Figure 2.6, which shows that most of the research on CPPS is conducted in Europe.

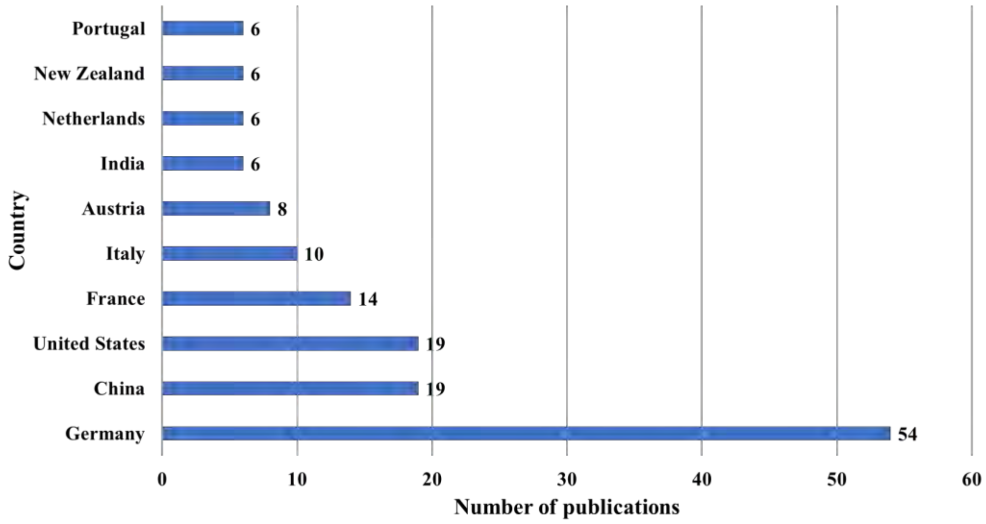


Figure 2.5 Geographical distribution of literature

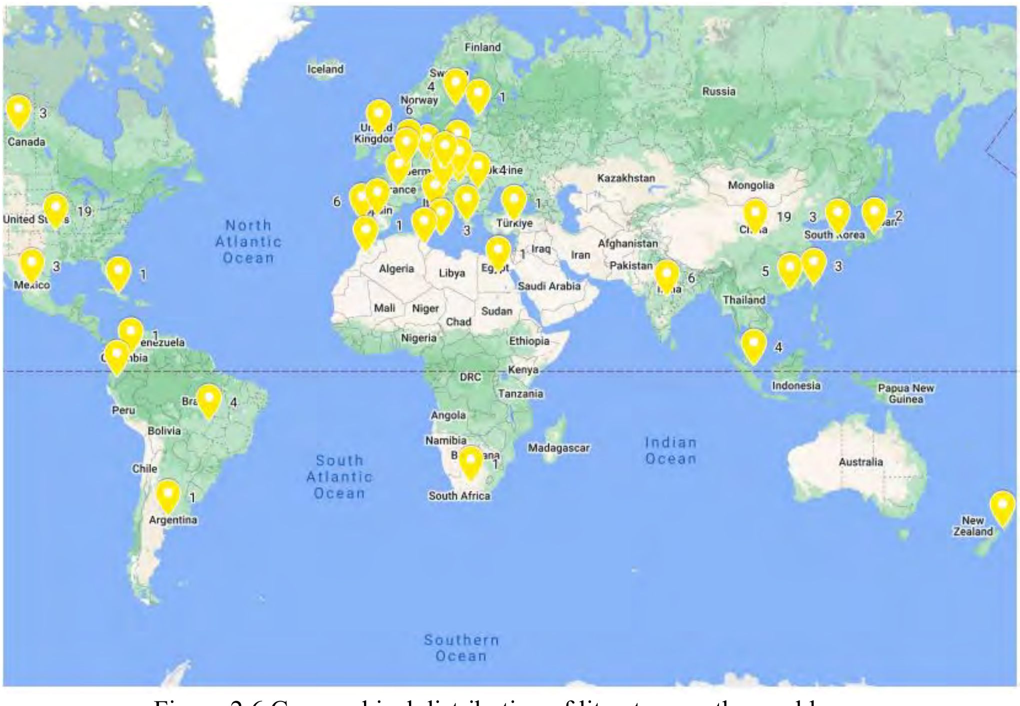


Figure 2.6 Geographical distribution of literature on the world map

2.3.4 Source Analysis

Figure 2.7 shows the source analysis of articles according to their type. It can be observed that most of the articles are from the journal (around 62%), followed by conferences (around 35%). Reports and book chapters contribute only a few of the total articles.

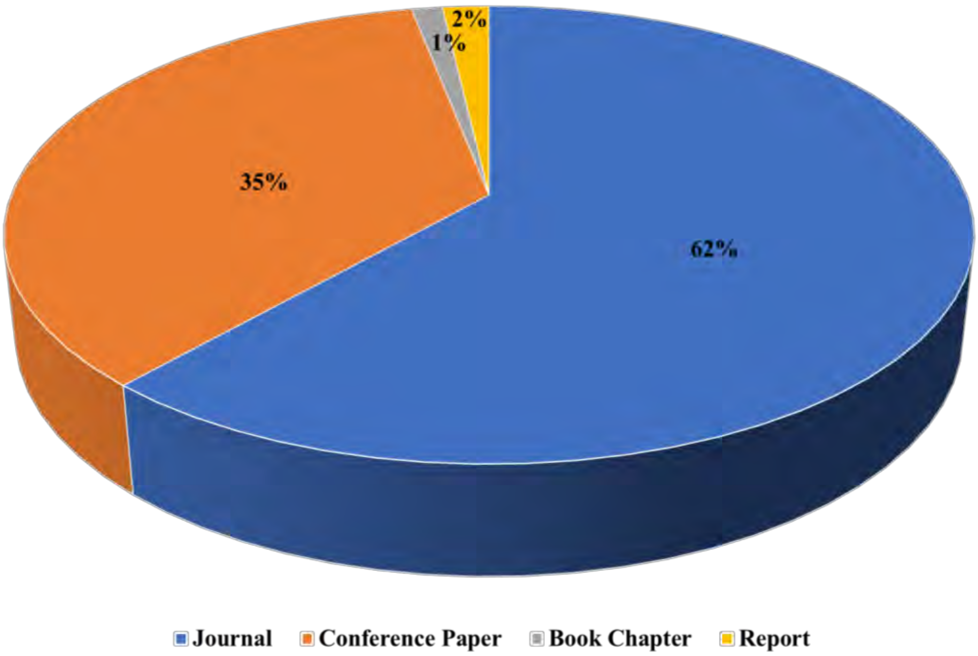


Figure 2.7 Source analysis (source type)

Figure 2.8 shows the source analysis of articles according to subject discipline. It can be observed that CPPS involves a multidisciplinary approach. Most of the articles are distributed over engineering and computer science disciplines. Other disciplines such as energy, mathematics, environmental science, business, management & accounting, material science, decision and social sciences also contribute. This supports the statement of Monostori *et al.* (2014) about CPPS – “a convergence of the physical and cyber worlds through the parallel development of computer science, information and communication technologies and manufacturing automation has been observed over the years”.

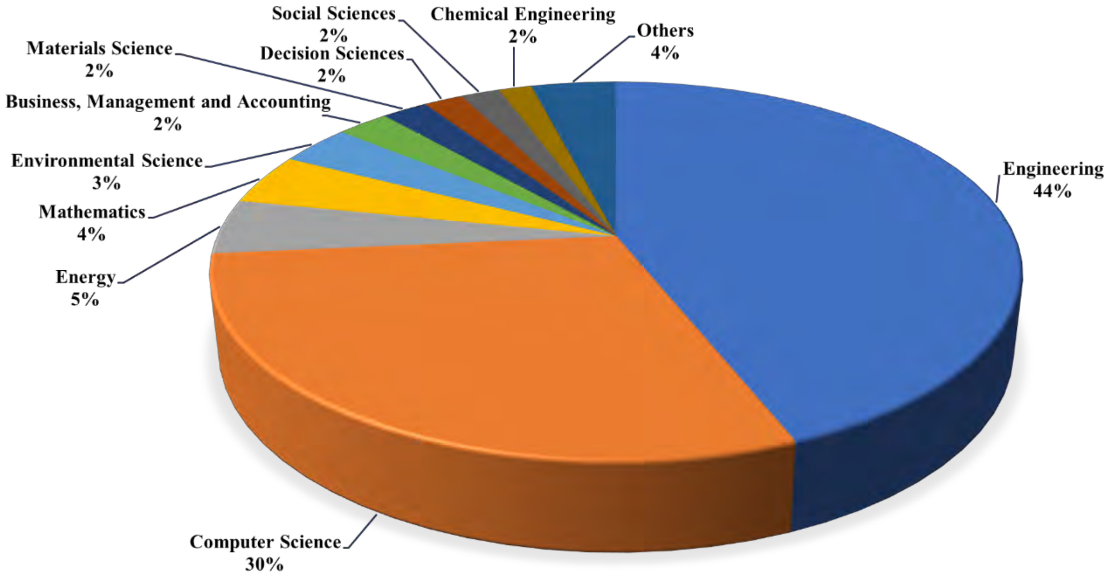


Figure 2.8 Source analysis (subject discipline)

Figure 2.9 shows the source analysis of articles according to source title. It can be observed that Procedia CIRP has the highest number of articles, followed by IEEE proceedings, Journal of Manufacturing Systems, Computers in Industry, International Journal of Advanced Manufacturing Technology, International Journal of Computer Integrated Manufacturing, *etc.*

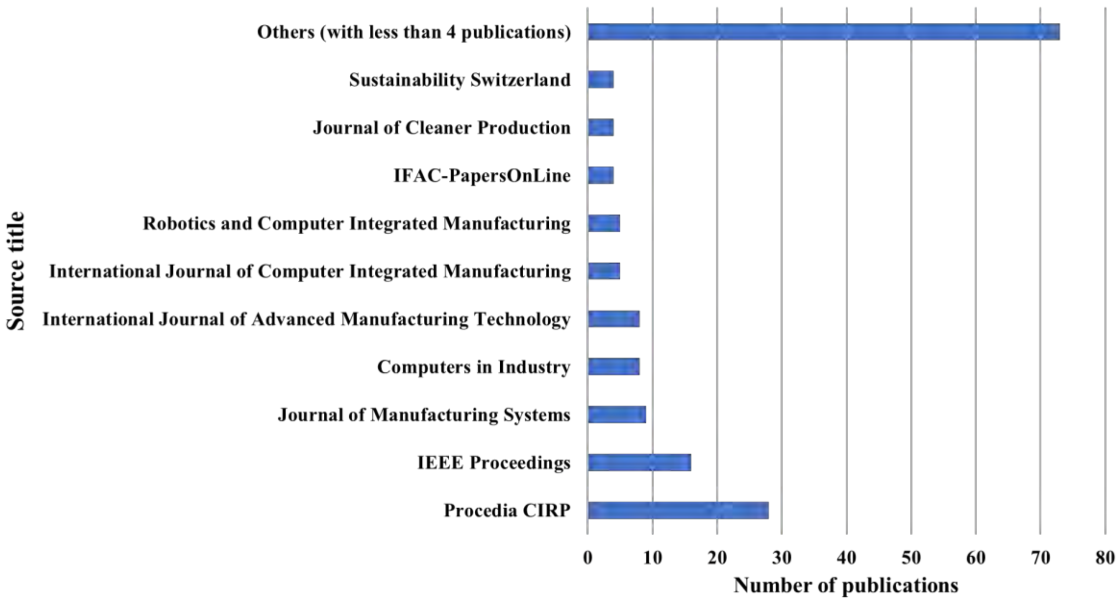


Figure 2.9 Source analysis (source title)

2.3.5 Sustainability Development Goals (SDGs) Analysis

The data for mapping SDGs with the articles is extracted from the Scopus database. According to the information provided on the Scopus website "Sustainable Development Goals (SDGs) are specific research areas that are helping to solve real-world problems. Elsevier data science teams have built extensive keyword queries, supplemented with machine learning, to map documents to SDGs with very high precision. Times Higher Education (THE) also uses the Elsevier SDG data mapping as part of their Impact Rankings" (Scopus, 2023).

Figure 2.10 shows the SDGs mapping for the published articles. It can be observed that more than two third of the articles are mapped to SDG 9 that aims to foster Industry, innovation, and infrastructure. SDGs 7 & 8 aim for affordable & clean energy, decent work & economic growth have been provided equal coverage (around 8%). The published articles are also mapped with SDGs 13, 17, 8, 6 & 11 in the order of their percentage coverage.

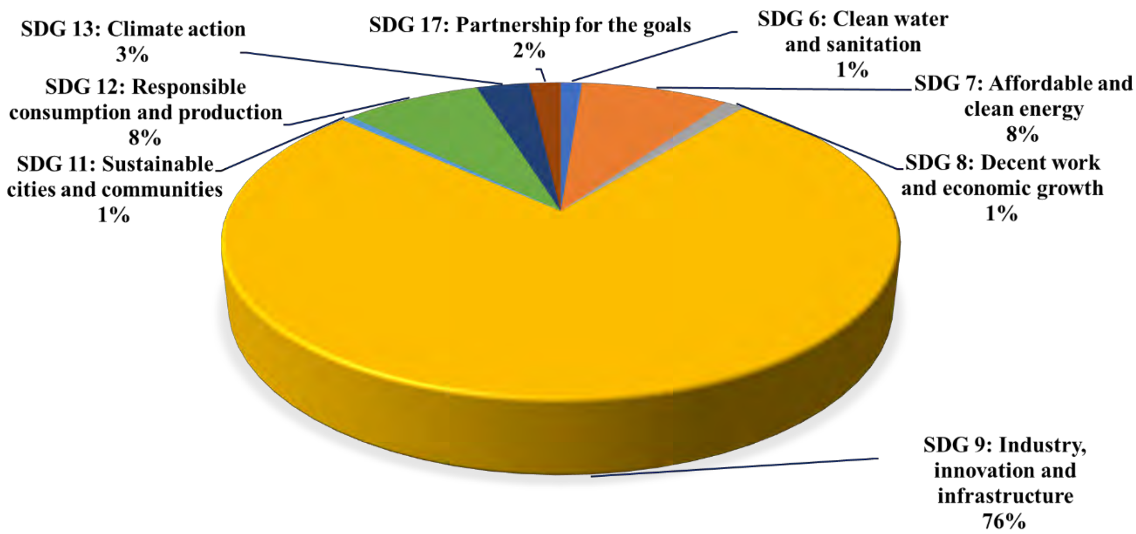


Figure 2.10 Sustainability development goals (SDGs) mapping for the published articles

2.3.6 Keyword Co-occurrence Analysis

The keywords provided for an article are useful in measuring the research topic and determining the interrelationship of these topics (Castillo *et al.*, 2022). A keyword co-occurrence analysis was conducted to examine research trends and focus of the reviewed topic of "cyber physical production systems". This was performed using VOSviewer, a commonly used software tool for constructing and visualizing bibliometric networks by extracting significant terms from scientific literature (VOSviewer, 2023). A bibliometric file containing author and indexed keywords generated from the Scopus database is used as a source file for the VOSviewer software. The threshold limit was set at five, indicating that the same word must have appeared in at least five articles for a visual link to be generated. The threshold was set to improve the visibility/readability of the generated network diagram.

Figures 2.11 illustrate the overlay network visualization for keywords co-occurrence. The size of the circle represents the number of occurrences of the keyword, while the lines or connections illustrate their relationship. The more the keyword co-occurrences, the closer and stronger the link.

The most frequently used keywords indicate the most studied research issue between the years 2010 to 2022. The decreasing order of keywords with respect to frequency of occurrence is CPPS, embedded system, Industry 4.0, internet of things, production control, decision making, life cycle, artificial intelligence, maintenance, *etc.* The change of colour from blue to yellow represents a change in the average publication year of the keywords between the years 2010 to 2022. The yellow colour of nodes indicates the recent trends of the researcher's interest and are gaining on topics such as CPPS, energy efficiency, machine learning, industrial internet of things, big data, *etc.*

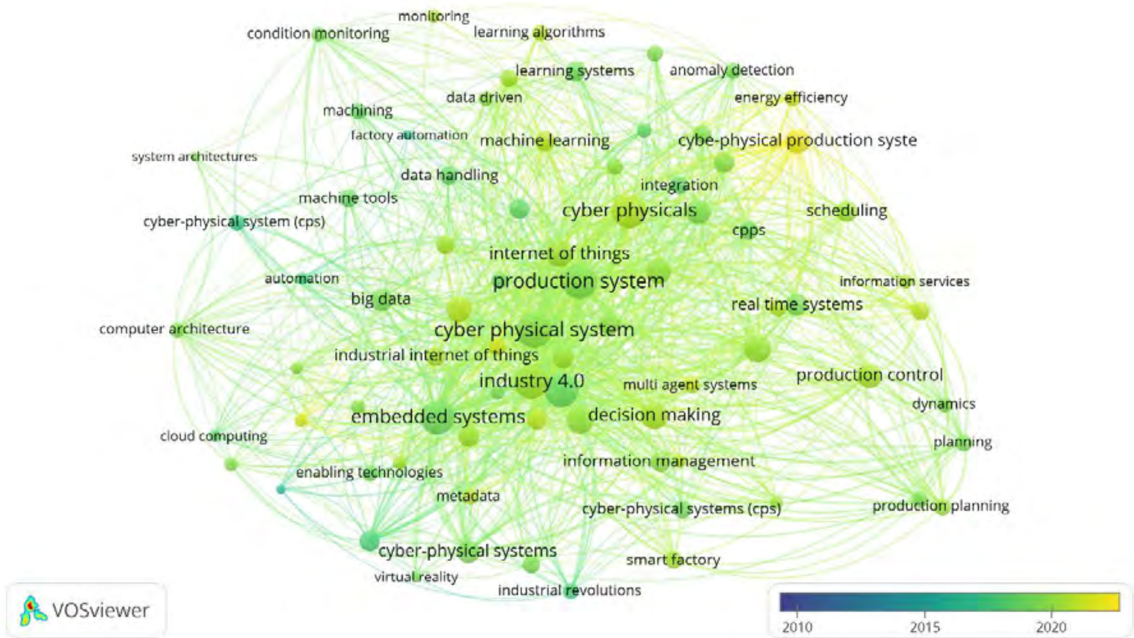


Figure 2.11 Overlay network visualization for keywords co-occurrence

Figure 2.12 shows the density network visualization for keywords co-occurrence wherein the yellow colour and larger font size indicate the strength of the keywords, while their proximity denotes their relatedness. Industry 4.0 has the strongest link strength and is closely related to cyber physical system, embedded systems, decision making, industrial internet of things, *etc.*

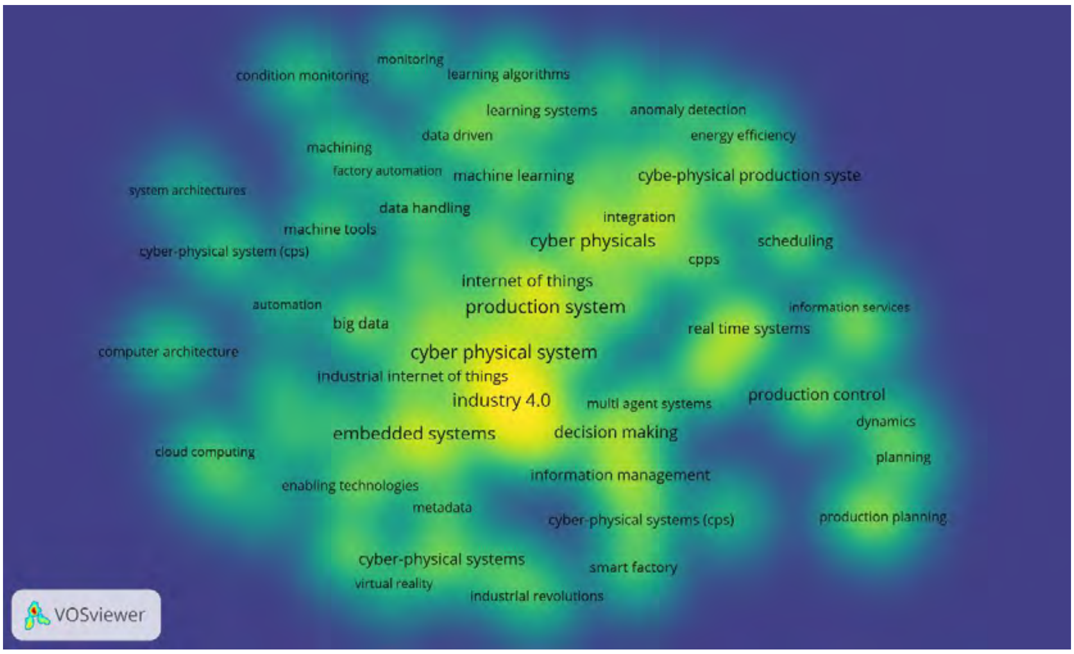


Figure 2.12 Density network visualization for keywords co-occurrence

2.3.7 Co-authorship Among Countries

Figure 2.13 shows the network visualization for co-authorship among eleven countries created using the VOSviewer software. The circle size corresponds to the number of publications in the country/region. The thickness of the links indicates the frequency of co-authorship between the two countries. The threshold was set at a minimum of two co-authorship articles between countries. It can be observed that Germany, followed by China, the United States, and France, has the most significant number of co-authorships. The strongest collaborations are between Germany and the United States; China and New Zealand; Germany and India; Germany and Italy, while France and China; Hungary and Austria; are also involved in collaborations on a lesser scale.

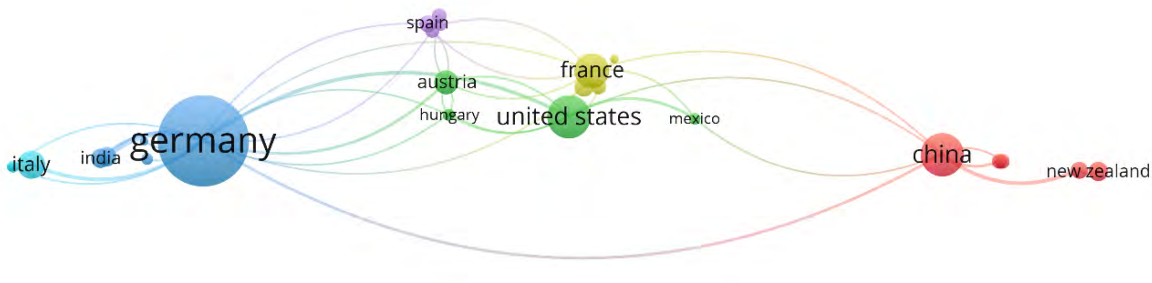


Figure 2.13 Network visualization for co-authorship among countries

2.3.8 Author and Co-citation Analysis

Author and co-citation analysis is a method used to identify influential authors in a particular research field. It also examines the connections between authors through their co-citations. Figure 2.14 shows the network visualization for authors and their co-citation. The circle's size indicates the frequency of co-citations among authors or papers, while the thickness of the lines indicates the degree of co-citation strength. The threshold was set at a minimum of twenty citations for an author in the VOSviewer software to improve the visibility/readability of the generated network diagram. The authors Monostori L., Wang L., Xu X., Lee J., and Tao F. have the highest number of co-citations with other authors, suggesting their significant contributions to the advancement of this research area.

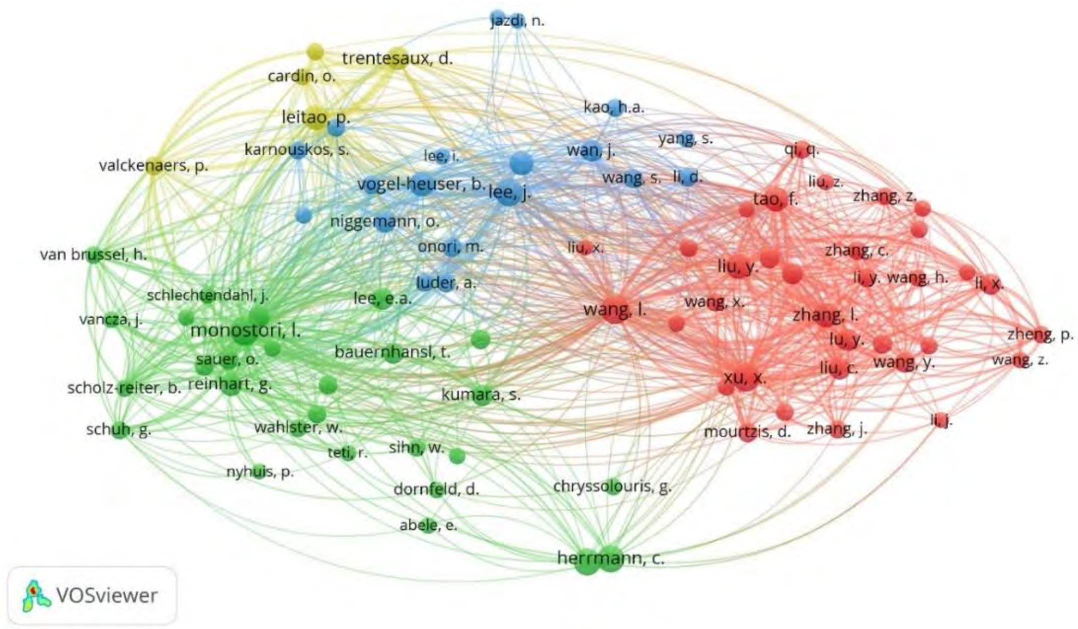


Figure 2.14 Network visualization for author and their co-citations

2.4 CONTENT ANALYSIS

This section discusses the results obtained by analysing the content of the literature. The information extracted from the literature is analyzed and organized for categorizing hierarchical levels, data types, autonomy levels, analytics types, modelling techniques, enabling technologies, and analyzing applications area, barriers/challenges, engineering needs/requirements, and significance of implementing CPPS.

2.4.1 Hierarchical Levels in CPPS

CPS can generally range in size from small-scale devices such as pacemakers to large-scale systems such as national power grids (Wang *et al.*, 2015). Therefore, it is essential to differentiate these ranges precisely and concisely. There are a few articles (Qi *et al.*, 2018; Tao *et al.*, 2019; Wang *et al.*, 2015; Nota *et al.*, 2020) where information regarding hierarchical levels is provided. The hierarchical levels of the CPPS can be classified into three broad categories: unit, system, and system of systems level. Figure 2.15 illustrates the categorization for these hierarchical levels, and Table 2.3 provides a concise distinction between these hierarchical levels, with descriptions and examples.

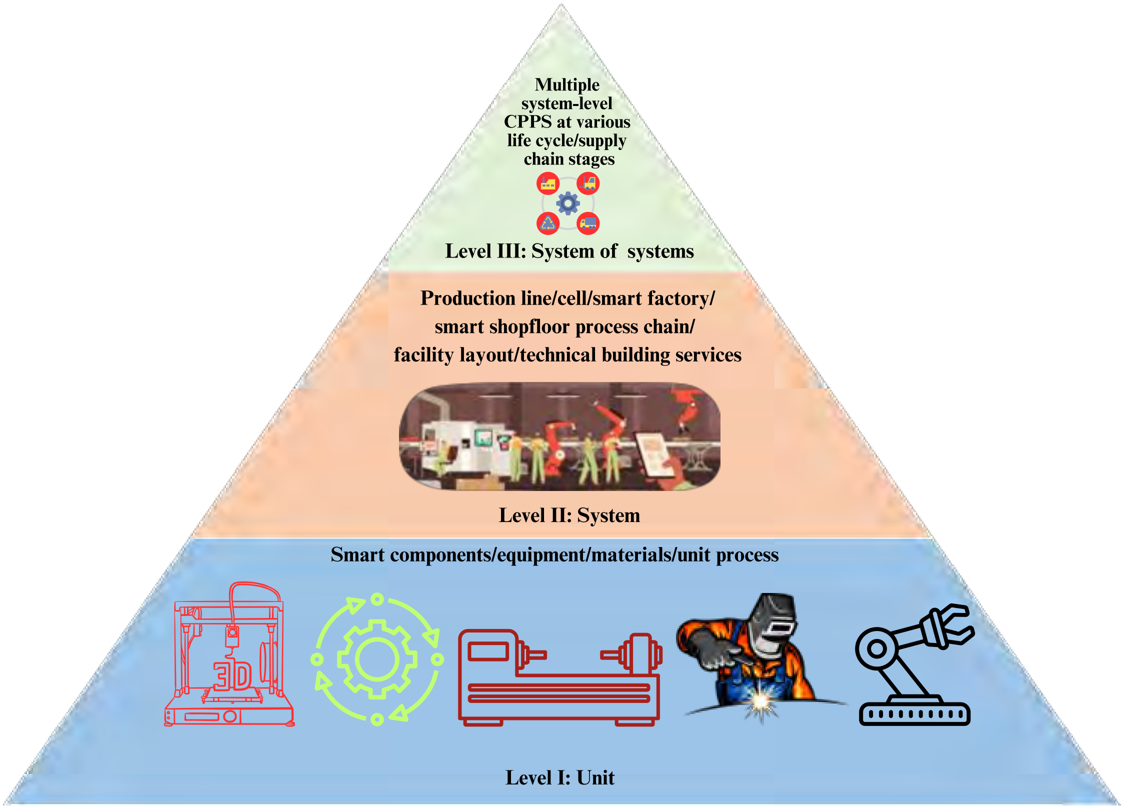


Figure 2.15 Hierarchical levels in CPPS

Table 2.3 Description of hierarchical levels in CPPS

Hierarchical level	**Description**	**Examples**
Level I: Unit	It is the lowest hierarchical level of CPPS. It includes smart components/equipment/ materials (Qi *et al.*, 2018)/individual devices performing a unit process (Nota *et al.*, 2020).	CNC machines, smart robots, material embedded with RFID; AGV embedded with sensors (Qi *et al.,* 2018); 3D printers; welding; casting, *etc.*
Level II: System	It is the intermediate hierarchical level of CPPS. It integrates multiple unit-level CPPSs that work in collaboration (Qi *et al.,* 2018). It includes production line/cell/smart factory/ smart shopfloor process chain/facility layout/ technical building services.	Shopfloor with more than one machine tool (CNC machines, smart robots, AGVs, and conveyor belts, *etc.*) & process chains; automotive production line; manufacturing assembly process, *etc.*
Level III: System of systems	It is the highest hierarchical level of CPPS. It integrates multiple system-level CPPSs at life cycle/industrial symbiosis/enterprises/supply chain stages and constitutes a smart service platform (Qi *et al.,* 2018). Coordination and collaboration between these systems and subsystems involve complex interactions (L. Wang *et al.,* 2015; Lin *et al.,* 2019).	Multiple production lines/multiple factories (Qi *et al.,* 2018); collaborative services between production, design, and service companies (Tao *et al.,* 2019); MSMEs; large-scale enterprises, *etc.*

2.4.2 Data Types

Data is often metaphorized as the oil of the 18th century due to its potential as an unexplored resource. If utilized systematically, it has the potential to facilitate data-driven applications that provide manufacturing companies with growing competitive advantages (Kusiak, 2022). The categorization of data types is a crucial process in unlocking the vast capabilities and potential of CPPS *via* their smart management systems. Only a few researchers (Beckers *et al.,* 2022; Rogall *et al.,* 2022) have attempted to classify the data generated in a CPPS. However, these are more specific to applications (*e.g.,* metal cutting/3D printing). Therefore, the contents of 164 articles have been analyzed to provide a holistic view of various data types into six broad categories. Table 2.4 lists a wide range of data type categories that are managed using CPPS.

Table 2.4 Classification of data that can be managed using CPPS

Sl. No.	Data types	Sub-types	Description	Examples
1	Metadata		It describes the higher-level fixed characteristics of a component/process/ machine/product.	Date & time, component ID, process name, geometry feature, tool used, cutting fluid, machine tool, process parameters, product properties like material type, hardness, *etc.*
2	State variables or process data		It describes the changing system behaviour within a process step.	Time series data of power, force, vibration, *etc.*
3	Process metadata		It provides specific descriptions of the origin of the process data.	Sampling rate/measuring range/voltage range of the sensor, *etc.*
4	Event data	Machine	It describes various conditions of the machine.	Idle, set up, operate, alarms, power on/off, *etc.*
		Product	It describes various statuses related to the product.	Finished product, inventories, delayed product, defective products, *etc.*
		Event time	It describes various events related to time.	Set up time, lead time, takt time, cycle time, waiting time, throughput time, assembly time, *etc.*

Table 2.4 Classification of data that can be managed using CPPS (Contd.)

Sl. No.	Data types	Sub-types	Description	Examples
5	Performance indicators	Technological	It describes data that can be utilized to evaluate technological performance.	Concentricity, surface roughness, RUL, MTBF, MTTR, *etc.*
		Environmental	It describes data that can be used to estimate environmental impacts.	Energy consumption (machine, auxiliary units), material inputs & outputs, waste & emissions, *etc.*
		Economic	It describes data that can be used to measure economic performance.	Cost, utilization level, OEE, average worker occupancy, manufacturing time, *etc.*
6	External influencing factors		It describes data regarding external factors that influence the performance of a CPPS.	Ambient temperature, humidity, atmospheric pressure, *etc.*

2.4.3 Autonomy Levels

The level of autonomy refers to CPPS's ability to develop and implement its own strategies and plans as well as response to identified tasks or problems (Ansari *et al.,* 2018). The classification of autonomy, which ranges from fully automatic to fully manual, is essential for understanding the level/degree of human interaction with CPPS (Cardin, 2019). The level of autonomy depends on how autonomous and self-reliant/independent a system element is in its interactions with other system elements (Schmidt *et al.*, 2015). There are only a few articles (Ansari *et al.*, 2018; Schmidt *et al.*, 2015; Thiede *et al.*, 2016; Cardin, 2019) where autonomy levels have been classified to determine the degree of human interaction with the CPPS. Based on literature, following are the levels of autonomy in a CPPS:

- Level 1 autonomy (Manual): CPPS only provides data and transparency of KPIs to a human who oversees all decisions and actions to be taken manually.

- Level II autonomy (Semi-automatic): CPPS acts as an active decision support tool and takes simple decisions itself and leaves complex decisions to human for execution.
- Level III autonomy (Fully automatic): CPPS controls the physical world automatically without any human intervention. The role of humans is limited to the supervision of the CPPS, *i.e.,* transparency regarding KPIs and control actions.

2.4.4 Modelling Techniques

Modelling techniques are essential for establishing correlations among processed data, which enables data analytics and optimization techniques to generate valuable insights in subsequent steps. It is used to understand/predict/optimize/simulate the behaviour of physical systems (Mendia *et al.*, 2022). Only a few researchers (Mendia *et al.*, 2022; Thiede *et al.*, 2016; Rai *et al.* 2020) have classified and described some of the modelling techniques. Therefore, based on the literature, following classification and description of modelling techniques with their relative advantages and limitations emerges:

- Physics-based models: They are used to model the dynamics of a system and consider various assumptions or simplifications to solve the complexities of a physical system (Rai *et al.*, 2020). The main advantages of physics-based modelling are reduced experimental efforts, time, material, and costs (Malakizadi *et al.*, 2020; J. Wang *et al.*, 2020). However, non-availability of in-depth prior knowledge of system behaviour and the inability to be updated with the dynamic changes in physical parameters result in lower accuracies, effectiveness, and flexibilities of these models (Wu, *et al.*, 2017a; P. Wang *et al.*, 2019; Zhao *et al.*, 2019).
- Empirical/mathematical models: These are mathematical equation-based models derived from statistics and data analysis rather than physical laws. They are based on experimental data and do not necessarily have a theoretical basis. Empirical models have the advantage of being simple and easy to use because they do not require a deep understanding of the underlying physical principles (Chakrabortty & Bose, 2017).

These models can also be useful for making predictions or optimizing processes when theoretical models are not available or are too complex to use (Yuan *et al.*, 2022). However, it may be challenging, time-consuming, and expensive to conduct multiple experiments (Denkena *et al.*, 2020). These models may not always be accurate or reliable, especially when applied outside the range of conditions for which they were developed (Yuan *et al.*, 2022).

- Data-driven models: They rely on machine learning techniques to learn from data patterns and predict future behaviour. The advantages include its capability to handle complex systems where it is challenging to develop the input-output relationship between input and output variables. They can adapt to changes in the system over time, making them more flexible than physics-based models that are based on fixed equations. These models are easier to implement than physics-based models because they don't require detailed knowledge of the system's physical dynamics (Rai *et al.*, 2020). However, these models do not incorporate domain knowledge of physical systems and are, therefore, unaware of the physical laws inherent to industrial processes, resulting in the identification of unconnected patterns (Mendia *et al.*, 2022).
- Hybrid models: They combine physics and data-driven models to utilize both prior scientific knowledge and data to improve performance (Rai *et al.*, 2020). Hybridization enables data-based insights and explanations of machine learning algorithms based on domain expertise and application environment. Consequently, this improves the interpretability of the results, which is crucial in a CPPS for effective human-centric decision-making in situations where humans interact with machines (Mendia *et al.*, 2022). Despite several advantages, hybrid models can be computationally expensive, time-consuming, and difficult to develop because they require both physics-based equations and machine-learning techniques, which can be complex and difficult to integrate (Rai *et al.*, 2020).

2.4.5 Analytics Techniques

Analytics is the process of transforming raw data into actionable insights using a variety of tools, technologies, and processes to identify trends and solve problems (AWS, 2023). Analytics is used in the manufacturing industry, for basic monitoring and diagnosis to advanced predictive maintenance and process automation. It enables contextual awareness in real-time and provides actionable insights for decision support that improves equipment utilization, cost, process, human-based errors, productivity, and profitability (IIoT World, 2023).

A search on the internet provides many analytics terminologies, which is confusing many a times. Some universities, like the University of New South Wales (UNSW, 2020), provide a good classification of different analytics techniques. Only a few articles (Menezes *et al.*, 2019; Ferreira & Gonçalves, 2022; Ansari *et al.*, 2019b; Vater *et al.*, 2019) provide description of these widely used terminologies. Moreover, the meaning, scope and significance of the various analytics techniques may vary depending upon the objective and domain of the study. The various domains in which these terminologies are widely used these days are healthcare, retail & sales, marketing, maintenance, search engines, oil & gas exploration, manufacturing, *etc.* Table 2.5 briefly describes the different types of analytics and modelling techniques.

Table 2.5 A brief description of various data analytics techniques

Technique	**Description**	**Modelling techniques**
Descriptive analytics	The analysis of current/historical data to answer questions about what is happening/ happened.	Statistical/machine learning modelling techniques are used to analyze raw data to identify trends and relationships between variables to convert into meaning information.
Diagnostic analytics	It explains why it happened by analysing distinctive characteristics related to abnormal behaviour in the data.	Probability theory, filtering, classification/clustering, regression analysis and time-series data analysis to detect the anomalies in the data.

Table 2.5 A brief description for various data analytics techniques (contd…)

Technique	Description	Modelling techniques
Predictive/prognostic analytics	It analyses data to predict future values for a variable/KPI/component's life before its failure or unsatisfactory performance.	Analysis of historical data to detect patterns in the data using machine learning algorithms.
Prescriptive analytics	It employs data and models to prescribe/recommend the most effective strategies based on management needs.	Analysis of historical and current data to create models to prescribe the optimum outcome based on machine learning algorithms in conjunction with statistical and computational modelling.
Cognitive analytics	It achieves full automation of the analytics through automated detections, predictions, and prescriptions, resulting in smarter decisions over time.	It achieves human-like intelligence using advanced AI techniques such as computer vision, adaptive machine learning, *etc.*

2.4.6 Application Scenarios of CPPS

The tools, techniques, and procedures discovered in theoretical research are used to solve practical problems through applied research. An overview of application scenarios is significant for understanding the current state of the developments taking place in CPPS implementation. This would provide useful information to a researcher/practitioner in exploring the unaddressed domain in manufacturing where CPPS has not yet been implemented. The contents of 164 articles were investigated to provide a view of various CPPS application scenarios. Table 2.6 presents the application scenarios of CPPS, considering the three hierarchical levels namely unit, system, and system of systems. CPPS application is widely used in both additive and subtractive manufacturing domain. In 3D printing domain, CPPS has only been implemented in FDM and multi-jet fusion processes, whereas for other processes, namely SLA/SLM/DED, CPPS approaches are yet to be applied.

Table 2.6 The application scenarios of CPPS at different hierarchical levels

Hierarchal level	**Domain**	**Subdomain**
Unit	3D Printing	Fused deposition modelling (C. Liu *et al.*, 2022; Mennenga *et al.*, 2020; Rogall, *et al.*, 2022)
	Machining	CNC drilling (R. G. Lins *et al.*, 2020)
		CNC lathe (Parto *et al.*, 2022)
		CNC milling (C. Liu *et al.*, 2027; Wu *et al.*, 2017b; Zhu & Zhang, 2018; C. Liu *et al.*, 2018; Y. Zhang *et al.*, 2020)
	Others	Burnishing process (Patalas-Maliszewska *et al.*, 2022)
		Casting process (J. H. Lee *et al.*, 2018)
		Robotic arm (T. Lins & Oliveira, 2020)
		Cooling tower (Schulze *et al.*, 2019)
		Metal forming (Ralph *et al.*, 2022; Lu & Xu, 2019)
		Injection molding (Hürkamp *et al.*, 2021)
		Rolling mill (Bampoula *et al.*, 2021)
		Punching process (Iber *et al.*, 2021)
		Robot servo system (Gao *et al.*, 2021)
		Resistance spot welding (Ahmed *et al.*, 2019)
System	3D Printing	Multi-jet fusion process chains (Wiese *et al.*, 2021)
		Vehicle manufacturing factory providing customized customer services combining multiple services, such as 3D printing, robot, and welding services (Lu & Ju, 2017)
		Multiple 3D printers on the shopfloor connected to cloud platform for fabricating customized products and enabling remote services (Cui *et al.*, 2022)
	Machining	Energy efficient scheduling optimization in machining (Liang *et al.*, 2018)
		Machining production line (Herwan *et al.*, 2018)
		Shopfloor with more than one machine tools & process chain (CNC machine, bending center, punching machine, press brake machine, laser, robots, AGVs, industrial vision systems, ASRS, conveyor, *etc.*) (Tang *et al.*, 2018; Mahmood *et al.*, 2019; H. Zhang *et al.*, 2020; Borangiu *et al.*, 2020)
	Other	Automotive production line (Mendia *et al.*, 2022)
		Manufacturing assembly process (Attajer *et al.*, 2022)
		Ball screw manufacturing company (J. Lee *et al.*, 2017)
		Bearing manufacturing company (Von Birgelen *et al.*, 2018)
		Drum manufacturing line (Siaterlis *et al.*, 2021)
		Electroplating process chain (Leiden *et al.*, 2021)

Table 2.6 The application scenarios of CPPS at different hierarchical levels (contd…)

Hierarchal level	**Domain**	**Subdomain**
System	Other	Facility layout (Farooq *et al.*, 2021)
		Manufacturing turbomachinery components for the oil and gas industry in a factory (Padovano *et al.*, 2021)
		Battery lab factory (Vogt *et al.*, 2022; Schlichter *et al.*, 2022)
		Factory manufacturing spindles, bearings, and gears (Song *et al.*, 2021)
		MPS/prototype digital factory/ pilot factory (consisting of intralogistics test platform; conveyor system; heating process, milling process, handling process, *etc.*) (Thiede *et al.*, 2016; Coito *et al.*, 2022; Tang *et al.*, 2018; Garcia *et al.*, 2016; Berger *et al.*, 2016; Stock *et al.*, 2020)
System of Systems		Multi-national enterprise to automate inter-factory production management (Lu & Xu, 2018)
		Supply chain activities (logistics, purchasing, production, distribution, intralogistics, recycling) (Pei *et al.*, 2019)
		Supply chain activities (production, logistic system for material handling & ware housing) (Bayhan *et al.*, 2020)
		Manufacturing company for gearboxes and engines for the automotive sector, *etc.* (Ansari *et al.*, 2019b)

2.4.7 Enabling Technologies of CPPS

The enabling technologies of CPPS include a wide range of technologies that serve as its fundamental building blocks and provide numerous benefits to facilitate future advancements. Its classification assists in identifying the key driving technologies and identifying areas where further research and development is required to fully realize the potential of CPPS. Several literatures have classified the enabling technologies for Industry 4.0, which is a much broader concept, *e.g.*, Boston Consulting Group (Rüßmann, *et al.* 2015) classified the enabling technologies of Industry 4.0 into nine clusters: additive manufacturing, augmented reality, big data and analytics, autonomous robots, simulation, horizontal and vertical system integration, IIoT, cybersecurity, and cloud. Only a few articles have classified the enabling technologies of CPPS. Pei *et al.* (2019) classified enabling technologies into five clusters, namely manufacturing process, information and computing technology, big data/cloud, research and development, and logistics and supply chain management. However, these enabling technologies are primarily focused on intralogistics only. Therefore, the contents of articles selected using the PRISMA technique were examined to provide a comprehensive overview of the various CPPS-enabling technologies. Figure 2.16 illustrates the twelve main enabling technologies of CPPS, namely smart manufacturing technology; smart sensors, devices, and actuators; product design technology; information & communication technology; data management; data analytics; computing technology; modelling, simulation, and optimization; virtualization technology; servitization; cyber security technology; and didactics. Table 2.7 classifies the enabling technologies into twelve main categories and their respective subcategories.

Figure 2.16 The twelve main enabling technologies of CPPS

Table 2.7 Classification of enabling technologies into categories and subcategories

Sl. No.	**Enabling technologies (main categories)**	**Enabling technologies (subcategories)**
1	Smart manufacturing technology	3D printing, machining, casting, welding, forming, *etc.*
2	Smart sensors, devices, and actuators	Power analyzer, smart power grids, robots, RFID, NFC, AGV, HVAC devices, *etc.*
3	Product design technology	Plug & play, modular design, miniaturization, portable design, *etc.*
4	Information & communication technology	Server, protocol, connectivity, network; cellular, 4G & 5G data services, machine-to-machine & human to machine communication, integration, interoperability, *etc.*
5	Data management	Data transmission, data cleaning, data processing, signal conditioning, data fusion, data storage, *etc.*
6	Data analytics	Big data analytics, machine learning, artificial intelligence algorithms, descriptive analytics, diagnostic analytics, predictive analytics, prescriptive analytics, *etc.*
7	Computing technology	APIs, cloud, fog, edge, *etc.*
8	Modelling, simulation, and optimization	Modelling (empirical, physics-based, data-driven, hybrid); simulation (digital twin); optimization (evolutionary, non-evolutionary)
9	Virtualization technology	Dashboards for real-time monitoring & control, human robot collaboration, AR/VR/MR, *etc.*
10	Servitization	Real-time scheduling, quality management, maintenance management, production management, logistics and SCM, automated warehousing, real-time localization & tracing, ERP, PLM, MES, CRM, remote service, *etc.*
11	Cyber security technology	Firewall, VPN, access control, blockchain technology, *etc.*
12	Didactics	Learning factory, AR/VR based training, *etc.*

2.4.8 Barrier/Challenge to CPPS

Barriers or challenges in the CPPS context refer to obstacles that need to be addressed to fully realise the potential benefits of a successful implementation. The challenges can pertain to various aspects such as design, implementation, operation, and maintenance (Monostori, 2014). Several articles have identified challenges that are often generic. The CPPS challenges are classified as per CPPS elements as shown in Figure 2.17.

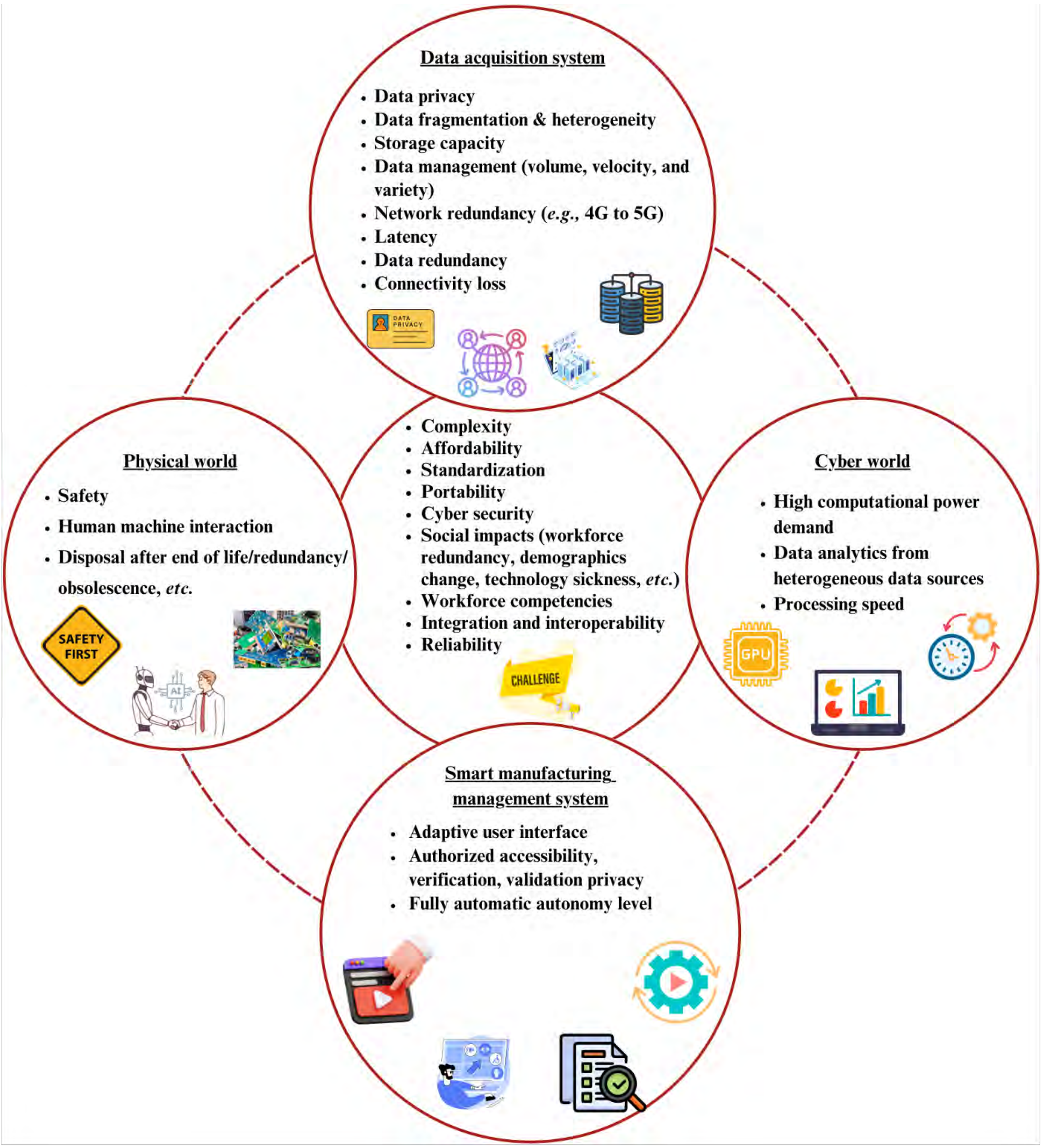


Figure 2.17 Barriers/challenges in CPPS

The significance of this classification lies in increasing the awareness of researchers/ practitioners in mitigating these challenges and realising the potential benefits of successful implementation.

The common challenges at all elements are: increase in complexity (Jiang *et al.*, 2018), affordability (Uhlemann *et al.*, 2017), standardization (Beregi *et al.*, 2019; Uhlemann *et al.*, 2017), portability, scalability, cyber security, and flexibility (D. Wu *et al.*, 2017b), workforce knowledge & competencies (J. Lee *et al.*, 2019), integration & interoperability

(R. Rojas *et al.*, 2021), reliability (Habib *et al.,* 2022), environmental impacts during life cycle stages (Thiede, 2022), social impacts (Ansari *et al.*, 2019b) including workforce redundancy, demographics change, technology sickness (*e.g.*, virtual reality sickness, *etc.*).

The challenges for the physical world are safety (Habib *et al.*, 2022; Jiang *et al.*, 2018; Ansari *et al.*, 2019b), human machine interaction (R. A. Rojas & Rauch, 2019), disposal after end of life, redundancy/obsolescence, *etc.* The challenges for data acquisition system are data privacy (R. A. Rojas & Rauch, 2019), data fragmentation & heterogeneity (Christou *et al.*, 2022), data management (volume, velocity, and variety) (Christou *et al.*, 2022; Lu & Xu, 2019), storage capacity (J. Lee *et al.*, 2019), network redundancy (*e.g.*, 4G to 5G), latency, data redundancy, connectivity loss, data democratization, *etc.*

The challenges for cyber world include high computational power demand (Verl *et al.*, 2013), include data analytics from heterogeneous data sources, processing speed, *etc.* The challenges for the smart manufacturing management system include adaptive user interface (Rojas & Rauch, 2019), authorized accessibility, verification, validation privacy (Ansari *et al.*, 2019b; J. Lee *et al.*, 2019), attaining level three autonomy for immediate responsiveness to feedback & control, *etc.*

2.4.9 Engineering Needs/Requirement Analysis

Engineering need/requirement analysis is a method for extracting information from stakeholders, such as customers, users, and other interested parties, to understand their expectations and requirements for the system. It is a crucial step in the design of any complex system, as it ensures that the system will be effective and efficient in achieving its intended objectives (Francalanza *et al.*, 2018). Only a few researchers (Francalanza *et al.*, 2018; R. G. Lins *et al.*, 2020) have conducted engineering need/requirement analysis for a CPPS for specific scenarios. The contents of 164 articles selected using the PRISMA technique have been analyzed to provide a comprehensive view of engineering need/requirement analysis across different hierarchical levels, namely unit, system, and system of systems. In addition, the requirements of external stakeholders, such as regulatory authorities, customers, market, *etc.*, have also been analyzed. Table 2.8 enumerates various engineering needs/requirements across different hierarchical levels and from the external stakeholders' perspective. The fulfilment of these needs/requirements would enhance the capabilities and advance the development of a CPPS towards achieving the objectives of Industry 4.0.

Table 2.8 Various engineering needs/requirements across hierarchical levels and from the external stakeholders' perspective

Hierarchical levels	**Engineering needs/requirements**
Unit level	Process understanding (Hürkamp *et al.*, 2021)
	Online monitoring of state variables & KPIs (Wiemer *et al.*, 2017; J. Lee *et al.*, 2017)
	Online resource monitoring (Lu & Xu, 2018)
	Traceability (Wessel *et al.,* 2019)
	Machine failure detection (Y. Zhang *et al.*, 2020; Ansari *et al.*, 2019b; J. Lee *et al.*, 2017)
	Product defects (J. H. Lee *et al.*, 2018)
	Machine breakdown (Okpoti & Jeong, 2021)
	Zero-defect manufacturing (Christou *et al.*, 2022)
	Quality prediction (Ahmed *et al.*, 2019; Ahmed *et al.*, 2021)
	Predictive maintenance (J. Lee *et al.*, 2017; Kroll *et al.*, 2014; Christou *et al.*, 2022)
	RUL prognosis due to machine/component degradation (Ansari *et al.*, 2019b; D. Wu, *et al.*, 2017b)
	Optimal adjustment of process parameters (Wiemer *et al.*, 2017)
	Optimized decision-making (Wiemer *et al.*, 2017)
	Energy substitution (Thiede, 2022)
	Energy flexible operation (Grosch *et al.*, 2022)
	Process transparency (Rogall *et al.*, 2022)
	Process visibility (Fang *et al.*, 2020)

Table 2.8 Various engineering needs/requirements across different hierarchical levels and from the external stakeholders' perspective (contd…)

Hierarchical levels	Engineering needs/requirements
Unit level	Resilient and autonomous responses to failures (catastrophic operational disruptions, stoppage, breaks, *etc.*) (Tomiyama & Moyen, 2018)
	Safety, security & reliability (Sinha & Roy, 2020)
	Computational power demand (Verl *et al.*, 2013)
	Experimental testing and prototyping (Hürkamp *et al.*, 2021)
	Simplicity (easy setup, easily removable, easy integration)
	Transforming existing/legacy system into a CPPS (Ralph *et al.*, 2022; T. Lins & Oliveira, 2020)
	Low price (T. Lins & Oliveira, 2020)
	Openness
	Real-time capabilities/decreased latency for time sensitive decisions and control (Prenzel & Steinhorst, 2021; Berger *et al.*, 2019)
	Decentralization (Prenzel & Steinhorst, 2021; Berger *et al.*, 2019)
	Self-X capabilities (robustness, autonomy, organization, maintenance, repair, adaptability, reconfiguration, *etc.*) (Stock *et al.*, 2020)
System level	Autonomous production scheduling (X. Wu *et al.*, 2021)
	Decentralized production control for dynamic scenarios such as order change, operation failure, machine breakdown, *etc.* (Okpoti & Jeong, 2021; Meissner & Aurich, 2019)
	Dynamic or context aware scheduling (Wan *et al.*, 2022)
	Efficient management for handling disturbances (Tomiyama & Moyen, 2018)
	Energy efficient scheduling (Nouiri *et al.*, 2019; Fernandes *et al.*, 2022)
	Flexible worker allocation (Fang *et al.*, 2021)
	KPIs (cycle times, delays, OEE, *etc.*) analytics & management (J. Lee *et al.*, 2015; Menezes *et al.*, 2019)
	Networked production lines (Verl *et al.*, 2012)
	Production planning for optimal manufacturing process sequence (Beckers *et al.*, 2022)
	Self-aware, flexible, lean, agile, reconfigurable production lines (Borangiu *et al.*, 2020; Lu & Xu, 2018)
	System optimization (Habib *et al.,* 2022)
System of systems	Flexible, lean, agile, and reconfigurable supply chains (Lu & Ju, 2017; Ghouat *et al.*, 2021)
	Dynamic business and engineering processes (Kagermann *et al.*, 2013)
	Integrated and collaborative value networks for organization and sharing of manufacturing resources online (Moghaddam *et al.*, 2018)

Table 2.8 Various engineering needs/requirements across different hierarchical levels and from the external stakeholders' perspective (contd…)

Hierarchical levels	**Engineering needs/requirements**
	Intelligent intralogistics to meet volatile market and individualized needs (Pei *et al.*, 2019)
	Product lifecycle management (Pei *et al.*, 2019)
External stakeholders	Regulaory authorities: environmental performance, impacts, transparency, hotspots identification, benchmarking, *etc.* (Leiden *et al.*, 2021)
	Customer: volatile behaviour, mass customization, in-time delivery, high quality, low cost, carbon footprint data for every product (Francalanza *et al.*, 2017; Chakroun *et al.*, 2022; Ghouat *et al.*, 2021)
	Workplace safety and worker health risks assessment (Leiden *et al.*, 2021; Q. Liu *et al.*, 2015)
	Global and competitive market (Q. Liu *et al.*, 2015)
	Training employees/didactics (Seitz & Nyhuis, 2015)

2.4.10 Significance Analysis of CPPS Deployment

Significance analysis of the existing literature facilitates understanding the possibilities of CPPS deployment. Figure 2.18 illustrates the quantitative and qualitative significance of CPPS deployment by existing researchers across various dimensions. It can be observed that deployment of CPPS has positive effects (quantitively and qualitatively) on all dimensions of sustainability (environmental, economic, and social) as well as technological advantages. The results of this analysis would provide a researcher/ practitioner confidence and support for enhancing the sustainability and technological performance of their manufacturing systems.

From the environmental perspective, implementing CPPS has resulted in energy/resource savings (Liang *et al.*, 2018; Schulze *et al.*, 2019; Leiden *et al.*, 2021; Thiede, 2022; Vogt *et al.*, 2022; Schlichter *et al.*, 2022) through several facilities such as smart energy management (Tan *et al.*, 2021), product lifecycle management (Bagozi *et al.*, 2021), detection of anomalous energy consumption patterns (Mendia *et al.*, 2022), energy-flexible operation of production machines (Grosch *et al.*, 2022), real-time monitoring of

Significance of deploying CPPS across various dimensions

The three pillars of sustainability

Environmental

Quantitative

- Energy saving (around 40%) in European machining companies
- Reduction potentials of water demand (-7%) and energy demands (-27%)
- Electricity and resource savings of up to 10%
- Industrial decarbonization potential estimated to be 15–25%
- Energy savings (around 5%) through demand-driven control of HVAC system
- Significant reduction in final energy demand (around 37.29%) using model-predictive control

Qualitative

- Enhances resource and energy efficiency
- Smart energy management
- Product lifecycle management
- Detects anomalous energy consumption patterns
- Energy-flexible operation of production machines
- Real-time monitoring of the environmental impacts
- Energy-efficient scheduling
- Increased transparency regarding environmental performance

Economical

Quantitative

- Productivity improvement (around 30%) in European machining companies
- Reduces down-time by about 35 % from 3.68 % to 2.41 %
- Reduces production rejects by 12%

Qualitative

- Minimizes business risks
- Reduces production cost
- Reduces unexpected downtime to increase productivity
- Decentralized production planning and control
- Reduces lead time
- Improves production efficiency
- Improves overall equipment effectiveness
- Reduces redundant and preventive stoppages in the production line and decreases the cost of maintenance operations
- Service-oriented smart manufacturing through resource virtualization
- Increases productivity and decreases production loss through efficient fault management and quick amendment of faults in production lines
- Increases productivity, performance and functionality of products

Societal

Qualitative

- Promotes occupational safety
- Enhances ability for humans to interact and control the physical world
- Provides better services for customers
- Enables easy decision making & control for practitioners through user guided visual analysis tool
- Supports human resources and assist them to take insightful decisions using augmented reality and virtual reality
- Enables communication between humans, machines and products
- Enables symbiotic human–robot collaboration

Technological foundation for the three pillars of sustainability

- Provides better product quality and system reliability
- Enables self-organizing manufacturing, context/situation-aware control
- Enables optimal adjustment of process parameters
- Enables M2M or plant floor communications
- Enables adaptiveness, autonomous cooperation capabilities, improved product quality
- Monitors machine health conditions
- Facilitates dynamic resource management to mitigate negative effects, such as production downtimes or faulty productions
- Enables production system resiliently and autonomously responds to failures and avoid catastrophic disruptions

- Facilitates system reconfigurability and flexibility in the production system
- Enhances quality, and efficiency of a production line through early detection of tool wear, tool breakage and bad surface roughness of a product
- Agilely manage disturbances in dynamic environment and maintain high production performance
- Enables higher level of intelligence, autonomy, connectivity of the production system
- Provides least interferes with machine operation using anomaly localization
- Enables proactive decision making)
- Ensures secure and dependable functioning of manufacturing systems using blockchain enabled CPPS
- Facilitates on-demand manufacturing services

- Faciliates smart scheduling under dynamic and uncertain production environment
- Provides accurate and reliable assessments of product quality in real-time
- Enhances scalability and resiliency
- Enhances equipment health
- Enables smart production scheduling, anomaly detection, predictive maintenance, process monitoring
- Enables prognostics and health management
- Enables context-aware scheduling and control for dynamic scenarios such as orderchange, operation failure, and machine breakdown
- Facilitates remote diagnosis, remote services, remote control & condition monitoring

Figure 2.18 Significance of CPPS deployment across various dimensions the environmental impacts (Hagen *et al.*, 2019), energy-efficient scheduling (Fernandes *et al.*, 2022), and increased transparency regarding environmental performance (Rogall *et al.*, 2022). From the economic perspective, implementation of CPPS has resulted in productivity improvement (Liang *et al.*, 2018), reduced down-time (Schreiber *et al.*, 2018; Lee *et al.*, 2015; Ansari *et al.*, 2019b; Christou *et al.*, 2022), reduced production rejects (Hürkamp *et al.*, 2021), reduced business risks (Kagermann *et al.*, 2013), reduced production cost (C. Liu *et al.*, 2021), decentralized production planning and control (Ilsen *et al.*, 2017), reduced lead time (Ahmed *et al.*, 2021), improved production efficiency (Fang *et al.*, 2021), improved OEE (Nota *et al.*, 2020; Christou *et al.*, 2022), reduced maintenance costs (Bampoula *et al.*, 2021), service-oriented smart manufacturing (Cui *et al.*, 2022), increased productivity (Webert *et al.*, 2022; Monostori *et al.*, 2016) and decrease of production loss through efficient fault management and quick amendment of faults in production lines (Webert *et al.*, 2022).

From the societal perspective, implementation of CPPS has the potential to promote occupational safety of workers (Leiden *et al.*, 2021), provide better services to customers (Zhou *et al.*, 2016), enhance the abilities for humans to interact and control the physical world (Rajkumar *et al.*, 2010), and promote symbiotic human-robot collaboration (L. Wang *et al.*, 2015). These enhanced potentials are possible due to better and advanced communication between humans, machines, and products (Monostori, 2014) using user guided visual analysis tools (Post *et al.*, 2017) and advanced techniques such as augmented and virtual reality (Havard *et al.*, 2021).

The foundation for all the three pillars of sustainability lies in the technological advancements achieved through CPPS implementation. These advancements are possible due to higher levels of intelligence, autonomy, and connectivity of the production system (C. Liu *et al.*, 2018). There is a wide range of technological benefits such as better product quality and system reliability (Lee *et al.*, 2015; Herwan *et al.*, 2018), optimal adjustment of process parameters (Wiemer *et al.*, 2017), machine to machine/shop floor communications (Garcia *et al.*, 2016), adaptiveness, autonomous cooperation capabilities, improved product quality (C. Liu & Xu, 2017), advanced monitoring of machine health conditions (D. Wu *et al.*, 2017b), prognostics health management (Gao *et al.*, 2021), (Cody *et al.*, 2022), anomaly detection (Von Birgelen *et al.*, 2018), predictive maintenance (Bagozi *et al.*, 2021), proactive decision making (Mahmood *et al.*, 2019), and accurate and reliable assessments of product quality in real-time (Andronie *et al.*, 2021). CPPS enables self-organizing manufacturing & smart/context-aware scheduling and control under dynamic and uncertain production environments (Wang *et al.*, 2015; Wan *et al.*, 2022; Chawla *et al.*, 2020; Tang *et al.*, 2018), dynamic resource management (Engelsberger & Greiner, 2018; Tomiyama & Moyen, 2018; Siafara *et al.*, 2018), system reconfigurability and flexibility (Ribeiro & Bjorkman, 2018), and enhanced scalability and resiliency (Siaterlis *et al.*, 2021). CPPS also promotes on-demand manufacturing services (Lu & Xu, 2019), remote services (diagnosis, condition monitoring, *etc.*) (Zubrzycki *et al.*, 2021) and can secure and provide dependable functioning of manufacturing systems using blockchain technology (J. Lee *et al.*, 2019).

2.5 INTERPRETATION OF SCIENTOMETRIC AND CONTENT ANALYSES RESULTS

Interpretation of the results of scientometric and content analyses led to the following outcomes:

- Development of an impact-effort matrix for CPPS elements
- Identification of paradigm shifts in CPPS
- Development of a concept map for CPPS

2.5.1 Development of an Impact-Effort Matrix for CPPS Elements

The impact-effort matrix is a decision-making tool that helps in selecting the most effective solution from multiple options by evaluating the maximum impact achievable with minimal effort. It can be highly useful for researchers and practitioners in decision making *e.g.*, selecting CPPS elements as per the impacts required and the corresponding efforts needed in terms of skill, machinery, time, and money.

Figure 2.19 shows the impact-effort matrix plot for the different elements of a CPPS. The horizontal axis represents effort or complexity of CPPS elements in terms of time, money, skills, *etc.* The vertical axis represents impact or significance of the CPPS elements in terms of environment, economy, society, and technology. The matrix is divided into nine quadrants (I to IX) as shown in Figure 2.19. The sub-elements, namely direct data storage, monitoring, and level 1(manual) autonomy are in the first quadrant due to their relatively low impact and effort. The navigation system and external retrofitting module are placed in the second quadrant due to their relatively medium impact and low effort. The unit level, HVAC system, and social module are in the third quadrant due to their relatively high impact and low effort. The descriptive analytics is placed in the fourth quadrant due to its relatively low impact and medium effort. Several sub-elements, namely communication infrastructure, data management module, data, storage on network, communication module, computing platform module, analysis module, software module, visualization module, level two (semi-automatic) autonomy, and software module are placed in the fifth quadrant due to their relatively medium impact and medium effort. The sixth quadrant includes system level, internal retrofitting module, prescriptive analytics module, simulation/digital twin module, management system, decision support system (optimal settings recommender), remote accessibility & service module due to their relatively high impacts and medium efforts.

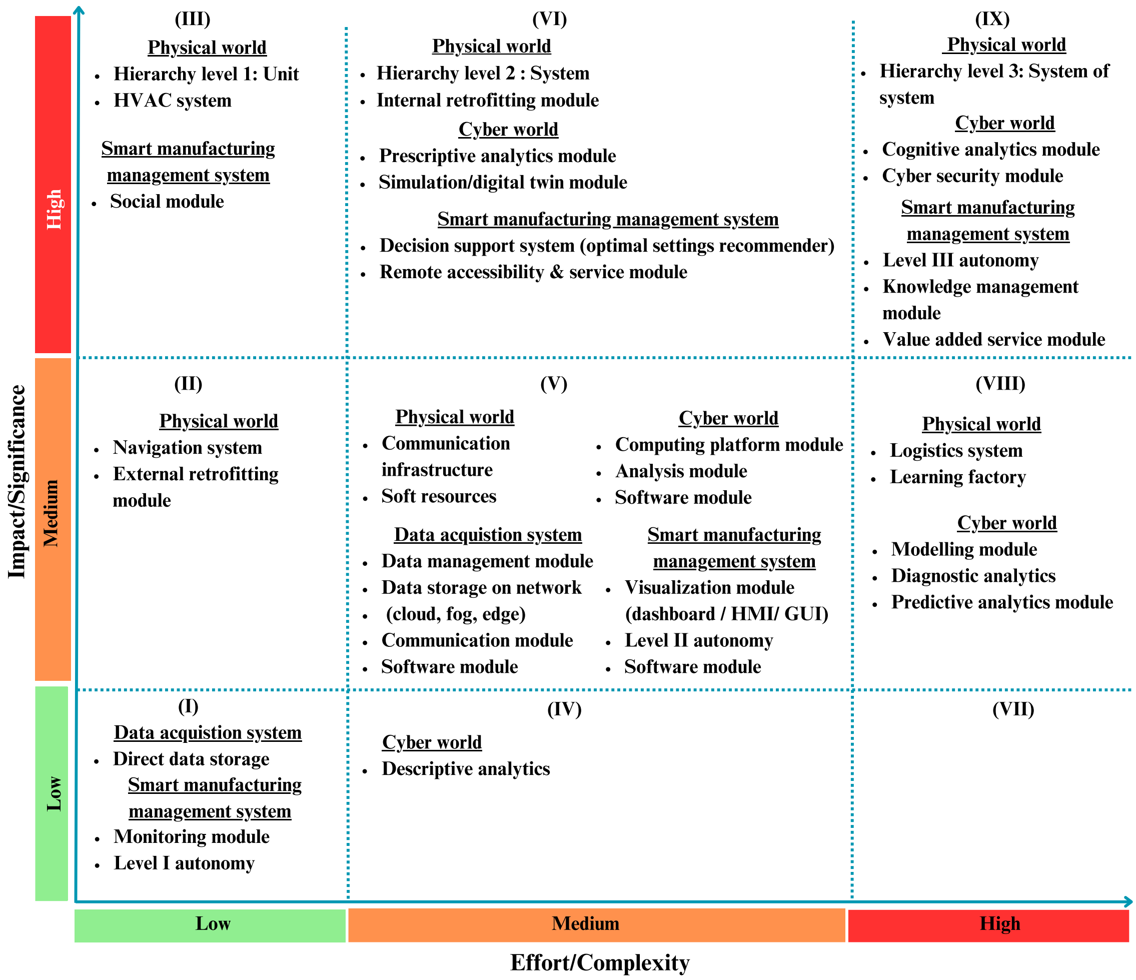


Figure 2.19 Impact-effort matrix for CPPS

There is no sub-element in the seventh quadrant having low impacts and high efforts. The sub-elements, namely logistics system, learning factory, modelling module, diagnostic analytics and predictive analytics module are placed in the eight-module due to their relatively medium impacts and high efforts. Finally, the ninth quadrant with the highest impact and effort includes system of system (hierarchy level three), cognitive analytics module, cyber security module, level three (fully automatic) autonomy, knowledge management module, and value-added service module.

2.5.2 Identification of Paradigm Shifts in CPPS

The study of future research directions contributes to the exploration of future research developments, such as innovative concepts, methodologies (tools/techniques), and practices based on their maturity levels that can be utilized to address the most demanding needs and advance knowledge within a domain. The literature review acts as a bridge between future research and previous studies. Based on the findings of the literature review, a paradigm shift diagram for various developments (concepts, methodologies, practices) over the past, at the present and in future is constructed based on their maturity levels. Figure 2.20 presents a glimpse of the paradigm shift over time. The horizontal axis represents the timeline and is segmented into the past, the present, and the future. The horizon of the future is further subdivided into the short term and the long term. The vertical axis represents the maturity levels of various concepts, methodologies, tools, techniques, and practices.

It can be observed that the first cluster consists of various concepts/methodologies/practices, such as descriptive analytics, 2G/3G wireless connectivity, and level one (manual) autonomy, static value stream mapping, static sequencing & scheduling, static production planning, static simulation, statistical analysis, non-evolutionary optimization, empirical, and physics models, *etc*.

The second cluster consists of various concepts/methodologies/practices, such as hybrid models; cloud, edge, fog computing; level two autonomy; dynamic value stream mapping; dynamic sequencing & scheduling; dynamic production planning; dynamic simulation/digital twin; evolutionary optimization; diagnostic and predictive analytics;

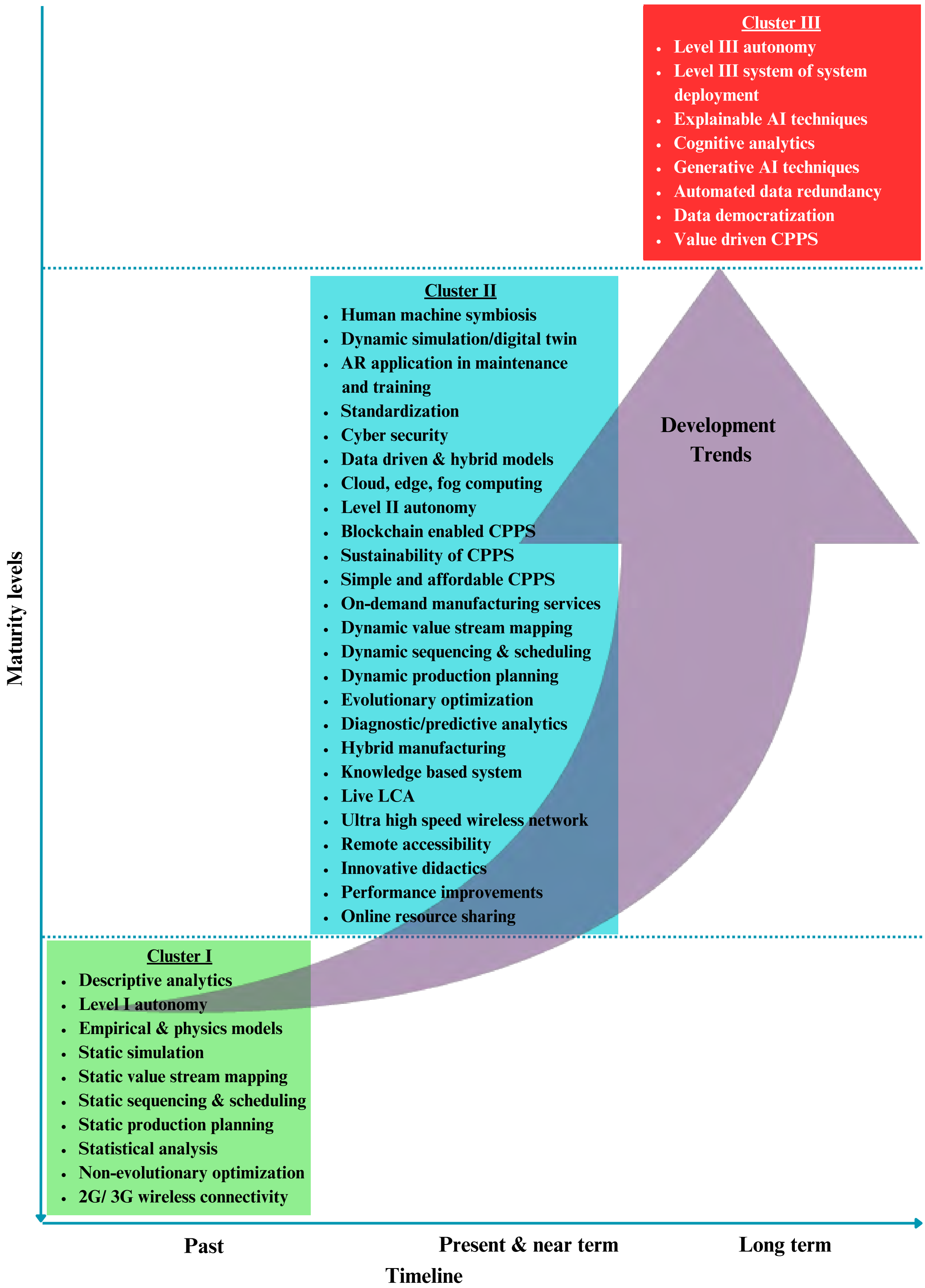


Figure 2.20 A paradigm shift diagram for various developments (concepts, methodologies, practices) over the past, at the present and in the future based on their maturity levels

hybrid manufacturing; standardization; cyber security; human machine symbiosis; knowledge-based system; live LCA; ultra-high speed wireless network; augmented reality application in maintenance, training, *etc.*; remote accessibility; blockchain enabled CPPS; sustainability of CPPS; simple and affordable CPPS; innovative didactics; real-time capabilities; performance improvements; online resource sharing; remote accessibility; on-demand manufacturing services, *etc*. Lot of research is going on these domains. These concepts/methodologies/practices have been used in the recent past, are still used and researched today, and will be used in the near future.

Lastly, the third cluster consists of various concepts/methodologies/practices, such as level three (fully autonomic) autonomy, system of system/hierarchical level three deployment; explainable AI techniques; cognitive analytics; generative AI techniques such as ChatGPT, Amazon Codewhisperer, *etc.*; automated data redundancy; data democratization; value driven CPPS in meeting SDG goals; *etc.* This group of concepts, methodologies, and practices is currently underdeveloped but holds significant importance for their application in both short-term and long-term manufacturing contexts. The descriptions of a few of these future research directions are as follows:

- Level III autonomy: This will lead to full automation in manufacturing with minimum human intervention. It will enable self X capabilities (robustness, autonomy, organization, maintenance, repair, adaptability, reconfiguration, *etc.*) and lead to zero-defect manufacturing. It will also increase productivity, product quality, profitability and effectively deal with demographic changes. However, it will also increase the complexity in manufacturing.
- Level III system of systems deployment: It facilitates interconnection and interoperability among multiple system level CPPSs and enables collaborative

application optimization with multiple stakeholders, such as personalization, intelligent design, and remote maintenance (Qi *et al.*, 2018). However, its full-scale deployment across industrial symbiosis, enterprises, life cycle phases has yet to be fully realized. Its large-scale deployment has enormous potential.

- Explainable AI techniques: Machine learning, as black box models, fails to explain the underlying reasoning behind the trend of a phenomenon and therefore lacks accountability & generality (Barredo *et al.*, 2020). Explainable AI techniques have the potential to effectively deal with these limitations and have a lot of potential in their future applications in smart manufacturing.
- Cognitive analytics: It will transform the traditional manufacturing using features such as automated detections, predictions, and prescriptions. It will help in achieving efficient production, managing unforeseen situations, predicting, and detecting machine failures/anomalies, and making smarter decisions over the time (Rousopoulou *et al.*, 2022).
- Generative AI techniques: These techniques have a great potential to revolutionize the manufacturing industry. It can be highly useful for knowledge modelling where users can easily code optimized tool paths in machining or 3D printing based on their organizational requirements. Recently, Badini *et al.*, (2023) has demonstrated the capabilities of ChatGPT, a very popular generative AI technique to generate Gcode for optimized performance in 3D printing application. These techniques will also be highly useful for users to develop machine learning algorithms for their specific use cases without requiring expert domain knowledge.

- Automated data redundancy: This feature aims to automatically delete the redundant data from the data acquisition platform, *e.g.*, cloud, fog, edge, local hardware devices. This feature will be an essential feature in future CPPS as it will help to minimize consumption of energy and resources required for data storage.
- Data democratization: It aims to democratize or provide accessibility of data and analytics tool to all stakeholders (Harland *et al.*, 2022). This will enable enhanced data driven transparency, easy adoption of analytics tools, benchmarking of tools and techniques. This will be highly useful to MSMEs as it will significantly reduce energy and resources.
- Value driven CPPS: The scientometric analysis showed that more than two thirds of the articles are mapped to SDG 9 that aims to foster industry, innovation, and infrastructure. There is a strong need to increase the sustainability dimensions of CPPS from technology to value driven so that it can be mapped to other SDG goals more effectively.

2.5.3 Development of a Concept Map for CPPS

A concept map is a visual representation of the interconnections among various elements within a system, which facilitates understanding and efficient implementation of the system. Based on the findings of the literature, a concept map is proposed for the understanding of the interrelationships among different components and information in a CPPS. This is expected to serve as a quick reference for researchers and practitioners in the manufacturing domain. Figure 2.21 presents a glimpse of interrelationships among various elements in a CPPS from a holistic perspective.

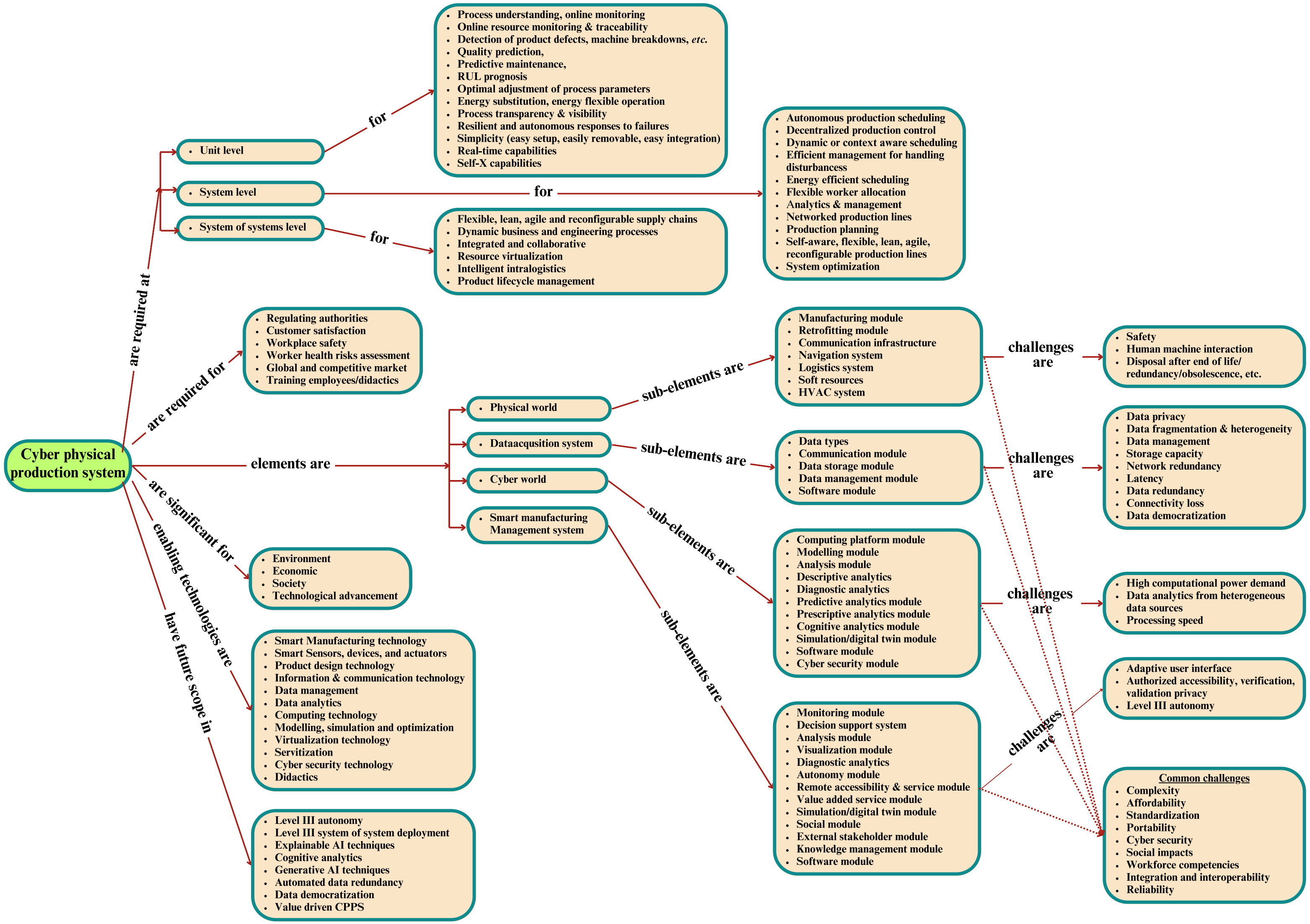


Figure 2.21 Proposed concept map for a CPPS from a holistic perspective*

*Reproduced enlarged in appendix C

2.6 SUMMARY

This chapter provides a systematic literature review on the topic of CPPS to provide an understanding of CPPS concepts, latest developments, potential benefits, enabling technologies, application areas, engineering requirements, challenges, future research directions, *etc.* Data analysis and synthesis for the systematic literature review were conducted using scientometric and content analyses of quantitative and qualitative data, respectively. The data analysis and synthesis were then interpreted to provide a understanding of CPPS from different perspectives. The important outcomes of the systematic literature review are as follows:

- The scientometric analysis provided an overview of the latest trends by analyzing various perspectives, namely research methodologies used, timeline distribution, geographical distribution, source analysis, SDGs analysis, keyword co-occurrence analysis, co-authorship among countries, and author and co-citation analysis.
- Content analysis provided useful insights to enhance the understanding of the multidisciplinary concepts of CPPS from a broader perspective by classifying/grouping various concepts of CPPS such as hierarchical level, data type, autonomy, analytics, modelling techniques, enabling technologies; and analyzing applications area, barrier/challenges, engineering needs/requirements, and significance.
- The impact-effort matrix for CPPS's elements has been proposed to select the most effective solution from multiple options by evaluating the maximum impact achievable with minimal effort. This would be highly useful for researchers and practitioners in decision making.

- A paradigm shift diagram for various developments (concepts, methodologies, practices) over the past, at the present and in the future based on their maturity levels has been proposed. This can be highly useful for a researcher and practitioner in addressing the needs and advancing the knowledge and development in the field of cyber physical production systems.
- The proposed concept map provides easy understanding of the interrelationships among different components and information in CPPS. This will serve as a quick reference for researchers and practitioners in the manufacturing domain.

Lastly, the main contribution of the present work lies in providing useful insights and knowledge updates for both the research community and industrial practitioners and guiding future developments in enhancing the management capabilities and potentials of CPPS.

Although, authors have tried to best to present analyses through proper reasoning using literature. However, impact-effort analysis has been performed based on authors knowledge, experience, and brainstorming with shopfloor practitioners. Therefore, there is a chance for disagreement among researchers. However, this also provides scope for improvement of these results through future research work and open discussions.

2.7 RESEARCH GAPS

Based on literature review, the following research gaps have been identified:

- There is hardly any architecture or framework that considers a holistic perspective, *i.e.*, a framework considering unit level, system level, and system of systems level, together indicating the possible elements and sub-elements. There is a need for a generic and holistic CPPS framework in smart manufacturing analytics and management that encompasses all relevant elements and sub-elements.

- Obtaining valuable insights through the application of analytics techniques is one of the primary reasons for implementing CPPS. Descriptive, diagnostic, and predictive analytics have been the primary focus of research. Prescriptive analytics, that provides real-time recommendations and allow practitioners to adjust variables according to managerial requirements is not yet proposed in CPPS domain.
- The implementation of CPPS to address pragmatic issues is still in its nascent stages and has not yet attained maturity. Implementing CPPS at the unit level is the essential first step in meeting other hierarchical levels' engineering needs/requirements. There have been only a few attempts to implement CPPS in applications such as 3D printing and CNC milling. These studies have focused primarily on facilitating data acquisition, online monitoring, and control. Incorporating these combined analytics techniques (descriptive, prognostics, prescriptive, and diagnostics) to facilitate online monitoring, visualization, decision support, knowledge management, feedback, and control is missing from the literature. There are still research gaps in fully utilizing the advantages of Industry 4.0 to improve the management capabilities of these conventional manufacturing equipment for increased productivity, reliability, and product quality at an affordable cost.
- The three computing technologies, cloud, fog, and edge have unique advantages and disadvantages. However, these three key technologies are implemented independently, with fewer attempts to integrate them to complement one another.
- The paradigm diagram indicates a requirement for the development of value driven CPPS. This can be accomplished through innovative research that can be more effectively aligned with other SDG goals. There is hardly any CPPS framework for the environmental sustainability of the 3D printing process. These frameworks should allow users to assess the environmental impact of 3D printed products by considering

various combinations of design and process parameters. Consequently, this could facilitate real-time monitoring of environmental impacts, providing timely decision support and valuable insights to operators, project managers, business managers, and customers, thereby enhancing visibility and transparency.

- The analysis of barriers/challenges identified workforce competencies as a prevalent obstacle to the success of CPPS. The analysis of the impact-effort matrix revealed that the learning factory is positioned in the eighth quadrant due to its moderate impact and significant effort. The impact can be enhanced by developing a CPPS framework for learning factories that facilitates knowledge transfer between innovation and learning for enhancing the technical skills of the Industry 4.0 workforce, industrial engineers, and engineering students. The effort can be reduced by employing affordable intelligent sensors, devices, and open-source software.

CHAPTER 3

DEVELOPMENT OF A GENERIC CPPS FRAMEWORK FOR SMART MANUFACTURING ANALYTICS AND MANAGEMENT

This chapter proposes a generic CPPS framework for smart manufacturing management system considering its elements and sub-elements.

3.1 INTRODUCTION

A framework refers to a structured set of rules, guidelines, or protocols that provide a roadmap for developing and implementing a system or application based on foundational review of existing theories. In the context of CPPS, several frameworks/architectures have been proposed and implemented by different researchers over the years using case studies. However, a holistic CPPS framework considering all three hierarchy levels, namely unit, system, and system of systems, is missing in the literature. Therefore, the review of existing literature has been conducted to extract possible elements and sub-elements of CPPS and propose a generic framework for smart manufacturing analytics and management based on its current status and advancement.

Section 3.2 presents the research background to provide an overview of various architectures and frameworks proposed by researchers over the years, outlines the research gaps, and develops the objectives. Section 3.3 proposes a holistic CPPS framework for smart manufacturing analytics and management. Finally, section 3.4 concludes the chapter by highlighting the significance of the proposed framework.

3.2 BACKGROUND

Several architectures and frameworks have been proposed for CPPS over time. This section provides a brief overview of various architectures and frameworks, including their components, sub-components, significance, and limitations.

Lee *et al.* (2015) proposed a 5C CPS architecture to improve Industry 4.0 manufacturing systems. The architecture comprises five layers: connection, conversion, cyber, cognition, and configuration. The proposed framework provides a comprehensive strategy for enhancing product quality and system reliability using more intelligent and robust manufacturing equipment. However, despite its wide adoption and usefulness in guiding CPS implementation in manufacturing, the framework mainly concentrates on hierarchical levels of units and systems and does not consider the system of systems level, making it less comprehensive.

Thiede *et al.* (2016) introduced a CPPS framework comprising four main components: physical world, data acquisition, cyber world, and feedback/control for implementing CPPS in learning factories. The proposed framework, with its four main components, is transferrable and has gained widespread acceptance among researchers to implement CPPS in other applications. However, it does not address the system of systems level, and the sub-elements are not explicitly defined or listed.

Liu *et al.* (2018) proposed an architecture consisting of several components, namely designers and planners, physical devices, networks, machine tool cyber twins, shopfloor technicians, smart HMIs, feedback loops, and cloud. The proposed architecture offers guidelines for enhancing conventional CNC machine tools into cyber-physical machine tools. This integration enables the seamless integration of machine tools, machining processes, real-time machining data, and intelligent algorithms through diverse network connections. The proposed architecture primarily emphasizes on CNC machines and lacks generality for other manufacturing applications.

Ansari *et al.* (2019b) introduced a CPPS framework designed explicitly for prescriptive maintenance applications. The system comprises of four layers: data management, predictive data analytics toolbox, recommender, and decision support dashboard. These layers aim to enhance functional capabilities, including processing large amounts of diverse data from various sources, and generating decision support measures and recommendations for improving maintenance plans aligned with production planning and control systems. The proposed framework is not versatile enough for other manufacturing applications.

Schulze *et al.* (2019) proposed a CPPS framework for managing cooling towers. This framework consists of four key components: physical world, data acquisition, cyber world, and feedback & control, which were originally introduced by Thiede *et al.* (2016). The framework was successfully implemented for an industrial cooling tower system at a German automotive manufacturing plant. The study demonstrated the potential for substantial reductions in water and energy demands by implementing adapted operational strategies.

Lee *et al.* (2019) revised their old (Lee *et al.,* 2015) CPS architecture for Industry 4.0 manufacturing systems based on blockchain technology. In addition to the already existing five layers (connection, conversion, cyber, cognition, and configuration) proposed by Lee *et al.* (2015), a blockchain-enabled CPS (BCPS) layer was added to ensure the safe and dependable operations. However, the revised framework too lacks a holistic approach and does not include all possible elements and sub-elements.

Lu *et al.* (2019) introduced a CPPS architecture designed specifically for cloud-based manufacturing equipment. The system comprises two primary elements: smart manufacturing equipment and cyberspace. It also includes various sub-components, such as artificial intelligence, machine condition monitoring, big data analytics, service management, and remote user. The implementation facilitated the connection of manufacturing equipment to the cloud, enabling the provision of on-demand manufacturing services.

H. Zhang *et al.* (2020) introduced a digital twin-based architecture for CPPS. The system comprises of four components: the physical layer, network layer, virtual layer, and application layer. The proposed architecture facilitates the integration and sharing of manufacturing resources, enabling seamless connectivity and access to real-time synchronized data through a semantic information model.

Fang *et al.* (2020) introduced a CPPS framework for shop floor applications. The system comprises of two primary elements: the physical and cyber worlds. The physical world consists a shop floor and an edge processing layer, while the cyber world encompasses data analytics and an intelligent service layer. The implementation of the proposed framework improved production efficiency by facilitating real-time data collection, processing, and visibility on the shop floor.

Y. Zhang *et al.* (2020) introduced a CPPS framework for a CNC milling center. The system comprises of two primary components: physical and cyber components. The physical component includes CNC indicators and real-time controller indicators. The cyber components comprise a cloud database, smart process monitoring system, and analytics capabilities of descriptive, diagnostics, and predictive analytics. The proposed framework outlines the data acquisition process from shop floor equipment, storage of data in a cloud-based database, and utilization of data analytics for process monitoring. The proposed framework was implemented and achieved an accuracy of approximately 73% in predicting failures during the milling process.

Song *et al.* (2021) introduced a CPPS framework for monitoring critical components in a smart production line. The system comprises of five layers: the smart connection layer, the physics-based modelling layer, the data-driven layer, the cognition layer, and the configuration layer. The framework combined physics and data-driven modelling techniques to establish a closed-loop workflow, minimizing the risk of failures that could disrupt smart production line operations.

Liu *et al.* (2021) developed a conceptual framework for cyber-physical machine tools. The system has three primary components: the physical level, edge server, and cloud services. The physical level encompasses various components such as a machine tool, cutting tool, data acquisition device, workpiece, sensor, camera, and RFID tags. The edge server consists of three sub-elements: the machine tool digital twin, edge computing services, and modularized intelligent algorithms. The cloud services included customised manufacturing services and intelligent human-machine interaction assisted by augmented reality. The proposed framework offers a comprehensive solution for the digitalization and servitization of next-generation machine tools at the system level, assist machine tool manufacturers understand the latest advancements in digitalization and servitization of machine tools, and develop practical solutions to meet the growing customer demand for digitalization and servitization.

Harvard *et al.* (2021) proposed a factory-level architecture for CPPS to facilitate maintenance activities. The system comprises of two layers: the physical reality and its digital twin. The real world consists flexible manufacturing systems, robots and workstations, augmented reality devices, and human-machine interface devices. The utilization of databases enables human-centric tools like augmented reality and virtual reality to assist human resources in making informed decisions. The suggested architecture enhanced the factory's ability to quickly adapt and recover from disruptions, resulting in increased flexibility and agility.

Leiden *et al.* (2021) introduced a CPPS framework to enhance the efficiency of planning and operating electroplating process chains. The system comprised of five components: physical system, data acquisition, cyber system, decision support, and control. The physical system comprised a chain of electroplating processes. The data acquisition system collected product, process, production, energy, and material flow information. The cyber system utilized agent-based simulation. A decision support system was employed to evaluate the environmental and economic effects. The control system oversees chemical monitoring, dosing, and adaptive logistics. The successful implementation of CPPS in the electroplating process chain led to significant electricity and resource savings (approximately 10 %).

Ahmed *et al.* (2021) proposed a CPPS framework for resistance spot welding to provide valuable insights and support practitioners' decision-making. It comprised six components: machine layer, data layer, analysis layer, optimization layer, design layer, and machine visualization layer. This method integrates data across all phases of the analytics lifecycle, including data collection, predictive analytics, and visualization. The integrated framework aims to help decision-makers understand how product design affects manufacturing. In addition to data analytics, the proposed framework includes optimization of closed-loop machine parameter considering the desired product design. The framework simultaneously optimizes the target product assembly, predicted response, process, and material design parameters.

Müller *et al.* (2022) introduced a CPPS architecture that integrates knowledge modelling and management to facilitate self-organized reconfiguration management. The system is comprised of a physical layer and a cyber layer. The physical layer encompasses physical assets, while the cyber layer is divided into four layers: asset layer, control layer, proxy layer, and management layer.

Vogt *et al.* (2022) introduced a CPPS framework for improving the energy efficiency of HVAC systems in industrial settings. The four main elements are the physical world, data acquisition, cyber world, and feedback and control. The pragmatic implementation of the proposed framework improved the energy efficiency of the HVAC system in the production environment by considering ambient conditions, production environment conditions, and process parameters, thereby reducing the final energy demand.

Ralph *et al.* (2022) presented a framework for transforming a rolling mill into a CPPS. The system comprises of six layers: machine layer, data acquisition layer, pre-processing layer, main processing layer, programming layer, and visualization layer. The framework incorporates two front-end human-machine interfaces, the first of which is a condition monitoring system for the rolling process. The second displays the outcomes of a robust machine-learning algorithm. The proposed framework was helpful in predicting and adjusting the rolling schedule.

A review of literature reveals that many of the frameworks are tailored to specific applications and some resulting in limited adaptability in other manufacturing contexts. Although practitioners have widely adopted some of these in implementing CPPS, there is hardly any architecture or framework that provides a generic perspective from which the researchers and practitioners can pick up the relevant elements and sub-elements for their research or application. The elements and the sub-elements are not explicitly defined or listed, resulting in a narrow scope. The architectures and frameworks in literature lack a comprehensive applicability of the multidisciplinary concepts of CPPS, resembling the parable of “The Blind Men and an Elephant”. A generic CPPS framework for smart manufacturing analytics and management is still missing in the literature. Moreover, without a holistic understanding and conceptualization of all possible elements and sub-elements of a CPPS, a practitioner may face difficulty in implementing CPPS for their specific use cases. Therefore, a generic CPPS framework for smart manufacturing analytics and management with possible elements and sub-elements is highly needed in the current scenario. The present work bridges this gap by extracting possible elements and sub-elements from existing literature and proposing a generic CPPS framework for smart manufacturing analytics that is adaptable for a wide range of manufacturing applications.

3.3 A GENERIC CPPS FRAMEWORK FOR SMART MANUFACTURING ANALYTICS AND MANAGEMENT

Figure 3.1 illustrates the proposed CPPS framework for smart manufacturing analytics and management with possible elements and sub-elements. The four main components are the physical world, data acquisition system, cyber world, and smart manufacturing management system. A brief description for each of these elements and its sub elements is as follows:

3.3.1 Physical World

The physical world comprises the manufacturing module (machine and material) at unit/system/system of systems levels integrated with various physical hardware and soft resources. Hardware and software resources are necessary for enabling smart capabilities, such as automated sensing, in both wired and wireless modes. These resources also facilitate smart functionalities in the manufacturing module.

The hardware resources include retrofitting module, communication infrastructure, navigation system, logistic system, and HVAC system. The retrofitting module consists of smart sensors, controllers & actuators; computational, storage, visualization, and testing equipment, *etc.* These can be integrated either internally or externally into the machine. The communication infrastructure consists of servers, WIFI-routers, ethernet ports, wires, connectors, *etc.* The navigation system enables real-time tracking and tracing of material flows and consists of GPS devices, RFID and NFC system, *etc.* The logistics system enables transportation and handling of materials and consists of robots, AGVs conveyors, *etc.* The HVAC system consists of devices and equipment required for technical building services such as maintaining temperature, humidity, air quality, *etc.* The soft resources include software, human, and knowledge in the form of expertise, standard documents, *etc.*

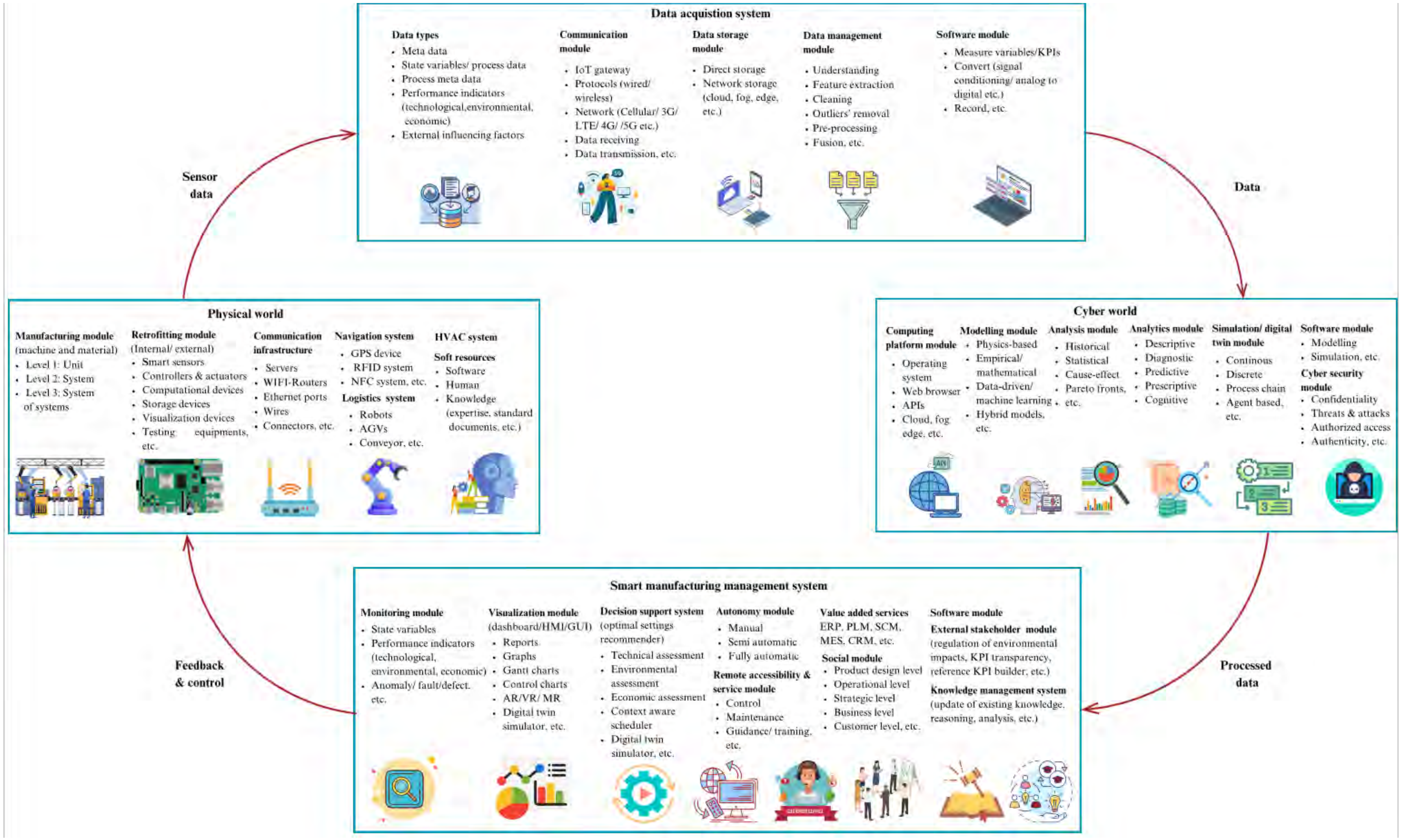


Figure 3.1 A generic CPPS framework for smart manufacturing analytics and management*

*Reproduced enlarged in appendix C

3.3.2 Data Acquisition System

The data acquisition system connects the elements of CPPS and is responsible for the automatic storage, communication, and management of various types of data, namely meta data, state variables/process data, process meta data, performance indicators (technological, environmental, economic), and external influencing factors. This is achieved using a variety of sub-elements, namely communication module, data storage module, data management module, and software module.

The communication module consists of receiving & transmitting data using IoT gateway, protocols (wired/wireless), network (cellular/3G/LTE/4G/5G, *etc.*), *etc.* The data storage module consists of acquiring data directly on a local hardware device or on a network using any of the computing platforms, such as cloud, fog, edge, *etc.* The data management module consists of understanding the data, extracting its features, and performing various tasks such as cleaning, outlier removal, pre-processing, fusion, *etc.* to make it suitable for subsequent steps. The software module consists of data acquisition software (*e.g.*, LabVIEW, DynoWare) that is responsible for measuring variables/KPIs, conditioning/converting signals from analog to digital, and recording data.

3.3.3 Cyber World

The cyber world serves as the digital brain of CPPS by performing various tasks such as computation, modelling, analysis, and analytics on data to generate meaningful information using artificial intelligence techniques. It consists of various modules, namely computing platform, modelling, analysis, analytics, simulation/digital twin, software, and cyber security modules. The computing platform module consists of the operating system, web browser, APIs, cloud, fog, edge, *etc.*, where these tasks (computations, modelling, analysis, and analytics) are carried out. The modelling module consists of various models such as physics-based, empirical/mathematical, data-driven/machine learning, hybrid, *etc.*

These are essential for establishing correlations among processed data, which enables data analytics and optimization techniques, to generate valuable insights in subsequent steps. The analysis module consists of various analyses such as historical, statistical, cause-effect, Pareto fronts, *etc.,* for a better understanding of the manufacturing process and the system. The analytics module consists of various analyses such as descriptive, diagnostic, predictive/prognostic, prescriptive, cognitive, *etc.* This facilitates basic monitoring and diagnosis, as well as advanced predictive maintenance and process automation, by identifying trends and generating valuable insights. The simulation/digital twin module enables up-to-date virtual representations of the physical world through a variety of simulation types such as continuous/discrete events, process chains, agent-based, *etc.* The software module consists of various modelling, analyses, analytics, and simulation software to carry out these tasks. Lastly, the cyber security module serves as a shield for the entire CPPS by enabling confidentiality, authorized access, authenticity, and preventing cyber threats, attacks, data loss/theft, *etc.* using a variety of security features (*e.g.*, VPN, firewall, network protection, *etc.*) and solutions (*e.g.*, anti-malware software, blockchain technology, *etc.*).

3.3.4 Smart Manufacturing Management System

The management system in the CPPS framework acts as a decision-making tool at all levels of the hierarchy, where management decisions are made based on the organizational needs and implemented in the physical world. Various sub-elements that play an essential role in its successful execution include the monitoring & visualization module, decision support system, autonomy module, remote accessibility & services module, value-added services module, social module, external stakeholders' modules, knowledge management module, and software modules.

The monitoring module is the most basic sub-element of a management system for monitoring state variables, performance indicators (including technological, environmental, and economic factors), and anomalies. It allows control decisions to be made based on predefined threshold limits for these variables & KPIs. The visualization module employs a dashboard/HMI/GUI to display data and information in an efficient and user-friendly manner using various tools and techniques, such as reports, graphs, Gantt charts, control charts, AR/VR/MR, digital twin simulators, *etc.* This allows a practitioner to quickly evaluate the status, identify bottlenecks, and guide maintenance activities or process variables based on organizational needs. The decision support system recommends optimal settings based on various assessments such as technical, environmental, economic, *etc.* It is also used for making scheduling decisions based on the context/dynamic requirements of the production. The digital twin provides decision support for evaluating the current state of actual production taking place at the unit/system/system of systems level, predicting future trends, and optimizing its activities. The remote accessibility & services module is used to provide remote access and services for controlling, maintaining the manufacturing process, and guiding or training the workforce remotely using advanced techniques, such as AR/VR/MR. The value-added services include various services, such as ERP, PLM, SCM, MES, CRM, *etc.* that are useful for managing manufacturing activities at higher hierarchical levels, such as the system of systems level, effectively and efficiently. The social module involves internal stakeholders at various levels, including product design, operations, strategy, and business levels. The external stakeholder module consists of government regulators, non-governmental organizations (NGOs), and certifiers with the goal of regulating environmental impacts, incorporating KPI transparency, and developing reference KPIs for benchmarking. The knowledge management module updates the existing system's knowledge, reasoning, and analysis based on feedback received during each iteration, thereby enhancing the CPPS's performance and robustness over time. The software module consists of various management software to carry out these tasks. Finally, the loop is closed using the autonomy module, which controls the physical world based on its level of maturity (manual/semi-automatic/fully automatic).

3.4 SUMMARY

This chapter proposes a generic CPPS framework for smart manufacturing analytics and management by developing possible elements and sub-elements from the literature. The significance lies in providing a comprehensive understanding of CPPS from a holistic perspective considering all three hierarchy levels, namely, unit, system, and system of systems. The proposed framework would provide a roadmap/guideline and higher confidence to a practitioner in implementing CPPS for a wide range of manufacturing applications, thereby enhancing the management capabilities and performances of manufacturing applications at all three hierarchy levels.

CHAPTER 4

DEVELOPMENT OF A CPPS FRAMEWORK FOR SMART 3D PRINTING ANALYTICS AND MANAGEMENT

This chapter provides a proof of concept by proposing a CPPS framework for smart 3D printing analytics and management where in a conventional 3D printer is transformed into a smart 3D printer by integrating cost-effective solutions to enable smart management capabilities of online monitoring, data acquisition, visualization, control, and analytics.

4.1 INTRODUCTION

Additive manufacturing (AM), popularly known as 3D printing, is a group of technologies used to produce an object layer by layer through material deposition directly from a computer-aided design (CAD) file. It has been widely adopted in aerospace, automobiles, energy, and healthcare industries (Z. Li *et al.*, 2019), with several advantages such as low production cost, ability to make complex geometries and shapes, reduced inventory, and faster deliveries (Ford & Despeisse, 2016). However, 3D printing is a relatively immature technology (Amores *et al.*, 2022). There are several challenges that need to be mitigated such as product quality in terms of surface integrity (Ahn *et al.*, 2009), (Z. Li *et al.*, 2019); reliability, manufacturing efficiency (Fu *et al.*, 2021); printing cost & speed; and perception that it is unsuitable for mass production (Ford & Despeisse, 2016).

In recent years, 3D printing technology has been propelled by enormous improvement in computing power, availability of low-cost sensors and IoT devices, and miniaturization (Schlaepfer & Koch, 2015). It is expected to undergo rapid transformation using Industry 4.0 technologies, such as CPPS, artificial intelligence (AI), IoT, data mining, and computing technologies. These technologies can contribute to more autonomous and reliable 3D printing systems (Castillo *et al.*, 2022). It can facilitate affordable and efficient energy monitoring systems (Syafrudin *et al.*, 2018), where value-added and non-value-added energy stages can be identified to take corrective action in an Industry 4.0 environment.

There is an enormous potential and scope for implementing CPPS to achieve smart 3D printing systems. It can facilitate online monitoring, visualization, control, and analytics in a smart manufacturing system and enhances the potential of conventional 3D Printers. CPPS has made the availability of sensor data much easier and accessible that can be further analyzed using data analytics techniques for monitoring the condition, predicting, optimizing, and controlling a physical process, thereby significantly improving production efficiency and flexibility (Ding *et al.*, 2019), and allowing interconnected machines to operate effectively, cooperatively, and resiliently (J. Lee *et al.*, 2015).

Rapid digitalization of manufacturing systems has led to the availability of huge data. This data needs to be stored, processed, and analyzed in the cyber world, and sent back to the physical world with varying requirements of latency, bandwidth, security, *etc.* The three computing technologies, namely cloud, fog, and edge, enable the fusion and establishment of the closed loop between the physical and cyber worlds to complement and meet the specific requirements of latency, bandwidth, security, *etc.* (Qi *et al.,* 2018; Shi *et al.*, 2016). Therefore, engineering needs arise to utilize these computing technologies where they do not compete, but instead complement each other to enable intelligent capabilities like online sharing of resources with real-time monitoring, visualization, and control in a traditional 3D printer.

Descriptive analytics is the simplest form of data analytics, which analyses current/historical data to identify trends and relationships between variables and converts them into meaningful information to answer questions about what is happening/has happened using statistical/machine learning modelling techniques (UNSW, 2020). It facilitates the development of smart and energy efficient monitoring systems by providing a comprehensive understanding of the energy consumption pattern for a manufacturing system (Sihag *et al.*, 2018). There have been hardly any attempts to develop algorithms for the identification of process state in the case of FDM 3D printing process. Therefore, the present research develops a machine learning algorithm for characterization, as well as estimation of energy consumption at various stages during a 3D printing process. The proposed algorithm identifies the value-added energy (printing stage), non-value-added energy (standby stage), and non-value added but necessary energy (pre-heating stage).

Life cycle assessment (LCA) has become an important tool to identify, evaluate and assess the environmental impacts of a product, process, or system, along all the stages of product life cycle. However, several drawbacks such as complexity, uncertainty and impreciseness are also associated with this methodology. On the other hand, live LCA as a plausible solution, is gaining popularity with the advancements in Industry 4.0 tools and techniques, enhancing ability to collect and analyse live data from various processes, interpret results, identify hotspots, trade-offs, and present better ideas about the environmental impacts in-line with the process. Descriptive analytics facilitates the live estimation of environmental impacts. Therefore, the present research develops a computational model for live estimation of environmental impacts, in which real-time process data is acquired, processed, analyzed, visualized, and interpreted to calculate the environmental impacts for 3D printed products.

Prognostic analytics proactively predicts the remaining useful life (RUL) of a component before its failure using model-based, data-driven, and hybrid methods (Ferreira & Gonçalves, 2022). It has become a requirement for today's smart machines to increase productivity, maintain surface quality, prevent surface damage (Traini *et al.*, 2021), reduce machining and maintenance costs (Aramesh *et al.*, 2016), proactively schedule maintenance activities, efficiently manage assets, prevent failures and breakdowns (Moghaddass & Zuo, 2014), and better operational reliability and safety of the manufacturing system (Sun *et al.*, 2012). The nozzle in a 3D printer is one of the most wear-prone components as it is continuously subjected to stress during the material extrusion process. The side-effects of nozzle wear include the loss of print quality and the time-consuming adjustment of the nozzle clearance to the print bed to compensate for (Gühring, 2022). Prognostic analytics (RUL prediction) is one of the latest research topics for enhancing overall equipment effectiveness, reliability, maintainability, and product quality, particularly in machine tool, aerospace, and automotive industries. Researchers have developed machine learning algorithms for predicting performance measures of 3D printing. Machine learning models have been used for optimizing printing parameters, monitoring process, and detecting defects. This supports practitioners in premanufacturing planning (CAD design of parts), process parameter modelling, and quality inspection & assessment (Wang *et al.*, 2020; Xames *et al.*, 2022).

Prescriptive analytics aims to provide actionable recommendations for managerial decision-making and improve processes through optimization (Ansari *et al.*, 2019b). Methods for prescriptive analytics are generally classified into six categories, namely probabilistic models, machine learning/data mining, mathematical programming, evolutionary computation, simulation, and logic-based models (Lepenioti *et al.*, 2020). It can assist operations to improve the identification of existing correlations between parameters and outliers and optimize the process parameters. Therefore, a practitioner is facilitated to improve the design and change the parameters based on the management requirements (Ahmed *et al.*, 2021). A few researchers have implemented prescriptive analytics based on the CPPS framework for resistance spot welding (Ahmed *et al.*, 2021), weaving process (Saggiomo *et al.*, 2016), and milling process (Pantazis *et al.*, 2023).

Long-term use of a 3D printer can also cause anomalies, such as the loosening of connected components, screws, and belt slippage, which cause abnormal vibrations that affect product quality and lead to the failure of 3D printer components (Yen & Chuang, 2022). FDM is a widely used 3D printing technique for producing functional products due to its ability to fabricate intricate and precise parts (Sandanamsamy *et al.*, 2022). However, the FDM process is less reliable, with a failure rate of approximately 20% due to challenges like material runout, nozzle clogging, excessive vibration, under-extrusion, over-extrusion, and abnormal temperature (Fu *et al.*, 2021). Diagnostic analytics enables robust closed-loop process control for increased process efficiency (Fu *et al.*, 2021), lower failure rates, greater precision, and assured quality of the printed parts (Khusheef *et al.*, 2022). Anomaly detection is beneficial for managing machines and their components in a manufacturing environment (Kammerer *et al.*, 2019). An alert to pause or halt the printing process, upon the detection of an anomaly during the early stages of 3D printing is extremely important. This can avoid reprinting of the parts thereby saving material & time (Delli & Chang, 2018). This also improves customer confidence in the printed products and decreases rejection costs (Oleff *et al.*, 2021).

Conventional 3D printers sold in market are deprived of smart functionalities such as data acquisition, connectedness, smart decision making, intelligence, responsiveness towards internal and external changes, real-time monitoring, and control of state variables and performance measures. Implementation of CPPS in 3D printing can be instrumental to facilitate real-time online monitoring, visualization, decision support, planning, and control of the printing process, printer health, and RUL to improve quality, reliability, and performance. This chapter aims to propose a CPPS framework for smart 3D printing analytics and management. This is accomplished by incorporating the following:

- Transformation of a conventional 3D printer into a smart 3D printer using low-cost smart sensors, devices, and open-source software.
- Development of a CPPS framework for smart 3D printing analytics and management based on data-driven analytics techniques and computing technologies, namely, cloud, fog, and edge for real-time online monitoring, visualization, and control.
- Development of a machine vision-based defect detection algorithm to monitor, identify, and control defects during 3D printing process, resulting in less wastage of filament materials.
- Development of machine learning algorithms for live demonstration of energy consumption during printing stages (descriptive analytics).
- Development of computational model for live estimation of environmental impacts for 3D printed products (descriptive analytics).
- Development of a machine learning algorithm to predict the RUL of a 3D printer nozzle (prognostic analytics).
- Development of regression models using analysis of variables (ANOVA) to prescribe optimum printing parameters for minimizing carbon footprint and printing time at the targeted surface quality (prescriptive analytics).
- Development and comparison of machine-learning algorithms for anomaly detection in 3D printing using vibration data (diagnostic analytics).
- Development of smart management system for real-time monitoring, visualization and control using user-guided dashboards, decision support, feedback, and control.

This chapter is organized as follows: Section 4.2 presents the research background, outlines significant contributions, compares existing literature, and identifies research gaps. Section 4.3 presents the research methodology and proposes a CPPS framework for smart 3D printing analytics and management. Sections 4.4, 4.5, and 4.6 discuss the experimental planning, physical world, and data acquisition system, respectively. Section 4.7 discusses the cyber world through the development of machine learning and computational algorithms for executing different types of analytics, including descriptive, prognostic, prescriptive, and diagnostic analytics. Section 4.8 discusses the smart 3D printer management system based on monitoring, visualization, decision support, remote services, feedback, and control. Section 4.9 discusses the cost effectiveness analysis. Finally, Section 4.10 summarizes the chapter and highlights the major contribution of the present work.

4.2 BACKGROUND

This section provides a background of computing technologies and the analytics techniques used in this chapter.

4.2.1 Cloud, Fog, and Edge Computing Technologies

Verl *et al.* (2013) developed a cloud computing-based concept for controlling machine tools and demonstrated two decisive advantages of cloud computing technology for machine tool applications: one, it is possible to scale the performance of the machine tools; two, flexibility of the production is considerably increased because of centralized software interface. Coupek *et al.* (2016) connected the manufacturing and assembly processes with cloud computing, which offered more storage space and processing power than machine tool numerical controls, to improve product quality, decrease scrap, and save energy and raw material. Patel *et al.* (2017) outlined fog computing as an intelligent approach for IoT analytics that automated edge-to-cloud transitions and enabled the design of powerful sensing/actuating devices to perform a few computation tasks at the device or gateway level. Wu *et al.* (2017b) presented a data-driven process monitoring, and prognosis of machine health framework based on fog computing. A proof of concept was demonstrated to justify the capabilities and feasibility of fog computing technology to predict tool wear and schedule maintenance activities (Wu *et al.*, 2017b). Zhou *et al.* (2018) presented a fog computing-based architecture for cyber physical machine tool for a CNC machine tool and demonstrated that the application of fog computing improves autonomy, interconnection, intelligence, and interoperability. Zheng *et al.* (2018) reviewed smart manufacturing systems for Industry 4.0 and proposed a cloud-based smart control system for machine tools which allows servitization of machine control, implementation of complex algorithms and increase in flexibility, while highlighting cyber security and service availability as significant limitations. Hsu *et al.* (2018) developed a cloud-based advanced planning and scheduling system with real-time visualization of the analyzed data. The implementation at a manufacturing company demonstrated the effectiveness of cloud computing in enhancing planning quality with minimal implementation and maintenance costs. Omar *et al.* (2019) proposed a fog computing implementation architecture for manual and automatic workstations, mobile robots, robotic arms, and additive manufacturing systems. It was found that fog computing improved system latency, scalability, and interoperability. Lu & Xu (2019) proposed a cloud-based generic architecture and demonstrated the proposed architecture's ability to transform legacy production systems into cloud-based CPPS for enabling on-demand manufacturing services, which allowed manufacturing companies to share resources and knowledge with clients. Beregi *et al.* (2019) proposed a fluid CPPS architecture combining the cloud, fog and edge computing with mist and dew computing to provide the right data at the right location, speed, frequency, and quantity; which streamlined the data flow and accelerated the system communication. The implementation of the proposed architecture with the five computing technologies demonstrated the improvements in latency, data propagation and resource replication. Um *et al.* (2020) proposed an architecture for smart production based on edge computing. The pre-processed data from an augmented reality device was presented to update production lines and human-machine interaction to address cloud latency and dependability issues, to help maintain connections and fulfil requests in the event of network problems, and to improve quality of service. Yin *et al.* (2020) proposed an edge computing-based framework and demonstrated, through the implementation in a textile industry, the capability of edge computing to decrease latency and enhance production efficiency by effectively dealing with the dynamic disturbances of yarn breakage, machine failure, and yarn quality. Liu *et al.* (2021) integrated edge and cloud computing technologies to develop a conceptual framework of cyber physical machine tools. The databases and intelligent algorithms were hosted at edge server to enable users to configure/integrate edge computing as custom manufacturing services. The error compensation, process optimization, modelling & simulation, and value-added services were hosted as cloud services. Cui *et al.* (2022) proposed and implemented a cloud-based system architecture to create smart 3D printing cloud networks, which permitted the virtualization of the resources and capabilities into a shared pool, allowing users to obtain on-demand cloud services. Denker *et al.* (2022) utilized edge computing to monitor and control the temperature of a production line in a foundry facility. The analytical capabilities of the edge components avoided high-volume data transfers, thereby reducing latency for the real-time control.

Literature on computing technologies in manufacturing domain is shown in Table 4.1. The literature shows that most of the researchers have used cloud computing; a few have used either fog or edge computing; and even one researcher has used cloud, fog, edge, mist, and dew technologies.

Table 4.1 Literature on computing technologies in manufacturing domain

Author	**Application(s)**	**Engineering need(s)**	**Computing technologies(s)**
Verl *et al.* (2013)	Machine tool	Scalability and adaptability for dynamic requirements	Cloud
Coupek *et al.* (2016)	Production process	Large storage space and high processing power	Cloud
Patel *et al.* (2017)	--	Powerful sensing/actuating devices to perform computation tasks at reduced latency	Fog
Wu *et al.* (2017)	Power plant and CNC machines	Real-time sensing, monitoring, and scalable high-performance computing for diagnosis and prognosis applications	Fog
Zhou *et al.* (2018)	Machine tool	Accessibility of CNC machine tools with a higher degree of intelligence.	Fog
Zheng *et al.* (2018)	Machine tool	Servitization of machine control and increased flexibility	Cloud
Hsu *et al.* (2018)	Metal manufacturing company	Dynamic production and operations schedules and real-time visualization of data for production planning	Cloud
Qi *et al.* (2018)	--	Conceptual framework to demonstrate the complementary nature of cloud, fog and edge technologies at unit level, system level and system-of-system level	Cloud, fog, edge
Omar *et al.* (2019)	Laboratory demonstrator	Interoperability and scalability of the laboratory demonstrator	Fog
Lu & Xu (2019)	Light gauge steel framing production	On-demand manufacturing services, sharing resources and knowledge with clients	Cloud
Beregi *et al.* (2019)	Pilot factory	Right data at the right location, frequency, and quantity for decreased latency, faster decisions, and optimal data distribution	Cloud, fog, edge, mist, dew
Um *et al.* (2020)	Augmented reality device	Address network issues, cloud latency and dependability, and enhance quality of service	Fog
Yin *et al.* (2020)	Textile industry	Decrease real-time task processing latency and defect detection	Edge
Liu *et al.* (2021)	Machine tool	Hosts databases and intelligent algorithms to execute intelligent computing tasks and provide custom cloud services	Cloud, edge
Cui *et al.* (2022)	3D printing	Virtualization of 3D printing resources for on-demand sharing	Cloud
Denker *et al.* (2022)	Foundry production line	Real-time monitor and control of the temperature	Edge

The review also shows that the fog and edge technologies have been used for real-time task processing (Yin *et al.*, 2020), real-time control (Denker *et al.*, 2022), real-time defect detection (Yin *et al.*, 2020), and latency & service quality improvement in general (Patel *et al.*, 2017; Um *et al.*, 2020; Beregi *et al.*, 2019). Cloud computing has been used for the improvement of scalability (Verl *et al.*, 2013), large storage and faster processing (Coupek *et al.*, 2016), and for improved visualization, servitization, resource sharing, *etc.* (Cui *et al.*, 2022; Y. Lu & Xu, 2019; Zheng *et al.*, 2018).

These three computing technologies do not compete, rather complement each other. Each of these technologies has their own benefits and limitations. However, these key technologies are implemented separately, with fewer attempts to integrate all the three key technologies to complement each other. Only Qi *et al.* (2018) proposed a model for implementing cyber physical systems and digital twin for smart manufacturing using cloud, fog, and edge computing. However, a detailed methodology for implementation using a proof of concept on how to manage enormous amount of data generated and combine relative benefits of each one of these technologies is still missing in the literature.

The present work utilizes the computing technologies where they do not compete, but instead complement each other to enable intelligent capabilities and online sharing of resources which are scalable, reliable, and efficient. Cloud computing has been used to facilitate data storage, processing, monitoring, visualization, and analytics for temperature, humidity, and energy consumption, as these variables require high storage volumes, remote and easy accessibility, scalability, and redundancy. Fog computing facilitates local data storage, processing, analytics, monitoring, and control of volatile organic compounds, accelerations, and particulate matters, which also require online control, but the response will be after analyzing the data and need not be immediate. Edge computing facilitates automatic defect detection, filament runout, filament breakage, and smoke at its source, as these parameters require faster insights, very low latency, autonomous and prompt decision-making, and instant actuation without demanding resource-intensive processing and higher storage. A machine vision-based defect detection algorithm is developed to monitor, identify, and control defects during the 3D printing process, resulting in less wastage of filament materials.

The novelty of the present work lies in providing a CPPS framework for online monitoring, visualization, and control using cloud, fog, and edge computing technologies for proper management and efficient utilization of data in terms of latency, bandwidth, and security.

4.2.2 Descriptive Analytics of 3D Printing

4.2.2.1 Characterization and energy distribution in printing stages

There is a growing interest among researchers to automatically identify the process states using machine learning algorithms for machine tools (Sihag *et al.*, 2018; Petruschke *et al.*, 2021) injection molding (Pang *et al.*, 2011), selective laser melting (Z. Lu *et al.*, 2018). Sihag *et al.* (2018) developed a structured algorithm using KNN and PCA to identify the status of a machine tool in various operational states to improve both energy and time efficiencies. Similarly, Petruschke *et. al.* (2021) developed machine learning algorithms using both CNN and LSTM to automatically identify energy states of metal cutting machine tools based on the load profiles. LSTM architecture achieved a slightly better test accuracy as compared to convolutional neural networks. Pang *et al.* (2011) developed an algorithm to automatically identify the process states of an industrial injection molding machine using integrated Savizky-Golay filter and a neural network. Lu *et al.* (2018) developed an algorithm using Savizky-Golay filter and extremum slope of regression lines to automatically identify the process states (idle, prepare, powder-coating, laser-scanning, finish) for a selective laser melting based on power data.

The present work proposes a machine learning algorithm that identifies the value-added energy (printing stage), non-value-added energy (standby stage), and non-value added but necessary energy (pre-heating stage). The novelty of this work lies in enabling users to identify the non-value adding stage and the corresponding energy consumption to take corrective measures.

4.2.2.2 Live LCA implementation in 3D printing

Cerdas *et al.* (2017) proposed a framework integrating LCA methodology with the shop floor to automate data collection and enable visibility of environmental impacts on the shop floor. The real-time data obtained from the shop floor is transformed into life cycle inventories using discrete event simulation modeling. Using appropriate simulation techniques, the results are generated and visualized. The manufacturing systems are monitored using this framework that allows decision making for efficient use of energy and resources. Fang *et al.* (2020) explored the utilization of data analytics in achieving production visibility through the implementation of CPPS. The framework developed is then verified using a demonstrative case and it has been noted that some uncertainties arise because the production environment has not been factored in the proposed approach. Ding *et al.* (2021) proposed a production monitoring system combining product service systems, CPPS, and cloud-edge orchestration technologies This would allow the customer to be involved in the manufacturing phase and thereby catering to personalized customizations by providing flexibility and transparency with a business model and a framework developed along with production monitoring and energy monitoring systems which were verified using a case study.

Majority of the researchers have focussed mainly on life cycle assessment to identify and assess the environmental impact of manufacturing along with all the stages of the product life cycle. However, several drawbacks such as complexity, uncertainty and impreciseness are also associated with it. There has been limited research on implementation of live LCA using CPPS for 3D printed products to collect and analyse live data from various processes, interpret results, and present better ideas about the environmental impacts.

The novelty of the present work is that live LCA has been implemented on the 3D printing process based on the proposed CPPS framework. Environmental impacts such as GWP are calculated in-line with production and visualized depending on the energy and material consumption values assisting the operators in real-time monitoring of the environmental impact, assisting the operator to act based on the visibility and decision-making process. Also, the proposed methodology helps the customers to proactively decide which product best aligns with their sustainably conscious needs. This could also result judicial pricing of the sustainable products at a higher price by the companies.

4.2.3 Prognostic Analytics of 3D Printing

Advances in Industry 4.0 technologies, particularly the accessibility of advanced and affordable sensors, microcontrollers, processors, data acquisition systems, and better modelling techniques, have accelerated research into predicting 3D printing variables (Nam *et al.*, 2020). Z. Li *et al.* (2019) proposed an ensemble-based machine learning algorithm to predict the surface roughness of parts using temperature and vibration data in 3D printing. Nam *et al.* (2020) proposed a support vector machine (SVM) algorithm to monitor health and diagnose faults due to uneven levelling of the bed during 3D printing. Sampedro *et al.* (2021) proposed a long short-term memory (LSTM) machine learning algorithm to monitor and predict the temperature of the extruder and bed used in a 3D printer, thereby preventing defects and rejections. Z. Jin *et al.* (2020) proposed a deep learning algorithm to predict the onset of warping, thereby significantly reducing the warpage and twisting of layers in 3D printing. J. Li *et al.* (2018) proposed a hybrid algorithm to predict the thermal field in each layer during 3D printing. Integration of physics-based 3D finite element analysis thermal model with the data-driven surrogate model provided accurate and fast prediction.

The literature review reveals that prognostic analytics (RUL prediction) of either component (*e.g.,* nozzle life) or the 3D printer system itself has been hardly performed and remains largely an unexplored topic in the 3D printing domain.

4.2.4 Prescriptive Analytics of 3D Printing

Zhao *et al.* (2018) implemented CPPS in a photopolymer 3D printing process to get a real-time accurate estimation and control of cured height profiles. Wiese *et al.* (2021) implemented a CPPS, using an agent-based process simulation model, to develop an energy value stream map to support decision-making in the planning of different process chains. Elhoone *et al.* (2020) proposed a CPS framework for the dynamic identification of 3D printers and the allocation of digital designs for 3D printing. An ANN based expert system was modelled to predict optimal part designs. Implementation of the proposed framework resulted in improved resource utilization.

There is hardly any literature on prescriptive analytics based on the 3D printing CPPS framework. A few researchers have presented prescriptive analytics based on the CPPS framework in other manufacturing domains such as resistance spot welding (Ahmed *et al.*, 2021), weaving process (Saggiomo *et al.*, 2016), and milling process (Pantazis *et al.*, 2023).

4.2.5 Diagnostic Analytics of 3D Printing

In recent years, researchers have proposed several ML algorithms for monitoring and detecting anomalies such as process abnormalities, geometrical defects of parts, structural faults, *etc.* Paraskevoudis *et al.* (2020) proposed a deep convolutional neural network (CNN) algorithm for detecting stringing defects, using the real-time acquisition of 3D printing images, with high classification accuracy and speed. Its deployment in a live environment allowed the printing process to be terminated or parameters adjusted if any stringing defect was detected. Khan *et al.* (2021) also proposed a deep CNN algorithm that uses image processing of acquired images and computer vision to detect geometric distortions of the infill patterns caused by inconsistent extrusion, improper infills, lack of support, or sagging. Khusheef *et al.* (2022) proposed an LSTM algorithm to detect anomalies using acquired images with an accuracy of 99.85% and a detection time of sub-milliseconds, making it suitable for real-time process monitoring. Delli *et al.* (2018) proposed a support vector machine (SVM) algorithm to automatically evaluate 3D-printed products and detect filament runout and structural or geometrical flaws using acquired top-view images. However, disadvantages include the need to pause printing to capture images of a partially completed part and the inability to detect defects on the vertical plane. Chen *et al.* (2019) proposed a vision-based system using acquired images to detect and classify anomalies during 3D printing process with an accuracy of around 68.88%. The primary disadvantage of this setup is that the printing process must be halted for the raspberry pi camera to capture a full-view image of the top layer of the 3D print.

Y. Li *et al.* (2019) used vibration data and a back-propagation neural network (BPNN) algorithm to monitor and diagnose quality defects of warpage and material stack with an accuracy of more than 95%. Becker *et al.* (2020) proposed an LSTM algorithm to detect different states of a 3D printing process using acoustic signals. However, the algorithm was unable to differentiate between fan noise and improper nozzle height. Rao *et al.* (2015) proposed a Bayesian nonparametric analysis algorithm that employed heterogeneous sensor data from accelerometers, temperature sensors, and video borescope to detect anomalies and facilitate the correction of process drifts in real-time. Mishra *et al.* (2022) proposed an artificial neural network (ANN) algorithm for 3D printing to identify states of normal extrusion, blocked nozzle, semi-blocked nozzle, material runout, and filament loading/unloading using vibration signals.

Literature review reveals that anomaly detection using acquired images has numerous benefits, including real-time monitoring, inspection, and quality control. However, there are challenges, such as pausing the print to capture images, the inability to detect defects on the vertical plane, and the requirement of a camera with higher resolution, which limit its productivity, reliability, and economics. Anomaly detection using acquired signals of vibration, temperature, and acoustic provides insight into the process abnormalities and condition of the 3D printing and possesses advantages of real-time monitoring, analytics, visualization, and control without pausing the print. Vibration monitoring is an effective tool because it provides insight into the machine's condition (Mishra *et al.*, 2022). A literature review carried out by Fu *et al.* (2021) on online monitoring of a FDM 3D printing process emphasized the need for detecting anomalies due to structural faults that restrict the functionality of a component during 3D printing.

Most of the researchers identified the anomalies in the printed product. Only a few studies identified the anomalies in the printer causing the defective products. Y. Li *et al.* (2019) proposed least squares support vector machine (LS-SVM) algorithm to detect printer anomaly but only to detect the filament jam. Yen *et al.* (2022) proposed a neural network algorithm for detecting anomalies in the printer using vibration data. Yen *et al.* (2022) also proposed an integrated human-machine interface design using LabVIEW to achieve real-time fault diagnosis and control of a 3D printer. However, the accuracy of anomaly detection was relatively low (approximately 83.5%).

The present work proposes four ML algorithms – two supervised and two unsupervised – to evaluate and compare their application for anomaly detection in a 3D printer. The proposed research is a step in the forward direction to make it possible to integrate a simple 3D printer in an Industry 4.0 environment with low-cost sensors for real-time monitoring, fault detection, and control. Anomaly detection at source with higher accuracy would increase applicability under Industry 4.0 environment, which would be a significant step towards error-free 3D printing, resulting in lesser material wastage and improved product quality. Moreover, the low-cost anomaly detection system can assist MSMEs in realizing the Industry 4.0 benefits of increased productivity, reliability, and product quality at a reasonable cost.

4.3 RESEARCH METHODOLOGY

The research methodology used in this research is shown in Figure 4.1. It comprises four fundamental components of a CPPS: the physical world, data acquisition system, the cyber world, and the smart management system. In addition to these four fundamental elements, experimental planning is also added.

The first step in the research methodology is to plan the experiments through the proper selection of experimental equipment, filament materials, sensors & devices, printing parameters and their levels, and responses/performance characteristics. The experiments are then designed using Taguchi L27 orthogonal array, which provides a robust design for acquiring a wide range of data with fewer experiments and lower costs. The second step is to set up the physical world through the integration of hardware and software with the 3D printer. In the third step, experiments were performed to acquire state variables and

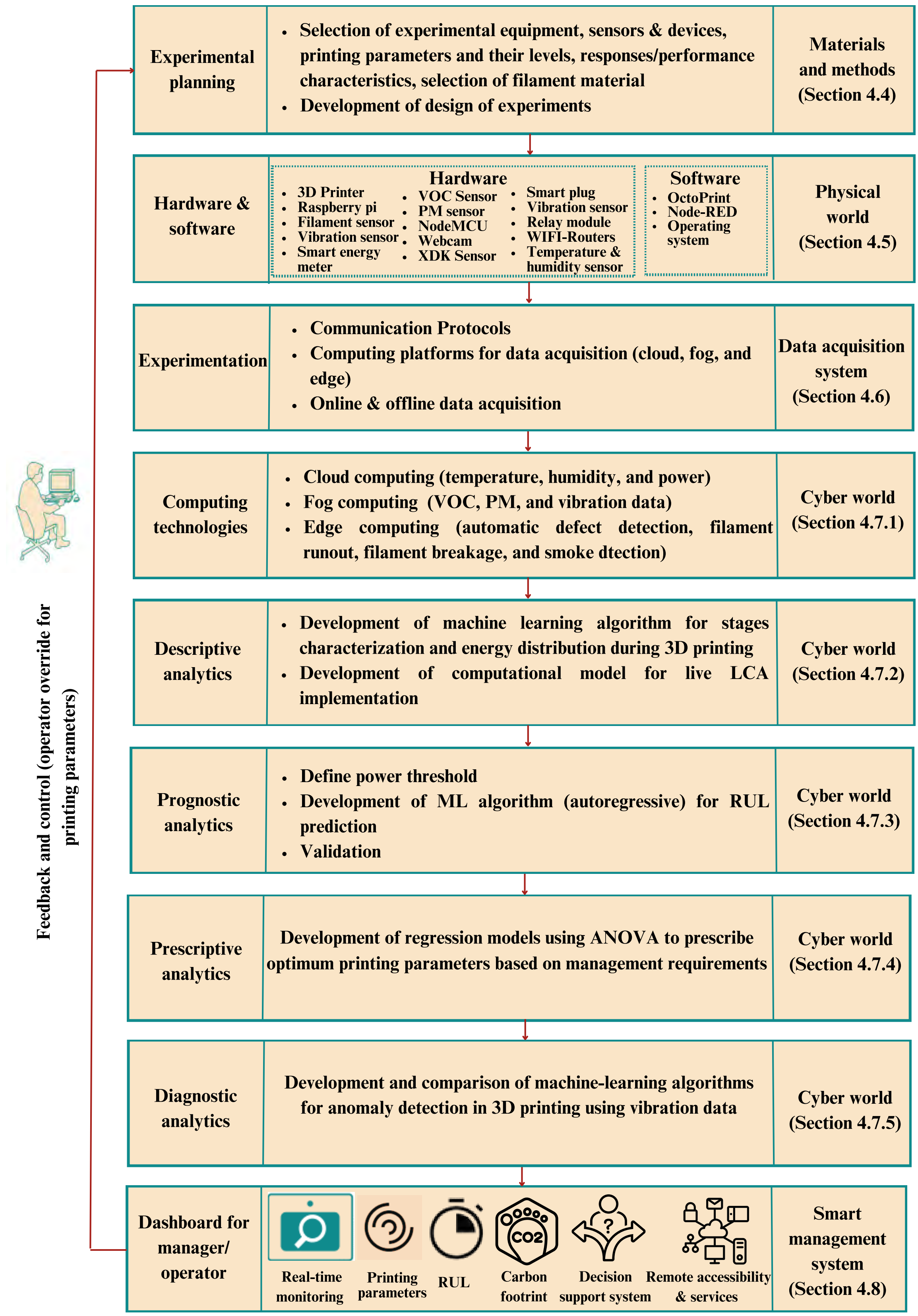


Figure 4.1 Proposed CPPS framework for 3D printing analytics

performance measures. Data transmissions are carried out using suitable communication protocols. The data is stored either directly on the local hardware device or on the network using computing technologies, namely cloud, fog, and edge. Data acquisition takes place in both modes i.e., online as well as offline. Data is then preprocessed, and features are extracted to make it suitable for better understanding and processing in the subsequent steps. The fourth steps show the development of cyber world, where various computing technologies, namely cloud, fog, and edge are used for data processing and analytics. The fifth to eight steps shows the development of cyber world where data are processed into meaning information for generating descriptive, prognostic, prescriptive, and diagnostic analyses using various modelling techniques such as machine learning algorithms and mathematical models. The ninth step shows the development of a smart 3D printer management system where various dashboards, such as live monitoring of the printing process, parameters, state variables, and performance measures are developed for supporting decisions on control actions to be taken by an operator depending on the organizational needs.

4.4 EXPERIMENTAL PLANNING (MATERIALS AND METHODS)

This section discusses the experimental planning in each sub section that involves proper selection of experimental equipment, sensors & devices, printing parameters and their levels, and responses/performance characteristics; selection of filament material; and development of design of experiments.

4.4.1 Experimental Equipment/Methods

A Prusa i3MK3S fused deposition modelling (FDM) 3D printer was used to print parts. Several alternative brands and models are available in the market like MakerBot Replicator, Ultimaker, Anycubic i3 Mega, Matterhackers Pulse, *etc.* The reason for selecting Prusa i3MK3S was its availability at our facility center. However, the proposed CPPS framework for 3D printing analytics is general, which is applicable and transferable to all the FDM 3D printers, irrespective of brand and size.

Various thermoplastic materials such as PLA, ABS, PETG, and polycarbonate are selected as filament materials based on the research requirements. Before the experiments were conducted, potential impact parameters, according to the experience obtained through pilot experiments for the responses on the Prusa i3MK3S 3D printer were analyzed. Pilot experiments were performed to correlate the effects of nozzle diameter on energy consumption. Two identical parts were printed using 0.4 mm and 0.5 mm nozzle diameters with the same settings. There was an increase of approximately 14.3 % in energy consumption using a 0.5 mm nozzle diameter. This increase can be attributed to the extra heat required to melt the filament material. According to the information provided by a 3D printer manufacturer company, a larger nozzle lays down a wider perimeter (PRUSA, 2018). This can also be interpreted as larger nozzle diameter leads to higher flow rate. Therefore, more filaments must be melted in a shorter time, and this is only possible with more power consumption (Gühring, 2022) However, detailed mathematical and physical justifications are beyond the scope of the present work.

In the present work, five printing parameters, namely infill percentage, layer height, extruder temperature, bed temperature, and scale/size were selected to study the influence on specific carbon footprint, print time, and surface quality. The product volume at 100% scale is 14286 mm^3 for the 3D printed product. Printing parameters were selected based on the review of the relevant literature. These parameters were found to have varying effects on the performance characteristics under consideration, namely specific carbon footprint, surface roughness, and printing time. The term infill as a process parameter refers to the density of the internal structure of the 3D printed product. According to Griffiths *et al.* (2016) a decrease in infill results in a reduction in printing time, part weight, and energy consumption. Layer height has a substantial impact on the product quality and surface finish (Ayrilmis, 2018; Poonia *et al.*, 2023). Increasing layer height, on the other hand, increases print height, thereby decreasing printing time and decreasing energy consumption (Ayrilmis, 2018). The bed temperature and extruder temperature parameters exhibit a direct correlation with energy consumption or specific carbon footprint. This is due to the continuous heating of the bed and extruder, which is necessary to ensure firm attachment of the printed product to the build platform and the continuous melting of the filament, respectively (Yang & Liu, 2020). Likewise, an increase in scale or part size leads to a reduction in specific energy consumption (Yi *et al.*, 2020).

Each parameter has three levels. The determination of levels was based on literature review, 3D printer manufacturer's recommendations, slicer software (Prusa Slicer), and the preliminary experimental trials. Literature provides recommendations for determining the levels of different process parameters. Researcher have varied the LH from 0.1 – 0.4 mm in literature [0.15 – 0.4 mm (Griffiths *et al.*, 2016); 0.1 – 0.3 mm (Poonia *et al.*, 2023); 0.1 – 0.2 mm (Yi *et al.*, 2020); 0.15 – 0.25 mm (Pérez *et al.*, 2018); 0.1 – 0.2 mm (Junwen *et al.*, 2019); 0.1 – 0.3 mm (Abas *et al.*, 2022); 0.1 – 0.3 mm (Kechagias *et al.*, 2023)]. The infill percentage is determined by the product's functionality and has a substantial effect on the product's weight and printing time (Griffiths *et al.*, 2016). Infill has been varied from 10 – 100% [60 – 100% (Griffiths *et al.*, 2016); 10 – 50% (Poonia *et al.*, 2023); 20 – 50% (Abas *et al.*, 2022); 80 – 100% (Kechagias *et al.*, 2023)]. Extruder temperature has been varied from 185 – 250°C [190 – 250°C (Poonia *et al.*, 2023); 195 – 225°C (Pérez *et al.*, 2018); 185 – 195°C (Junwen *et al.*, 2019); 190 – 220°C (Abas *et al.*, 2022); 195 – 215°C (Kechagias *et al.*, 2023)]. Bed temperature has been varied from 40 – 90°C [60 – 70°C (Junwen *et al.*, 2019); 70 – 90°C (Abas *et al.*, 2022); 45 – 60°C (Thumsorn *et al.*, 2022); 40 – 60°C (Kechagias *et al.*, 2023)]. The scale of the product depends on the physical limitation of the printer and the objective of the printing. It has been varied from 60 –120% [90 – 110% (Poonia *et al.*, 2023); 60 –120% (Yi *et al.*, 2020)]. The selected level values also lie within the acceptable range as specified on the manufacturer's website

(PRUSA, 2023). The levels also depend on the type of filament material being printed. In the present work, PLA as a filament material is used for which some recommendations are provided on the manufacturer's website (*e.g.*, extruder temperature of 215 ± 15 °C, bed temperature of 60 ± 10°C) (PLA, 2023). Experimental factors and levels are presented in Table 4.2.

Table 4.2 3D printing parameters and their levels based on Taguchi L27 orthogonal array

Parameters	**Symbols**	**Units**	**Levels**		
			Level 1	**Level 2**	**Level 3**
Infill	Infill	%	10	20	30
Layer Height	LH	mm	0.10	0.20	0.30
Extruder Temperature	ET	°C	200	215	230
Bed Temperature	BT	°C	50	60	70
Scale	Scale	%	50	100	150

4.4.2. Design of Experiments

Taguchi L27 orthogonal array has been selected for the design of the experiments. The Taguchi L27 design is a robust design of experiment technique to reduce variation in a process during experimentation (Bilga *et al.*, 2016). It uses orthogonal arrays to vary the process parameters affecting the responses (performance characteristics). An optimal and robust design is achieved through the exploration of a design that yields consistent performance despite the presence of noise factors (Y. Li & Zhu, 2019). The advantages of Taguchi L27 are enhanced process execution with the least number of experimental runs. This significantly reduces costs, material consumption, and experimentation time (Bilga *et al.*, 2016; Y. Li & Zhu, 2019). The disadvantage of the Taguchi method lies in its assumption that the sensitivity measures and process variances are constant and independent of control factor settings. However, noise factors may be uncontrollable or difficult to reduce, resulting in suboptimal solutions, information loss, efficiency loss, and decreased flexibility. Despite these drawbacks, the Taguchi method is widely used due to its simplicity, ease of understanding and application, and less prerequisite of statistical and mathematical knowledge (Tsui, 1996).

4.5 PHYSICAL WORLD (HARDWARE AND SOFTWARE USED)

The physical world is a manufacturing system performing the assigned task physically (Thiede *et al.*, 2016). Figure 4.2 illustrates the physical world where the Prusa MK3S 3D Printer is integrated with a low-cost sensor network for acquiring state variables and performance measures. The printer is enclosed in a chamber whose parameters can be controlled using open-source printer management software (*e.g.*, OctoPrint). Raspberry pi is used to integrate sensor, devices, and actuators with the 3D printer system to enable Wi-Fi connection, and to host OctoPrint, running locally on the web server for real-time monitoring and control. Table 4.3 lists the components of the proposed 3D printer CPPS (sensors/devices/actuators/software) with their technical specifications, applications, communication protocol, and data platform used with the 3D Printer.

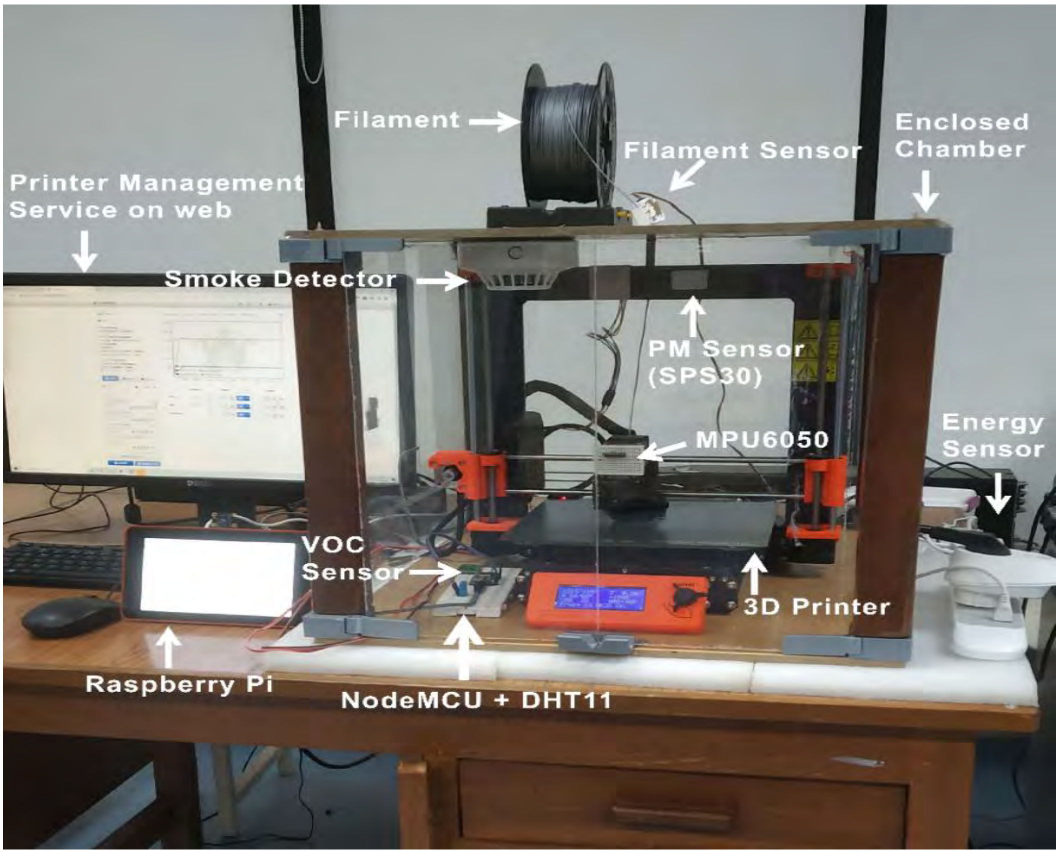


Figure 4.2 Physical world comprising of a 3D Printer with integrated sensor networks and devices

Table 4.3 CPPS components with their technical specifications, applications, communication protocol, and data platform

CPPS components (sensors/devices/software)	**Technical specifications**	**Application(s)/ measured parameters**	**Communication protocol**	**Data platform**
Printer management software	4 GB installation size	Extruder and bed temperatures, build time, filament usage	USB	Cloud
Raspberry pi	RAM: 8GB, processor: broadcom BCM2711, quad-core Cortex-A72 (ARM v8) 64-bit SoC @ 1.5GHz	Micro-processor	USB, I2C, SPI, UART	Depends on user
NodeMCU	Clock Speed 80 MHz, flash memory/SRAM 4 MB / 64 KB	Micro-controller	I2C, SPI, UART	Depends on user
Webcam (RGB-D)	HD 720p/30fps, field of View-60°	Live monitoring	USB	Edge/ cloud
VOC sensor (SGP40)	Specified range: 0.3 to 30 ppm, limit of detection: <50 ppb	Environmental emissions monitoring	I2C	Fog
PM sensor (SPS30)	Mass concentration range: 0 to 1’000 µg/m3, number concentration range: 0 to 3’000 per cm3	Environmental emissions monitoring	UART/I2C	Fog
Acceleration & gyroscope (MPU6050)	Working voltage: 2.375V-3.46V, typical X, Y & Z frequencies- 33, 30 & 27 per sec, output data rage up to 800 Hz	Vibration analysis	I2C	Fog
Ambient temperature and humidity sensor (DHT11)	Humidity measurement range: 20% to 90% RH at 25°C, temperature measurement range: 0°C to 50°C	Environmental variable measurement	Serial communication	Cloud
Filament sensor (FES V1.0)		Failure prevention	Serial communication	Edge
Smart energy meter (HS110)	Protocol: IEEE 802.11b/g/n, wireless type: 2.4GHz, maximum Load: 15A	Power, voltage, current	TCP/IP	Cloud
Smart energy meter (Beckhoff system module)	Supply voltage: 24 V DC, External feed current: 6 A	Power, voltage, current	Fieldbus	Direct storage
Relay module	Relay maximum output: DC 30V/10A, AC 250V/10A	Failure prevention	Serial communication	Edge

4.6 DATA ACQUISITION SYSTEM

Data acquisition system gathers influencing factors and state variables from the physical world and stores them in appropriate databases. It is the most critical part in CPPS implementation as interconnection of physical world to cyber world and feedback or decision support from cyber world to physical world depends on it. The data was acquired from sensors and measuring devices in hybrid mode – online measurements for acquiring state variables and performance measures, whereas nozzle wear and workpiece surface roughness were measured offline as listed in Table 4.4.

Table 4.4 Measurement of performance characteristics

Performance characteristics	**Measurement tool**	**Measurement parameter**
Quality parameters	Mitutoyo SJ-410	Surface roughness
Nozzle wear	Mitutoyo quick scope microscope	Nozzle diameter

The online monitoring and data acquisition systems were established using Node-Red; an open-source, browser-based programming tool for interconnecting IoT devices, application programming interface (API), online services, and python codes. Carbon footprint values were measured online at different combinations of printing parameters. Total carbon footprint is the sum of the carbon footprint for the filament material consumption and carbon footprint due to energy consumption during the printing process. Specific carbon footprint values were then calculated by dividing the carbon footprint by the amount of filament material consumed. Experimental results for all twenty-seven runs are shown in Table 4.5.

Table 4.5 Experimental data based on Taguchi L27 orthogonal array

Run Order	Infill (%)	LH (mm)	ET (°C)	BT (°C)	Scale (%)	SCF (CO_2-eq)	Ra (μm)	PT (min)
1	10	0.1	200	50	50	32.069	9.181	30
2	10	0.1	200	50	100	24.891	8.869	51
3	10	0.1	200	50	150	23.964	9.626	82
4	10	0.2	215	60	50	27.632	15.039	16
5	10	0.2	215	60	100	21.195	14.873	28
6	10	0.2	215	60	150	18.415	19.176	45
7	10	0.3	230	70	50	25.348	20.688	10
8	10	0.3	230	70	100	22.374	21.768	18
9	10	0.3	230	70	150	17.704	16.218	29
10	20	0.1	215	70	50	42.553	10.743	30
11	20	0.1	215	70	100	32.855	9.179	56
12	20	0.1	215	70	150	30.285	9.316	97
13	20	0.2	230	50	50	23.076	14.829	16
14	20	0.2	230	50	100	20.424	15.574	30
15	20	0.2	230	50	150	19.127	14.414	53
16	20	0.3	200	60	50	18.297	20.476	11
1	20	0.3	200	60	100	16.495	19.985	19
18	20	0.3	200	60	150	15.255	20.246	31
19	30	0.1	230	60	50	33.974	10.667	31
20	30	0.1	230	60	100	29.843	9.572	62
21	30	0.1	230	60	150	28.228	9.144	115
22	30	0.2	200	70	50	30.210	14.652	16
23	30	0.2	200	70	100	23.926	14.024	34
24	30	0.2	200	70	150	23.157	12.530	63
25	30	0.3	215	50	50	21.593	21.742	10
26	30	0.3	215	50	100	16.159	19.688	19
27	30	0.3	215	50	150	14.316	18.797	34

The nozzle diameter is measured after an interval of every 10 hours using Mitutoyo quick scope microscope to validate the gradual increase in nozzle diameter. Figure 4.3 shows the nozzle diameter at different intervals.

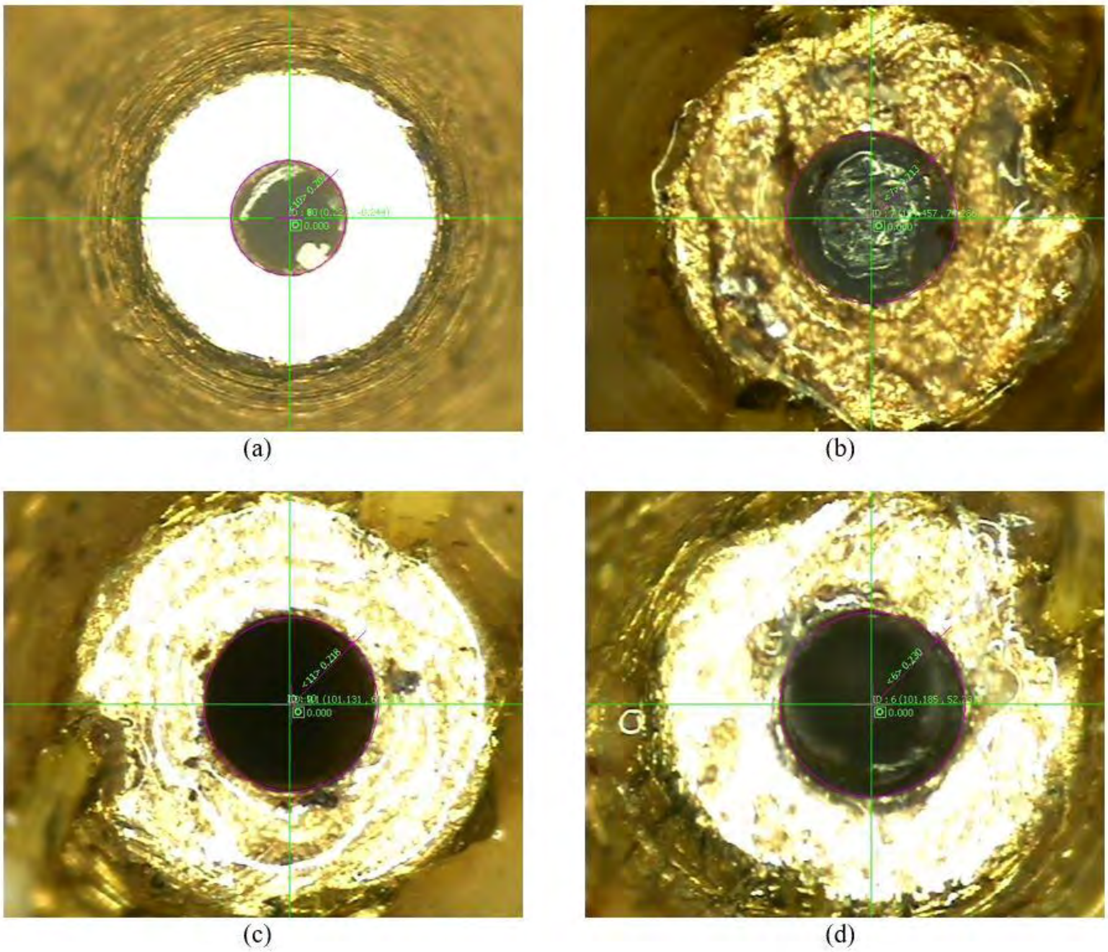


Figure 4.3 Nozzle images at different intervals (a) d = 0.4044 mm at zero hours (new nozzle), (b) d = 0.4216 mm after 10 hours, (c) d = 0.4340 mm after 20 hours, and (d) d = 0.4635 mm after 30 hours

4.6.1 Communication Protocols

A communication protocol is one of the key elements in a smart manufacturing system for supervisory control, data acquisition & transmission, and synchronous exchange of information in real-time (Göppert *et al.*, 2021). Acquisition of data is highly dependent on the sensor stacks being used, as listed in Table 4.3. These components require specific communication protocols and can therefore be interfaced with devices supporting the same protocol. PMS installed on the raspberry pi is integrated with the Prusa 3D printer, running on the same Wi- Fi network to set up a server connection to the network with all measuring devices and smart sensors. Sensor data is acquired by connecting the sensors to either a

NodeMCU or a raspberry pi via I2C or UART communication, respectively. MQTT communication protocol running on TCP/IP is also used to acquire and publish data from smart sensors *e.g.*, XDK sensor and smart energy meter. Beckhoff system module, running on TwinCAT software uses fieldbus communication module to acquire and record data. The vibration sensor is interfaced with a raspberry pi 4 (RAM: 8GB, processor: BroadcomBCM2711, 64-bit SoC @1.5GHz) using a python program. The data exchange between raspberry pi & accelerometer is performed using I2C communication protocol. The raw vibration (gyroscope and accelerometer) data generated during the printing process was sent to raspberry pi using vibration sensor for real-time monitoring and acquisition with a sampling rate of 5 Hz. A sensor which uses I2C communication protocol for data transfer is read by a micro-controller or microprocessor via I2C communication only.

4.6.2 Data Storage

Direct storage refers to the process of storing data locally on a hardware device and then processing it later. The Beckhoff system module, running on TwinCAT software is used to acquire and record data such as power, voltage, and current at every timestep of 250 milli seconds.

Multiple routes have been used to transfer data from various sensors to the cloud for analytics, storage, and visualization. Ambient temperature and humidity have been captured and stored on the cloud in Google spreadsheets using the inbuilt script editor of Google spreadsheets. A web app has been deployed at the receiving end, and the NodeMCU is flashed with a script at the sender end which communicates to the web app for sending data via HTTP requests. NodeMCU is configured to connect to the local network on start-up and which starts pushing recently recorded data from the sensor to the cloud. Similarly, smart energy meter is configured to send data to Google spreadsheets using its API on Google cloud console. Smart energy meter is configured to connect to local network at the start-up. Once available on the local network, a device on local network can host a JavaScript and a python script that starts capturing the data points and hosts the energy dashboard on the local host.

Sending data to fog layer is done using python scripts running on the raspberry pi. The scripts are written to communicate to sensors, namely VOC sensor and gyroscope sensor via I2C protocol. The data is saved in a CSV file as latest data points.

Some of the features implemented in the present work, such as automated image-based defect detection, and actuation based on threshold requires proximity to data (product snapshots) at its source using IoT devices or local edge servers for faster insights, reduced latency, and autonomous decision making and actuation.

4.7 CYBER WORLD

4.7.1 Computing Platforms for the Cyber World

According to Thiede *et al.* (2016), a cyber world is the virtual (model-based/data-driven/simulation) representation of the manufacturing system. A cyber system may have different types of modelling and computational capabilities, *e.g.*, data based (*e.g.*, regressions, decision trees), physical (*e.g.*, equations based on physical laws), numerical or discrete events. The processed data is then converted into useful insights in the form of visualization dashboard for improved transparency and feedback. Cloud, fog, and edge computing technologies, independently or in combination, are used as per the requirement or constraints related to the application and the technology. Figure 4.4 illustrates the proposed three-layer architecture for 3D printing reflecting the use of cloud, fog, and edge technologies and the associated tasks and flow.

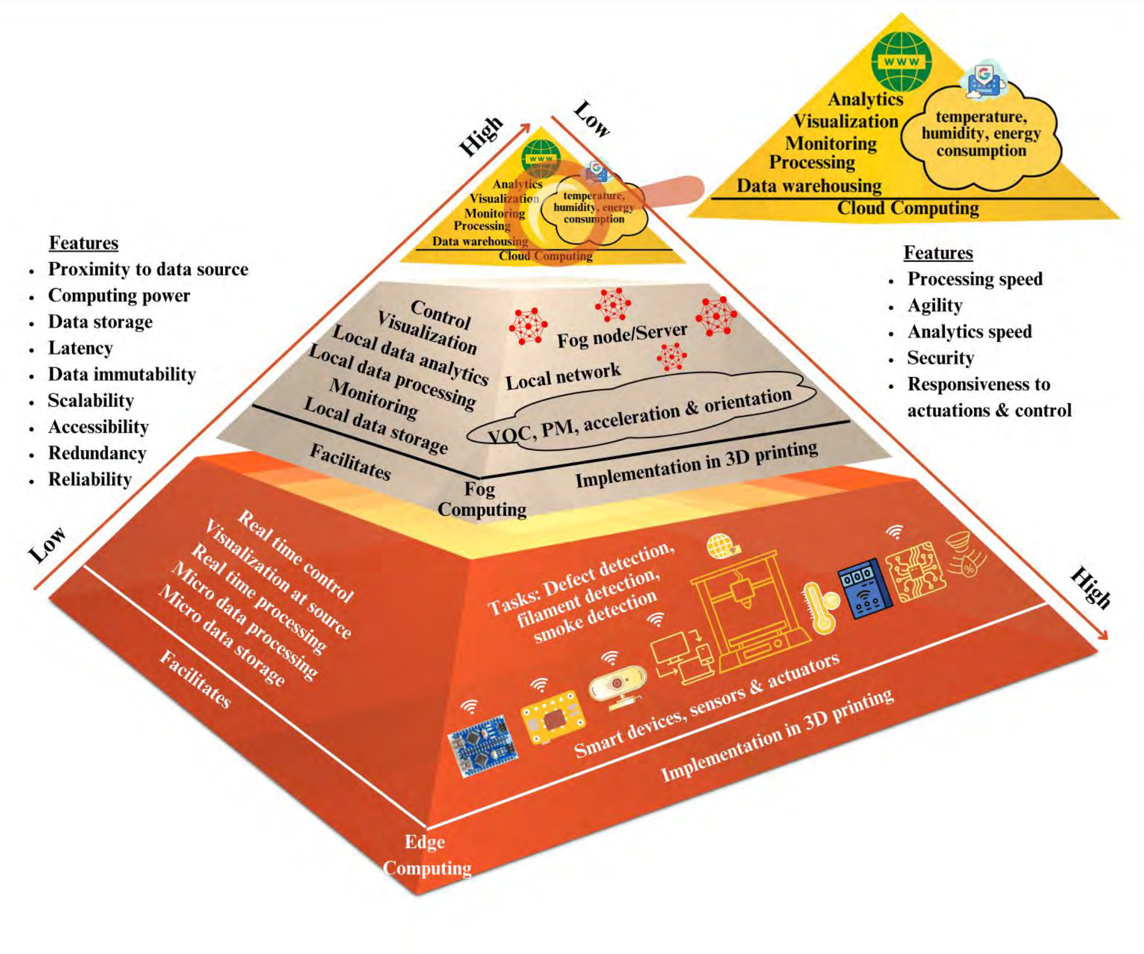


Figure 4.4 Proposed three-layer architecture for cloud, fog, and edge implementation in 3D printing, adapted from Yousefpour *et al.* (2019), Beregi *et al.* (2019), Winsystems (2022), Digiteum (2022)

The decisions regarding what data types need to be hosted on which computing layer depend on the degree of time sensitivity (Beregi *et al.*, 2019). Edge computing is used for time-sensitive data so that computations and analytics can be made closer to the data, saving network and storage costs. Fog computing is used for less time-sensitive data that can wait minutes for analysis and actions. Cloud computing is used for time-insensitive data that can be sent to the cloud for historical analysis and long-term storage.

Edge computing facilitates micro data storage & processing in real time for quick response tasks needing immediate action/control related to defects and smoke detection. Fog computing has been used for local data storage, processing, analytics, monitoring, and control of volatile organic compounds, accelerations, particulate matters, and orientation tasks, which also require online control, but the response will be after analyzing the data and need not be immediate. Cloud computing facilitates data storage, processing, monitoring, visualization, and analytics. In the present case, it is deployed to visualize temperature, humidity, and energy consumption.

4.7.2 Descriptive Analytics Modules

4.7.2.1 Development of a machine learning algorithm for characterization and energy distribution in printing stages

A component undergoes multiple stages during 3D printing process such as standby, pre-heating and printing. Figure 4.5 shows a sample of the power consumption time series data with the labelled regions for the different stages of the 3D printing process. This section focuses on the development of machine learning algorithms for live distribution of energy consumption during printing stages. Machine learning model is developed using long short-term memory algorithm, and is trained, validated, and deployed for the classification of various stages during 3D printing process. Furthermore, energy consumption in each stage is estimated based on Simpson's rule.

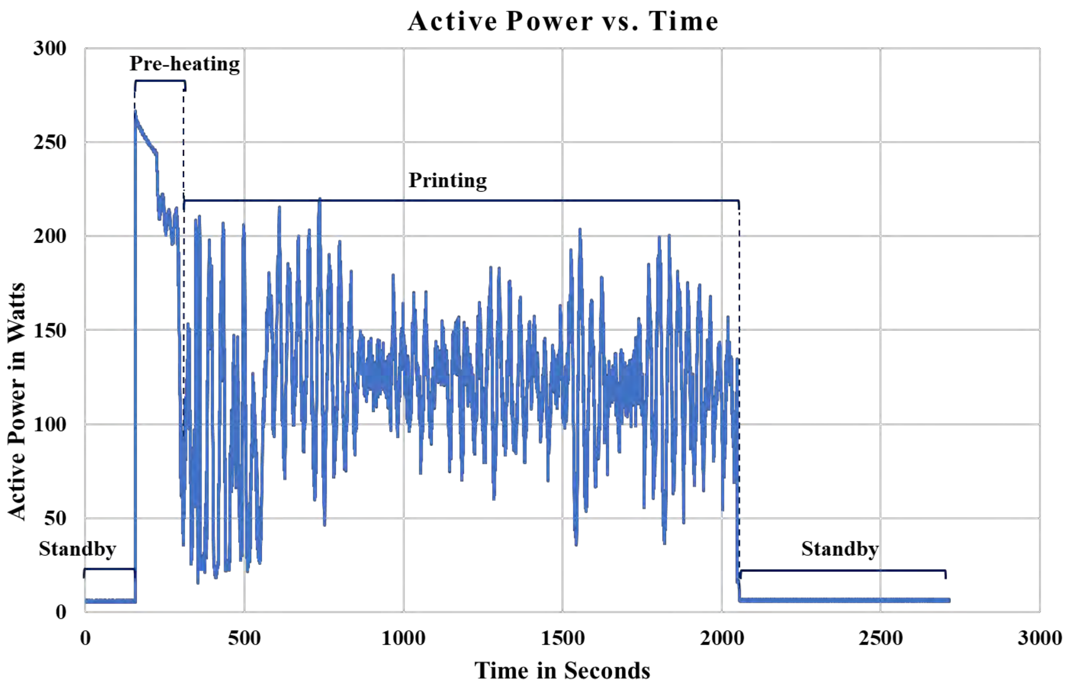


Figure 4.5 Active power with respect to time during 3D printing

Data preprocessing and feature extraction

Jupyter notebook with Python version 3.8.3 has been used for the pre-processing of the data and preparation of the LSTM model. Multiple features are extracted from the power time series data by grouping the data points into small bins of ten consecutive timesteps. The extracted features are mentioned in Table 4.6. The correlation of these features with the target value is computed, and the features with correlation value greater than or equal to 0.7 are used for training the machine learning model with the features like RMS power, form factor, mean of normalized data, and maximum of normalized data.

Table 4.6 Features extracted from power signature and correlation with labels of stages

Feature	**Formula**	**Correlation coefficient**
RMS Power	E_k	0.74
Minimum Power (E_{min})	Min (E_k)	0.69
Maximum of Normalized Data ($Enorm_{max}$)	Max (E_k) - Min (E_k)	0.77
RMS of Normalized Data ($Enorm_{rms}$)	$\sqrt{\frac{1}{n}\Sigma(E_k - E_{min})^2}$	-0.60
Mean of Normalized Data ($Enorm_{mean}$)	$\frac{1}{n}\Sigma(E_k-E_{min})$	0.73
Standard Deviation of Normalized Data ($Enorm_{SD}$)	$\sqrt{\frac{1}{n}\Sigma((E_k - E_{min}) - E_m}$	0.47
Crest Factor	$Enorm_{max}/Enorm_{rms}$	0.39
Form Factor	$Enorm_{rms}/Enorm_{avg}$	0.85
RMS Power	E_k	0.74

LSTM Model Preparation for Stage Characterization

LSTM is a type of RNN, used mostly to deal with time-series data. Unlike a typical RNN it overcomes the issue of long-term dependency, making it ideal for this use case. The architecture of LSTM is similar to that of a RNN having three parts or gates – forget gate, input gate and output gate.

The developed LSTM model contains a layer of 100 nodes and a dense output layer of three nodes as there are three classes for classification – standby, preheating and printing. The activation function used in the output dense layer is SoftMax function. The optimizer used is Adam optimizer and the loss function is categorical loss. The model is trained for 30 epochs and a batch size of 60. The model is trained using data obtained by conducting experiments. The final model is used to characterize the stages of new input datasets and for estimation of energy consumption in each stage.

The LSTM model is fitted with the training dataset. 67% of the dataset is used for training purposes, and 33% of dataset is used for validation purposes. Accuracy is calculated by comparing the actual labels with the predicted labels for the validation dataset. The network is trained for 30 epochs as further training did not decrease validation loss and produces a validation accuracy of 98.2% as shown in Figure 4.6 (a). Training loss is the error on the training set, whereas validation loss is the error obtained after passing the validation set through the trained LSTM. There is a drop in validation and training loss as the number of epochs increase.

Figure 4.6 (b) shows the confusion matrix obtained after running the LSTM model on a real data set of PLA filament material. There are three different labels- standby, preheating and printing. Confusion matrixes help to calculate performance metrics like accuracy, recall and specificity. According to the analysis, LSTM correctly classified 2570 points out of 2639 points i.e., it gives an accuracy of 97.38%. Similarly in Figure 4.6 (c), the confusion matrix for ABS filament material shows that 5959 points out of 6301 points are classified correctly with an accuracy of 94.57%. In Figure 4.6 (d), from the confusion matrix of PETG filament material, it is found that out of 11675 points, 11648 points are classified correctly giving an accuracy of 99.76%.

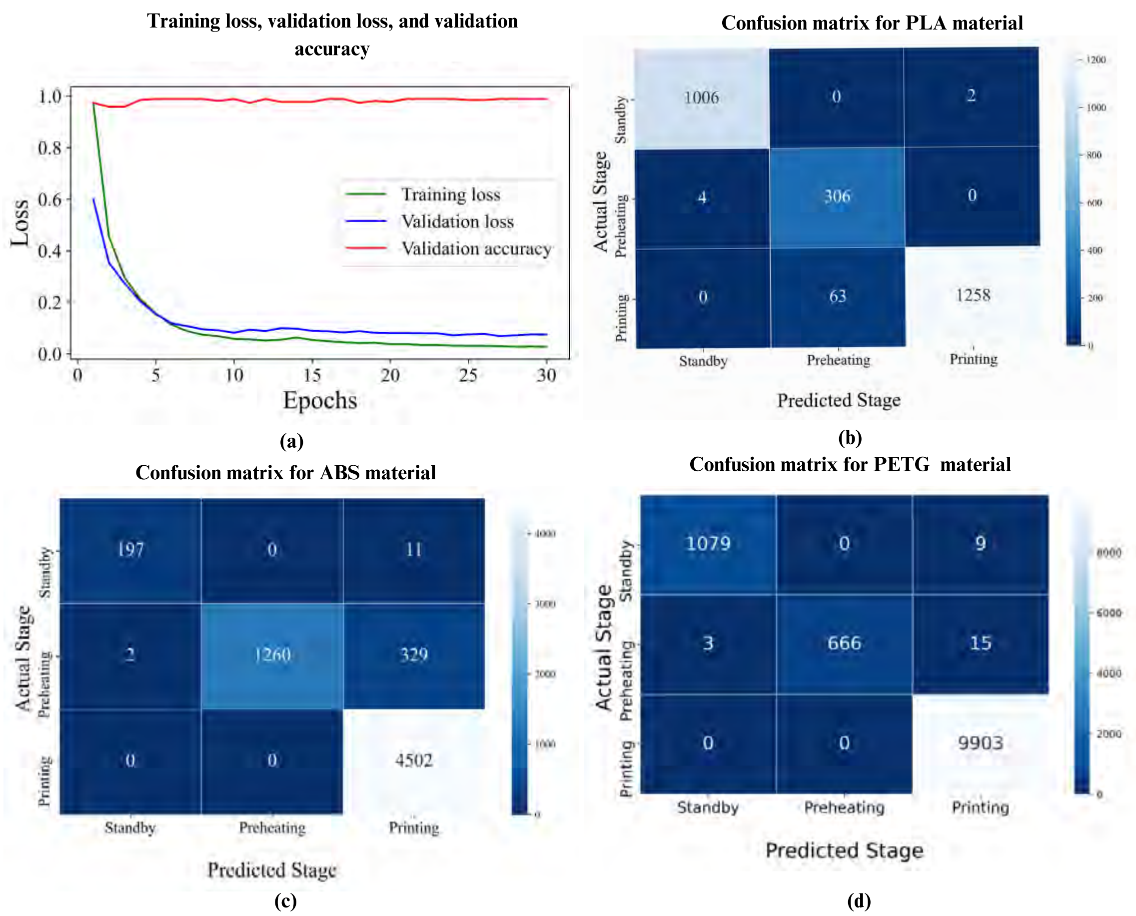


Figure 4.6 Plots for (a) Training loss, validation loss with accuracy, confusion matrix for (b) PLA, (c) ABS, and (d) PETG filament materials

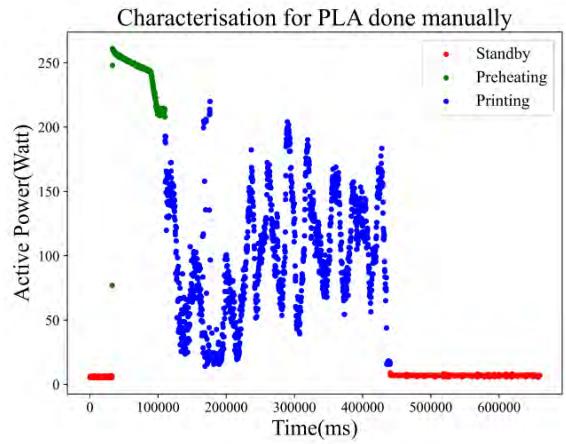
Characterization

Figures 4.7 (a), 4.7 (b), and 4.7 (c) illustrate the power time series data for the 3D printing processes for PLA, ABS and PETG filament materials, respectively with three distinct stages: standby, preheating and printing. The points are manually labelled for validating the LSTM model. The trained LSTM is then used to predict the labels as shown in Figures 4.7 (d), 4.7 (e), and 4.7 (f) for PLA, ABS and PETG filament material, respectively. It can be observed for PLA filament material in Figure 4.7 (a) and Figure 4.7 (d) that most of the points have been classified correctly and only a few points have been misclassified. Similar results can be seen for ABS filament material in Figures 4.7 (b) and 4.7 (e) as only a few points have been misclassified compared to the correct classifications. Similar results have been obtained in the case of PETG filament material as illustrated in Figures 4.7 (c) and 4.7 (f).

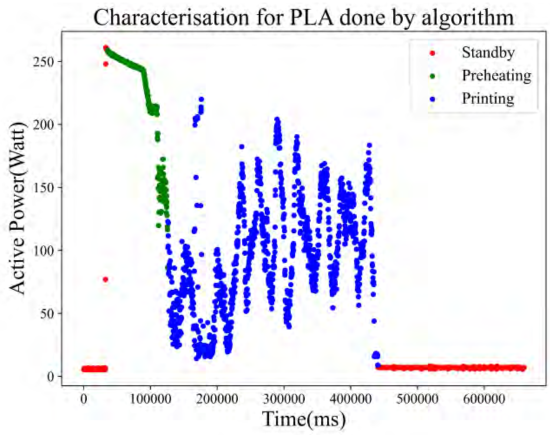
Estimation of energy consumption

After performing the stage characterization, energy consumed in each stage is calculated for PLA, ABS, and PETG filament materials as shown in Table 4.7. Predicted energy distribution for all the three filament materials is illustrated in Figure 4.8. This is performed by finding the area under the power time series curve for each stage using Simpson's rule, a numerical method for calculating definite integrals.

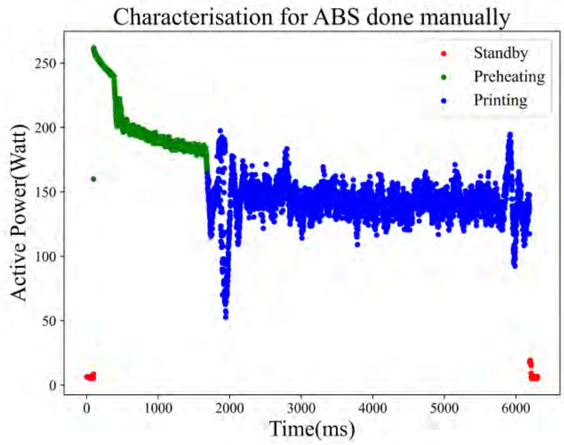
The maximum energy consumption takes place in the printing stage, followed by the preheating and standby stages. The prediction error in energy consumption for PLA filament material are 11.31%, 8.11%, and 5.51% for standby, preheating, and printing stages respectively. The developed model fits well for PLA filament material as all errors are in the acceptable ranges. However, the prediction error in energy consumption for ABS filament material are 13.37%, 18.88%, and 9.37% for standby, preheating, and printing stages respectively. The reason for higher errors in preheating and printing stages is due to misclassification of large number of data points. This can also be seen in the confusion matrix shown in Figure 4.6 (c), where 342 data points of the preheating stage are misclassified as the printing stage. Therefore, the predicted energy consumed in the preheating stage is less than the actual energy consumed, whereas the predicted energy consumed in printing stage is higher than the actual energy consumed. Similarly, the high error in the preheating stage for PETG filament material can be attributed to the misclassification of data points in the preheating and printing stages. Despite its good characterization accuracy for all three filament materials, the energy estimation for ABS and PETG is not so accurate for preheating and printing stages due to misclassifications occurring mainly at the transition from one stage to another.



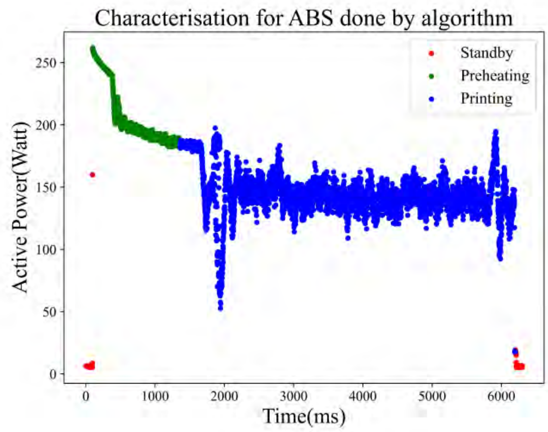
(a)



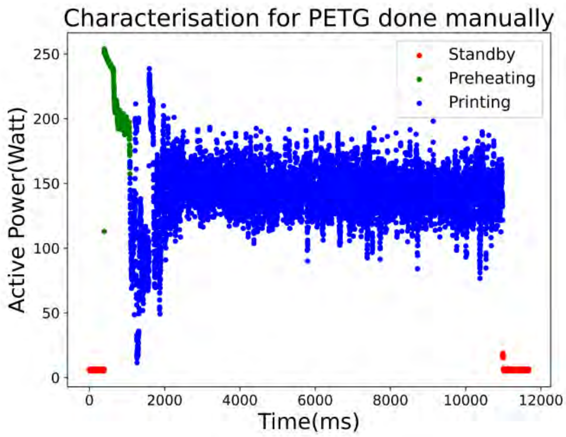
(d)



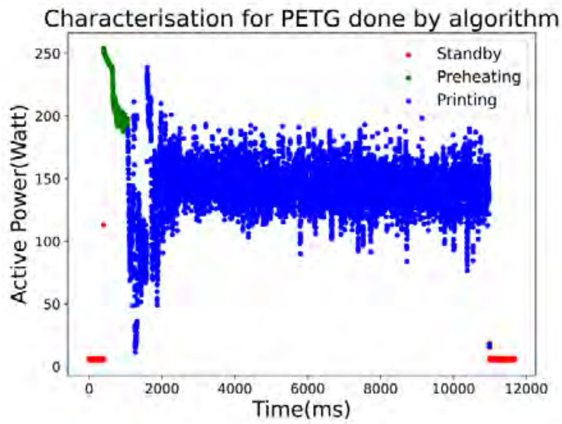
(b)



(e)



(c)



(f)

Figure 4.7 Characterization performed manually for (a) PLA, (b) ABS, (c) PETG, and performed through algorithm for (d) PLA, (e) ABS, and (f) PETG filament materials

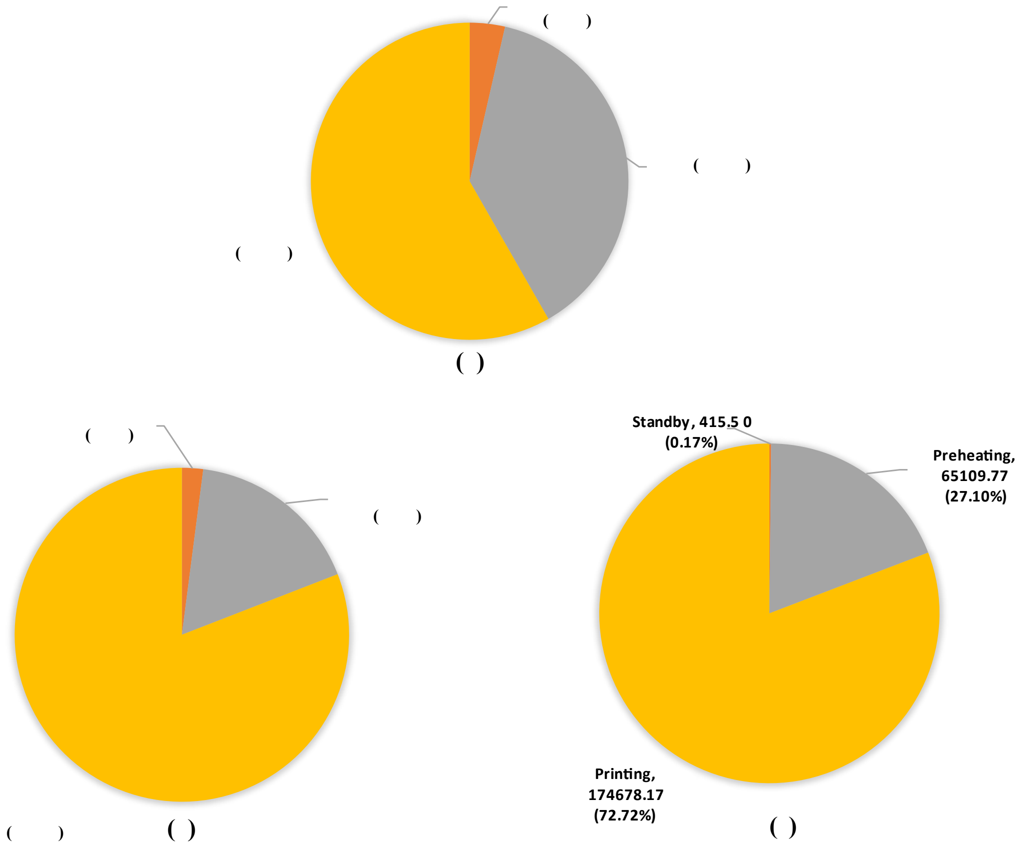


Figure 4.8 Predicted energy distribution for (a) PLA, (b) PETG, and (c) ABS filament materials

Table 4.7 Energy consumption in each stage for PLA, ABS, and PETG filament materials

Material	Stage	Actual (Watt)	Predicted (Watt)	Error (%)
PLA	Standby	1705.65	1898.64	11.31
	Preheating	18669.72	20185.41	8.11
	Printing	32627.89	30828.35	5.51
ABS	Standby	366.49	415.50	13.37
	Preheating	80261.10	65109.77	18.88
	Printing	159705.25	174678.17	9.37
PETG	Standby	1669.26	1794.49	7.50
	Preheating	36755.01	35904.60	2.31
	Printing	350640.90	351202.07	0.16

4.7.2.2 Development of a computational model for live LCA implementation

For the present case, the data collected from the physical stage is transferred to a SQL database. The cyber system is developed using Node-Red; an open-source, browsing based programming tool for wiring together IoT devices, APIs, online services, python codes, run locally at the edge of the network using the wide range of nodes in the palettes or modules connected graphically.

The cyber system performs a significant amount of computation, and analysis of GWP values using intelligent processing systems running on Brightway2, an open-source framework for LCA, supported on python program API with the Node-Red. The power consumption values stored in SQL database are summed up and processed at near real-time for each component produced. The GWP value is calculated just after the 3D printed product has been printed.

Several KPIs such as GWP, human toxicity potential, ozone depletion, *etc.* provide us with the measures of the environmental impacts of the production stage (Ecochain, 2023). GWP has been considered for the present use case as it is a characterization factor for the impact category of climate change, and indicates the energy absorbed by one ton of the specified atmospheric gas relative to one ton of carbon dioxide. GWP has been cited widely in several studies spanning various industries/sectors, illustrating the efforts across industries to reduce greenhouse gas emissions (Rigon *et al.*, 2019).

Live LCA has been implemented using the CPPS approach to intertwine the physical and cyber world using data acquisition and visualization resulting in real-time monitoring of the environmental impact, assisting operators to act based on the visibility. The decision-making process for customers, operators, and manufacturers also becomes transparent. Both energy and material consumptions have been considered to calculate the GWP values instantaneously as the product is printed.

4.7.3 Development of Prognostic Analytics to Predict the RUL of the Nozzle

Pilot experiments were first performed using new and old nozzles made of brass (E3D V6) to establish that energy consumption during 3D printing increases with respect to printing time as nozzle wear increases. Pilot experiments were conducted using polycarbonate filament material as polycarbonate materials have higher hardness and energy requirements, which result in faster degradation of the nozzle. The faster nozzle degradation saved experimental time and resources as compared to other commonly used filament materials like PLA, ABS, and PETG. TwinCAT software running on Beckhoff power module was used to measure power.

Power time series data of around thirty hours were acquired at a sampling rate of 4 Hz during 3D printing of similar cylindrical workpieces, repeatedly at the constant printing conditions to develop a machine learning model for the prediction of nozzle's remaining useful life. The data was first pre-processed (filtered, cleaned, and formatted into a feasible format) to make it appropriate for machine learning models. Google Colab, an open-source notebook environment with python version 3.7.12, was used to pre-process and develop the machine learning model to predict nozzle's RUL using linear regression, quadratic regression, cubic regression, exponential regression, LSTM, and autoregressive algorithms. Finally, an autoregressive model was found to be the most suitable among all the developed machine learning models after examining the evaluation parameter scores of RMSE, as listed in Table 4.8.

Table 4.8 Comparison of machine learning models for prediction of nozzle's RUL

Sl. No.	Model	RMSE
1	Linear Regression	11.074
2	Quadratic Regression	12.465
3	Cubic Regression	12.000
4	Exponential Regression	11.014
5	LSTM	6.819
6	Autoregressive	4.533

An autoregressive model is a time-series algorithm which uses observations from the previous time steps as input to predict the values at the next time step. The autoregressive model has been used in several applications such as RUL prediction of lithium-ion batteries (D. Liu *et al.*, 2014), forecasting of machine state (Pham *et al.*, 2010), detection of anomalous behaviour with RUL of bearing (X. Jin *et al.*, 2016).

Power time series data during the printing stage for every experimental run were combined and stacked together to create a single continuous array of target variables for better visualization of the trend as shown in Figure 4.9.

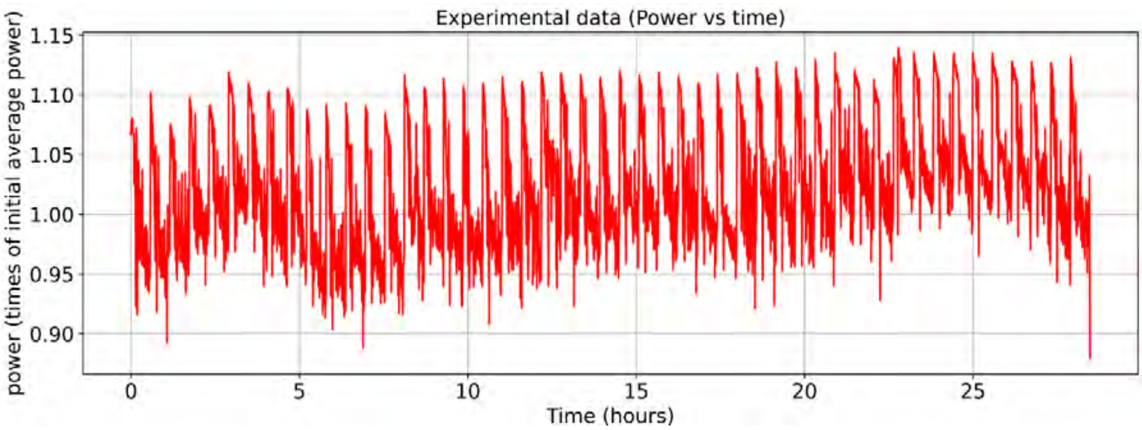


Figure 4.9 Power time series data during the printing stage

Data were resampled at 120 Hz to decrease computation time during the testing and prediction. Data was converted into 'differenced data' to prevent the autoregressive algorithm from exhibiting Naive forecasting behaviour (where the previous period's target variable value is used as the next period's predicted target variable value). Data was then used to train the auto-regressive model. 70% of the total data was used for training and the remaining 30% for testing as it is a standard practice among researchers, *e.g.*, (C. Qi *et al.*, 2018; Xu & Goodacre, 2018) to divide data in the ratio of 70:30 for training and testing the machine learning algorithms, respectively. The 70:30 ratio is found to provide an optimal performance of the machine learning algorithms (Nguyen *et al.*, 2021; Mirbolouki *et al.*, 2022). If the training set is too small then the model might not learn enough from the data, underfit the data, and have low accuracy. On the other hand, if the higher training data is used then the model learns too much from the data, overfits the data, and has poor generalization. Therefore, dataset of 70:30 is generally considered to provide the best performance for a machine learning algorithm (Nguyen *et al.*, 2021).

The coefficients learned by the model were extracted from the previous data to make future predictions over the test dataset. The number of lag variables used on differenced data sets during future predictions is 300. Predictions performed by the model on test data are shown in Figure 4.10.

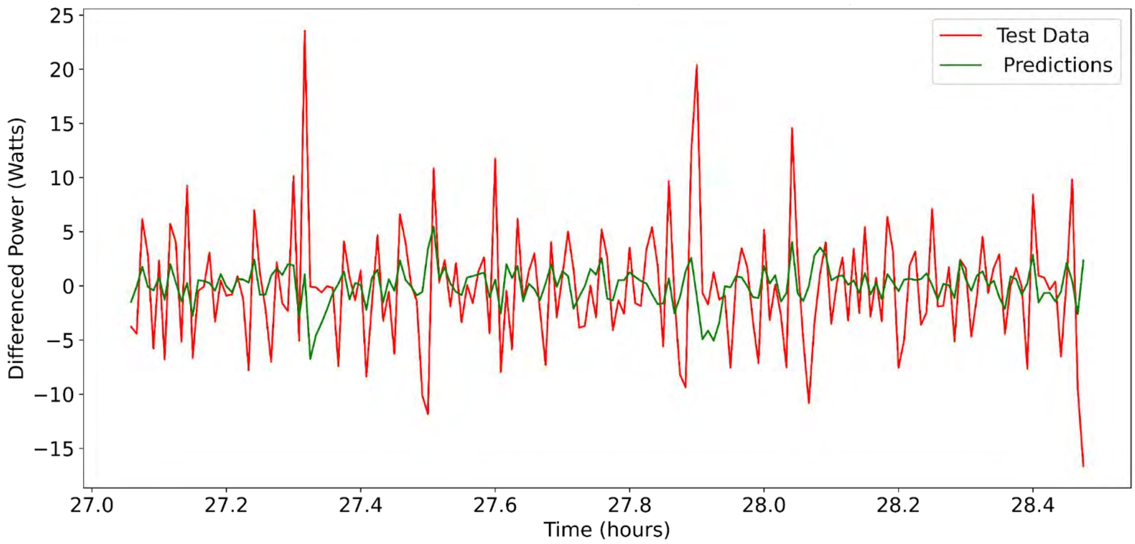


Figure 4.10 Predictions on test data

Figure 4.11 shows the variation of power in multipliers with respect to time that can be used to predict the nozzle's RUL. This was done by obtaining time (in hours) on the x-axis and selecting an appropriate y-axis value based on user preferences. As there has been no prior research work performed on setting the power threshold criterion for nozzle rejection, therefore, the power threshold multiplier has been set to 1.3 (130% of initial power consumption), which is a well-established cutting tool rejection criterion for machine tool industry (Dadgari *et al.*, 2018; Corne *et al.*, 2017). The nozzle's RUL at the defined threshold is found to be approximately 300 hours.

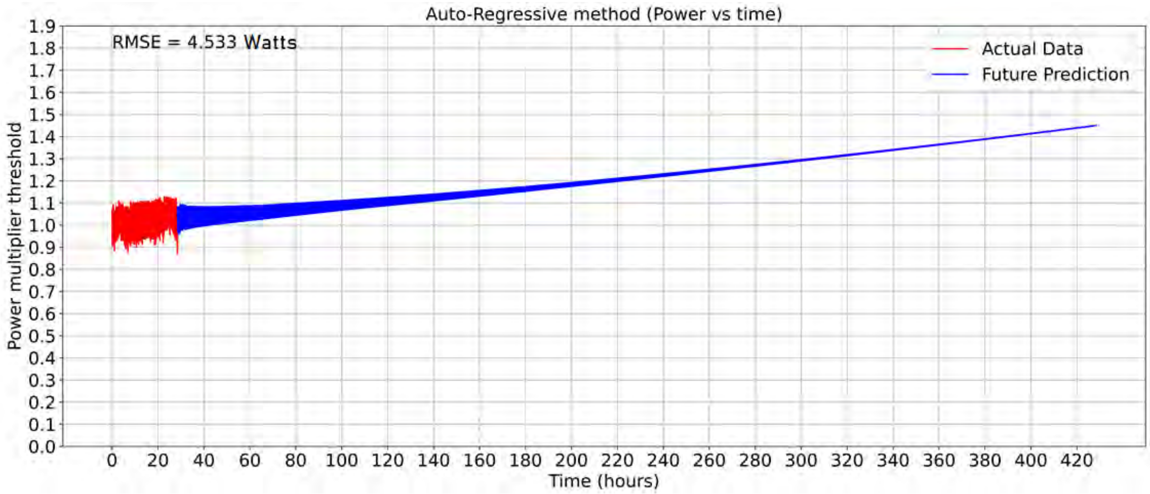


Figure 4.11 RUL of the nozzle as predicted by the proposed model using power data

4.7.4 Development of Prescriptive Analytics to Prescribe Optimum Printing Parameters

Regression models were developed using response surface methodology (RSM) to predict specific carbon footprint (SCF), surface roughness (Ra), and printing time (PT). These models were improved using a backward elimination technique that starts with all potential terms in the model and then removing the least significant term. Equations 4.1 to 4.3 are the developed mathematical models to describe the relationship between a set of continuous predictors (scale, layer height, bed temperature, infill percentage, and extruder temperature) and responses (specific carbon footprint, surface roughness, and printing time).

$$\text{SCF (CO2eq)} = 27.92 - 132.6\ \text{LH (mm)} + 0.0438\ \text{ET (°C)} + 0.2933\ \text{BT (°C)} - 0.1998\ \text{Scale (\%)} + 177.1\ \text{LH (mm)} \times \text{LH (mm)} + 0.000642\ \text{Scale (\%)} \times \text{Scale (\%)} \quad 4.1$$

$$\text{Ra } (\mu\text{m}) = 4.485 + 51.84\ \text{LH (mm)} \quad 4.2$$

$$\text{PT (min)} = 23.1 + 0.417\ \text{Infill (\%)} - 269.4\ \text{LH (mm)} + 0.510\ \text{Scale (\%)} + 739\ \text{LH (mm)} \times \text{LH (mm)} + 0.001889\ \text{Scale (\%)} \times \text{Scale (\%)} - 2.333\ \text{LH (mm)} \times \text{Scale (\%)} \quad 4.3$$

Table 4.9 shows the ANOVA results. A lower p-value corresponds to a higher level of significance for the process parameter's effect on the response. A deeper analysis of ANOVA literature shows that if the value of $p<0.05$, it is safe to reject the null hypothesis. However, even if the p value is much higher (*e.g.*, $p=0.2$) then the interpretation crucially depends upon whether the data can be well approximated by a normal distribution (Brereton, 2019). In the current scenario, the p-value for the extruder temperature is 0.138. In practice, the extruder temperature exhibits a direct correlation with energy consumption or specific carbon footprint as continuous melting and extrusion of the filament material is required during the 3D printing process (Yang & Liu, 2020). Therefore, extruder temperature is also included in the analysis and equation for the specific carbon footprint (SCF) even though the p-value is 0.138. Table 4.9 also shows the results of ANOVA tests to test the developed models' adequacy for specific carbon footprint, surface roughness, and printing time. The R-square values are 0.9446, 0.9029, and 0.9696 for specific carbon footprint, surface roughness, and printing time, respectively which indicate that 94.46%, 90.29%, and 96.96% of the total variations are explained by the model for specific carbon footprint, surface roughness, and printing time, respectively.

Table 4.9 Analysis of variance results for specific carbon footprint, surface roughness, and printing time

Analysis of variance for specific carbon footprint						
Source	DOF	Adj SS	Adj MS	F-value	P-value	%Contribution
Model	6	1112.60	185.434	56.82	0.000	94.46
Linear	4	1078.34	269.584	82.60	0.000	91.55
LH (mm)	1	686.00	685.995	210.19	0.000	58.24
ET (°C)	1	7.78	7.779	2.38	0.138	0.66
BT (°C)	1	154.84	154.845	47.45	0.000	13.15
Scale (%)	1	229.72	229.716	70.39	0.000	19.50
Square	2	34.27	17.134	5.25	0.015	2.91

Table 4.9 Analysis of variance results for specific carbon footprint, surface roughness, and printing time (contd…)

Analysis of variance for specific carbon footprint (…)						
Source	DOF	Adj SS	Adj MS	F-value	P-value	%Contribution
LH (mm)*LH (mm)	1	18.82	18.820	5.77	0.026	1.60
Scale (%) *Scale (%)	1	15.45	15.447	4.73	0.042	1.31
Error	20	65.27	3.264			5.54
Total	26	1177.88				
Model Summary	R-square = 94.46%					
Analysis of variance for surface roughness						
Model	1	483.70	483.698	232.34	0.000	90.29
Linear	1	483.70	483.698	232.34	0.000	90.29
LH (mm)	1	483.70	483.698	232.34	0.000	90.29
Error	25	52.05	2.082			9.72
Total	26	535.74				
Model Summary	R-square = 90.29%					
Analysis of variance for printing time						
Model	6	18116.6	3019.44	106.38	0.000	96.96
Linear	3	16021.9	5340.65	188.17	0.000	85.75
Infill (%)	1	312.5	312.50	11.01	0.003	1.67
LH (mm)	1	7729.4	7729.39	272.33	0.000	41.37
Scale (%)	1	7980.1	7980.06	281.16	0.000	42.71
Square	2	461.4	230.69	8.13	0.003	2.47
LH (mm)*LH (mm)	1	327.6	327.57	11.54	0.003	1.75
Scale (%) *Scale (%)	1	133.8	133.80	4.71	0.042	0.72
2-Way Interaction	1	1633.3	1633.33	57.55	0.000	8.74
LH (mm)*Scale (%)	1	1633.3	1633.33	57.55	0.000	8.74
Error	20	567.6	28.38			3.04
Total	26	18684.3				
Model Summary	R-square = 96.96%					

Main effect plots for specific carbon footprint, surface roughness, and printing time are shown in Figures 4.12, 4.13, and 4.14, respectively. The interpretation for different natures of the effect of printing parameters on responses is explained as follows.

The main effect plot for specific carbon footprint reveals that layer height has the strong effect, followed by scale, bed temperature, extruder temperature, and infill. Increasing layer height decreases the specific carbon footprint significantly as a larger height means faster printing, reducing the printing time and energy consumption, thereby decreasing the specific carbon footprint. Similarly, increasing scale or part size reduces the specific carbon footprint as larger prints result in lower specific energy consumption (Yi *et al.*, 2020). On the other hand, increasing bed temperature increases the specific carbon footprint as more energy is required to maintain the temperature of the heated bed. However, the specific carbon footprint increase due to bed temperature is insignificant as compared to layer height and scale. Similarly, increasing the infill percentage increases the specific carbon footprint as a larger infill percentage means more filament material consumption, which in turn increases the printing time and embodied energy of the filament material. However, its effect is insignificant as compared to other printing parameters.

The main effect plot for surface roughness reveals that only layer height is dominating the surface roughness of 3D printed products, as expected. Increasing the layer height increases the surface roughness. The reason is evident that larger layer height reduces the resolution and print quality, supporting the findings obtained by Pérez *et al.*, 2018. Scale or part size also influences the surface roughness of a 3D-printed part as increasing scale or part size decreases the surface roughness as contours are printed with finer details. Other printing parameters (infill, extruder temperature, and bed temperature) are insignificant for surface roughness.

The main effect plot for printing time reveals that scale or print size is the most significant printing parameter, followed by layer height and infill. The reason is that when the scale increases, printing time increases as more volume needs to be printed. Increasing layer height increases the print height, thus reducing the printing time. Therefore, printing time is inversely proportional to the layer thickness. Infill percentage increases the density of print, thereby increasing the print time. Extruder temperature is the least significant for printing time as a small part of the total time is consumed to heat the extruder in the range of 200°C to 230 °C from room temperature.

Residual plots for SCF, Ra, and PT (Figures 4.15, 4.16, and 4.17, respectively) show that there are no trends, and the errors are distributed normally. Outliers in the normal probability plots are unusual points at the upper/lower extreme/distant from the probability plot line (Tewari *et al.*, 2011). There are some outliers observed in the normal probability plot for specific carbon footprint, surface roughness and printing time as shown in Figures 4.15, 4.16, and 4.17, respectively. The outliers are caused due to one or several factors during the experimentation process such as failed experiments, uncontrolled factors (*e.g.*, ambient temperature, humidity, *etc.*), errors in the measurement, *etc.* Eliminating these outliers is not recommended because it can introduce bias into the data (Morgan, 2017). Most of the points in the current study are located along the probability plot line, indicating a high degree of linearity, and thus supporting the adequacy of the proposed models.

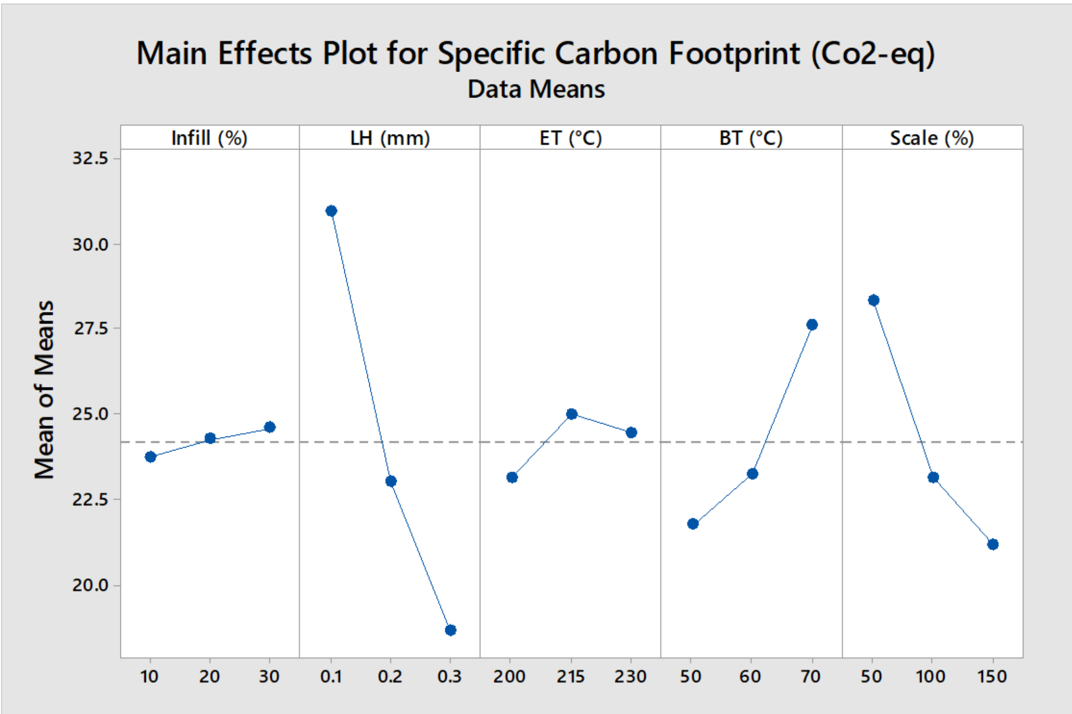


Figure 4.12 Main effect plot for specific carbon footprint

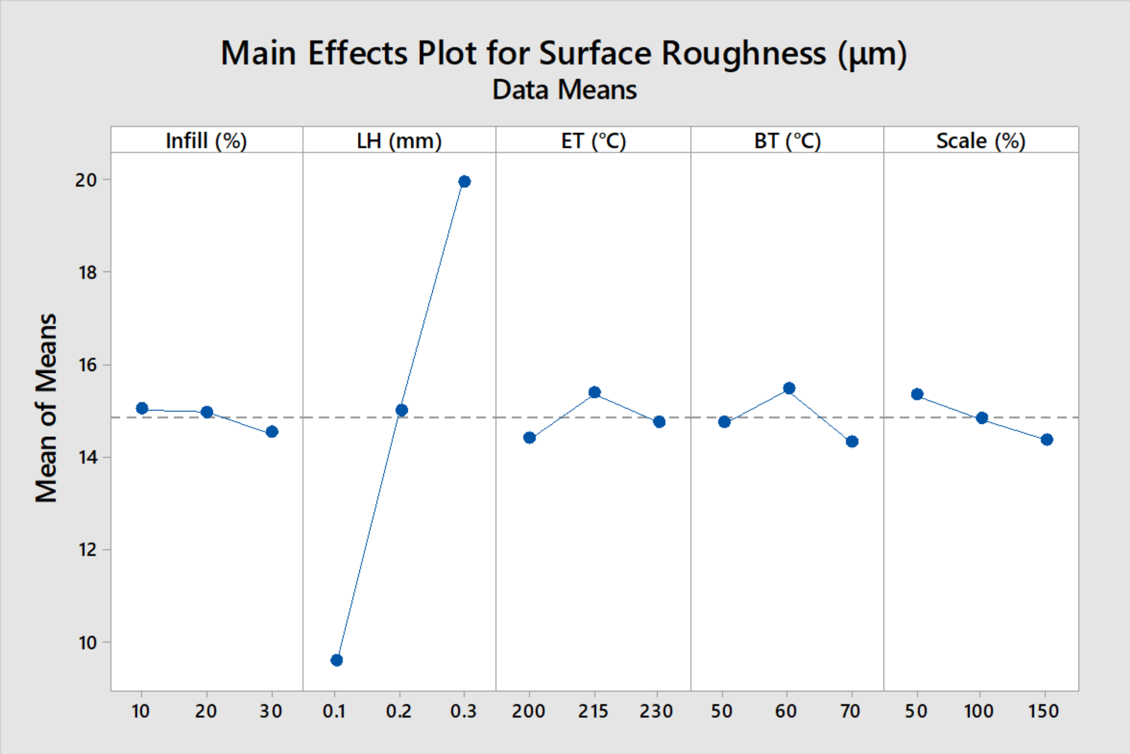


Figure 4.13 Main effect plot for surface roughness

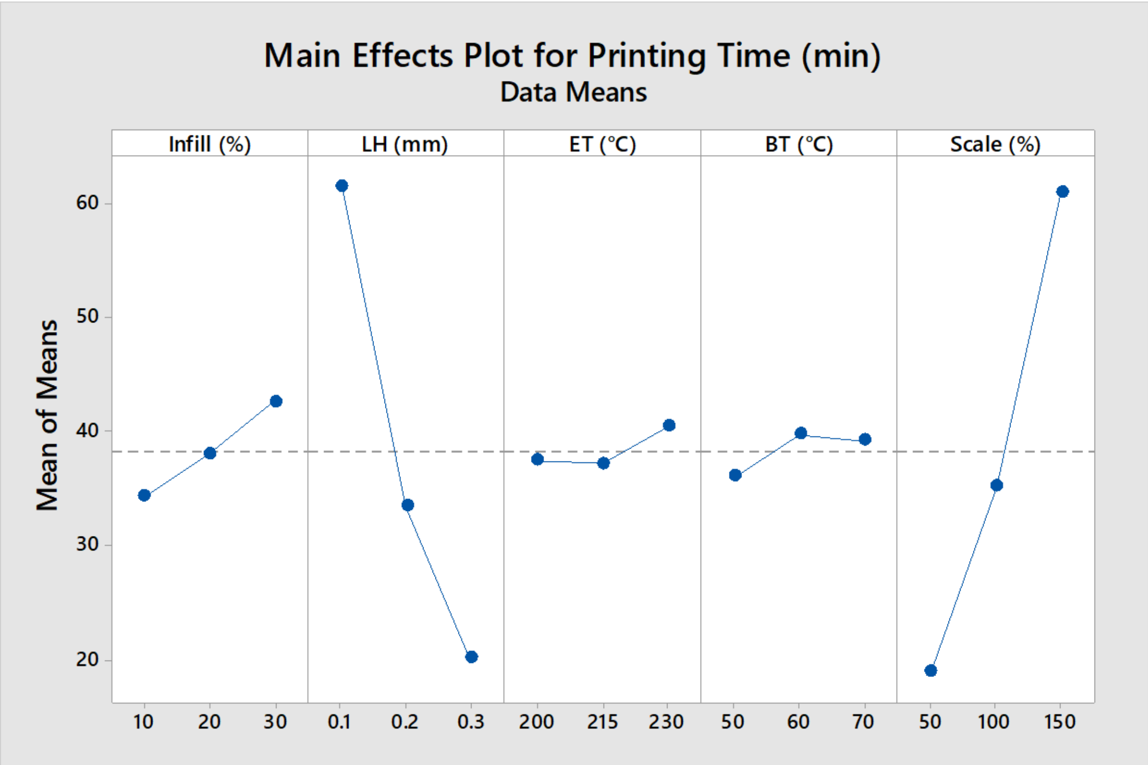


Figure 4.14 Main effect plot for printing time

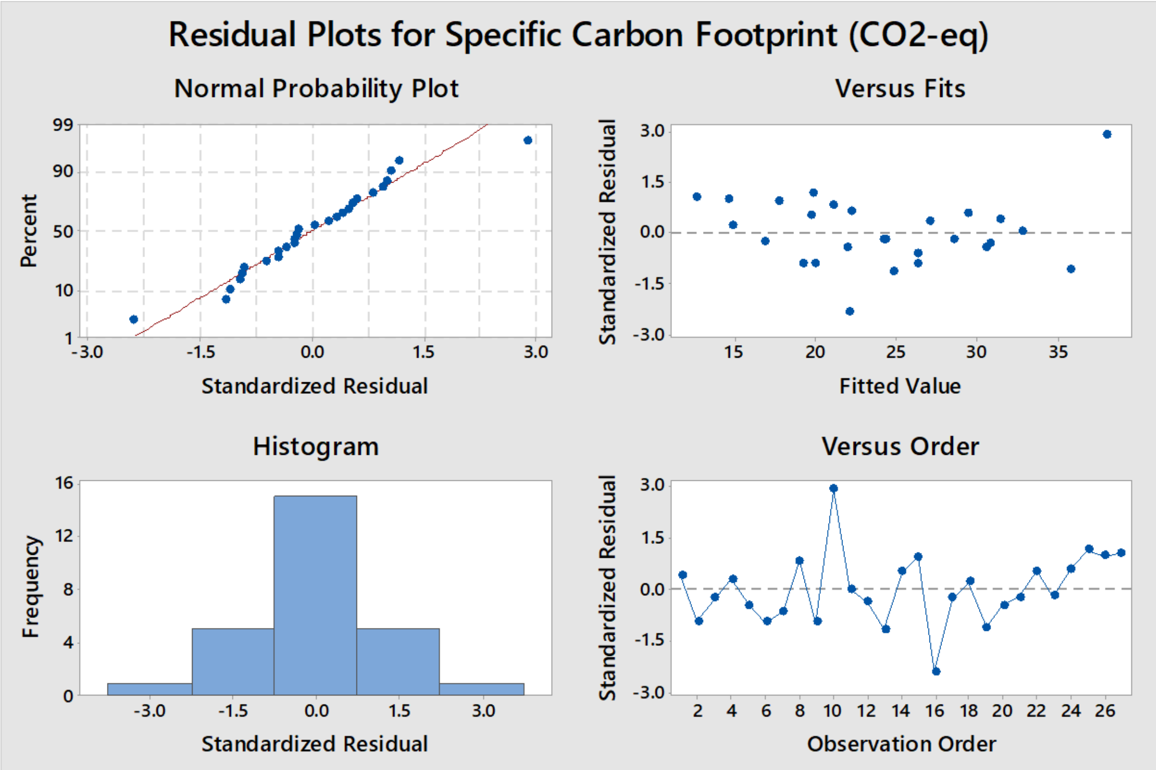


Figure 4.15 Residual plot for specific carbon footprint

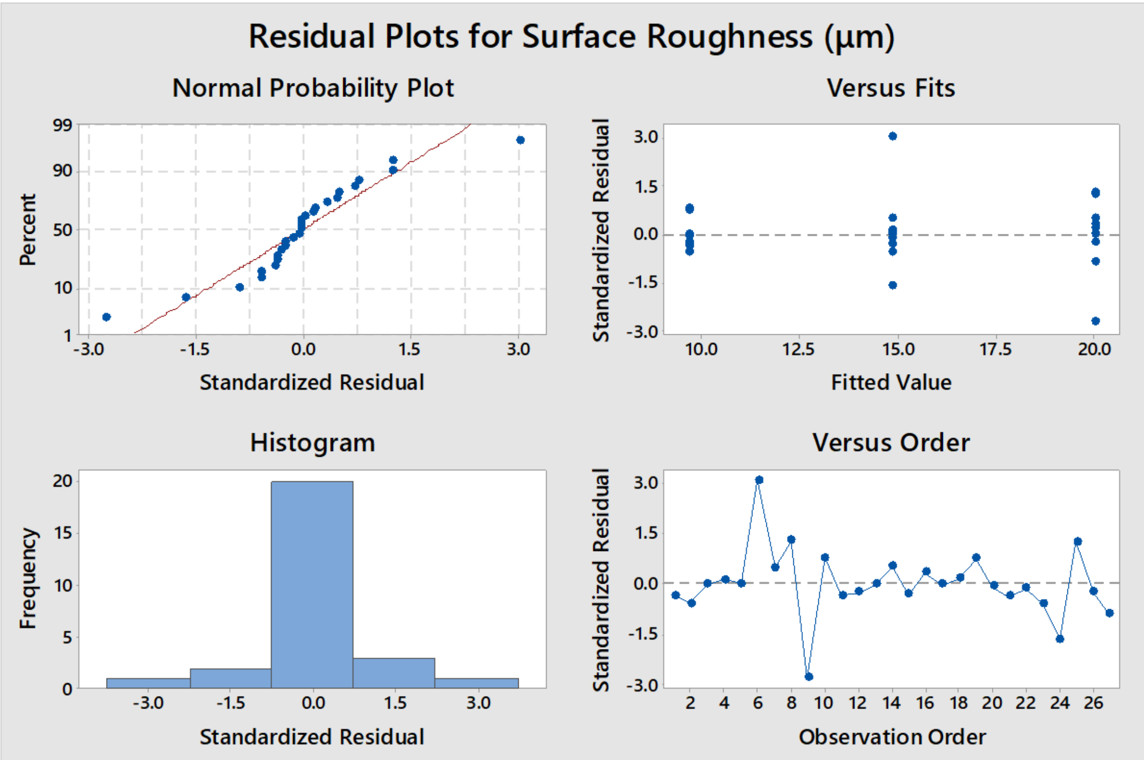


Figure 4.16 Residual plot for surface roughness

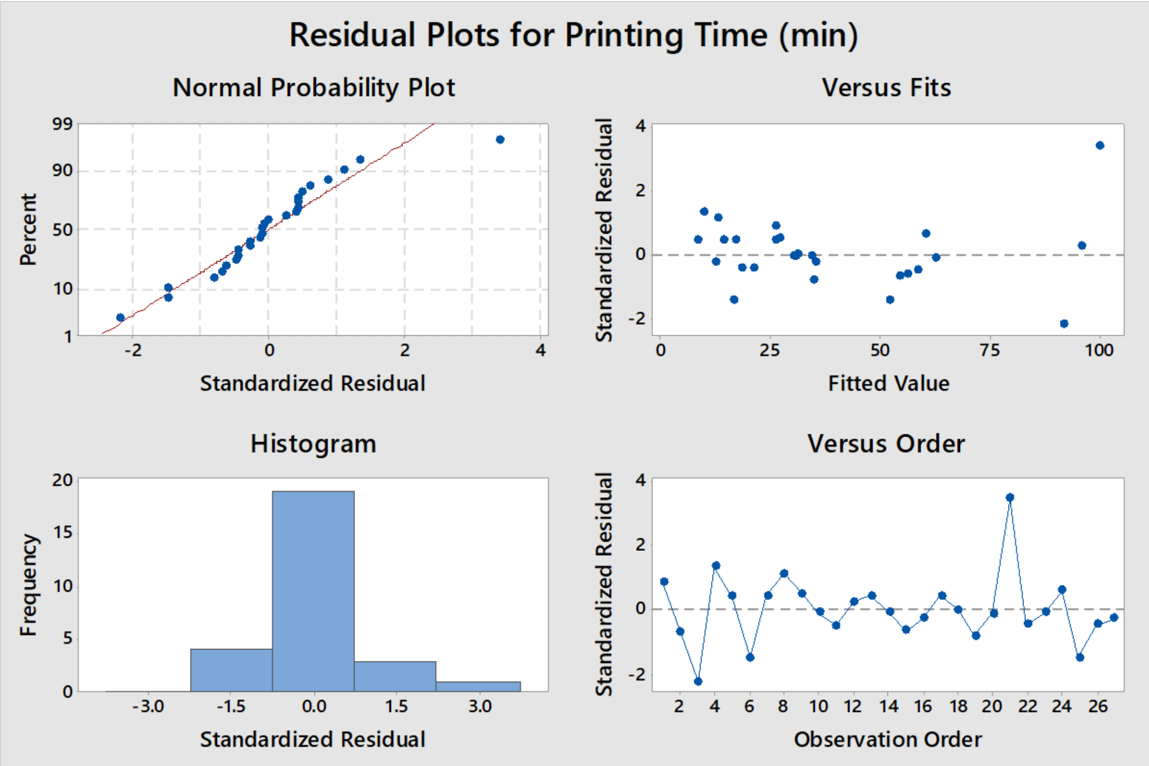


Figure 4.17 Residual plot for printing time

Optimization techniques are widely used in several disciplines such as economics, engineering, healthcare, biology, *etc.* (Gurgen *et al.*, 2015). These techniques aim to solve either a single or multi-objective problem by determining an optimal or multiple optimal solutions, respectively. The complexities arise in case of multi objective problems when the objectives conflict with each other or there exists a trade-off between them (Gurgen *et al.*, 2015). Optimization typically involves two steps. The first step is model development, which establishes the relationship between process parameters and objective functions. The second step entails obtaining optimal solution(s) through the application of appropriate optimization techniques (Dureja *et al.*, 2016). Various modelling and optimization methods have been utilized to determine the optimal conditions such as regression model combined with non-dominated sorting genetic algorithm-II (NSGA-II) technique for order preference by similarity to ideal solution (TOPSIS) and goal programming (Gurgen *et al.*, 2015); genetic algorithm (GA) and particle swarm optimization (PSO) (Gadagi & Adake, 2021)**;** RSM and desirability function (DF) (Camposeco-Negrete, 2015; Bagaber & Yusoff, 2017; Senthil *et al.*, 2020); RSM, ANN, and DF methods (Chabbi *et al.*, 2017), *etc.*

Derringer & Suich (Derringer & Suich, 1980) introduced the desirability function in 1980 to optimize multiple responses in manufacturing rubber compounds for tire treads. It works on the principle of a reduced gradient algorithm. It is one of the most widely used multi-objective optimization techniques for prescribing optimum parameters (Sangwan & Sihag, 2019), and scheduling jobs on shopfloor (Dabbas *et al.*, 2003). The advantages of the desirability function lie in its ability to generate optimal solution(s) in conflicting or adverse conditions. It is also simple to understand and implement for practitioners who require a quick and effective solution depending on managerial requirements (Costa *et al.*, 2011). Multi-objective problems are first converted into a single objective by transforming individual responses into a dimensionless desirability function value varying from zero to one, where '0' represents unacceptable and '1' represents completely desirable values (Chou & Chen, 2012). Multiple solutions are initially generated and converged to obtain the optimal solution representing the maximum value of composite desirability (Sarikaya & Güllü, 2014).

In the present study, the desirability function is used to determine optimal settings for simultaneously minimizing specific carbon footprint and printing time at the target surface roughness values by using Minitab 18. Figure 4.18 shows the optimization plot to visualize how responses change with the variation in printing parameters.

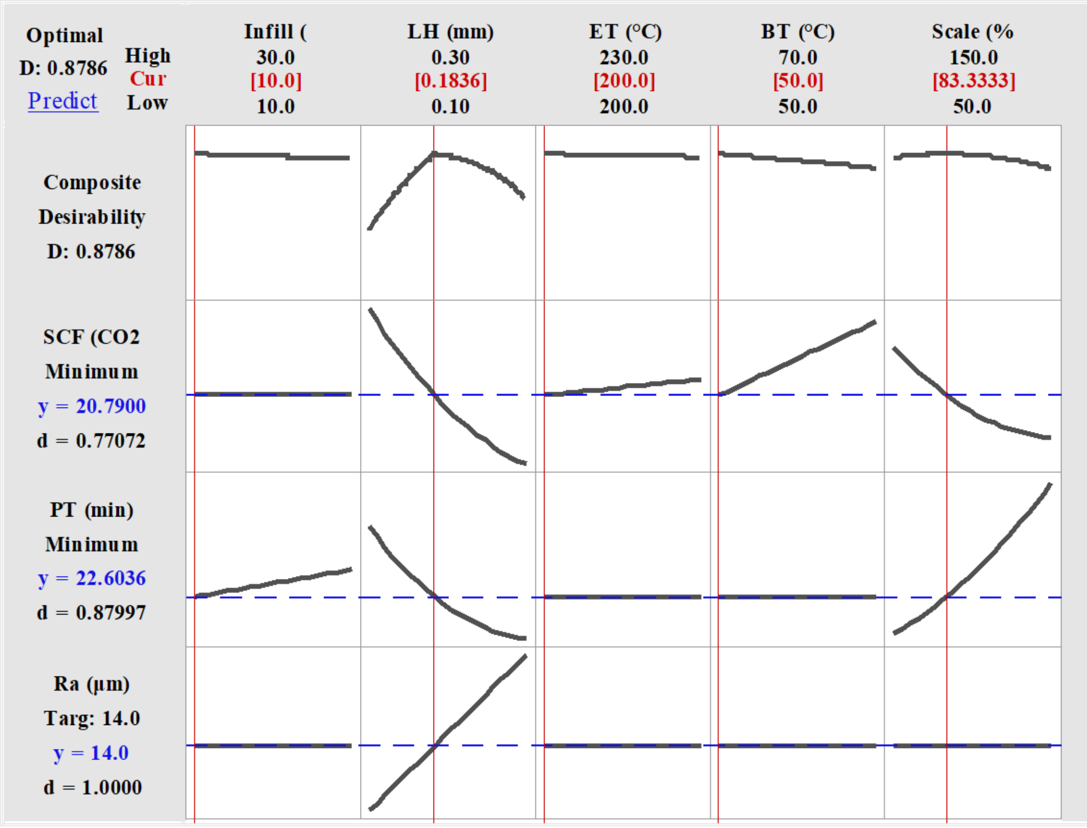


Figure 4.18 Optimization plot for minimization of specific carbon footprint and printing time simultaneously at target surface roughness value

The optimal printing parameters for minimum specific carbon footprint and printing time for target surface roughness values of 14.000 µm were found with an infill percentage of 10, layer height of 0.18 mm, extruder temperature of 200°C, bed temperature of 50 °C, and scale/ part size of 83.333% (volume of 11905 mm^3). The values of specific carbon footprint and printing time for the target surface roughness values of 14.000 µm were found to be 20.790 CO2-eq and 26.03 minutes, respectively.

A confirmation test was performed using the prescribed parameter settings to validate the effectiveness of the proposed model. Table 4.10 compares the results of the confirmation experiments with the optimal printing parameters for the proposed model at the target surface roughness value of 14.00 µm. It can be observed that the percentage errors for specific carbon footprint, printing time, and surface roughness are 14.14%, 2.74 %, and 4.86 %, respectively. This shows a good agreement between the predicted and experimental results.

Table 4.10 Confirmation test results for output response functions

Methodology	**Optimum printing parameters by the proposed prescriptive analytics**					**Output responses**		
	Infill (%)	LH (mm)	ET (°C)	BT (°C)	Scale (%)	SCF (CO_2-eq)	PT (min)	Ra (µm)
The proposed model results	10	0.18	200	50	83.33	20.790	22.603	14.000
The confirmation experiment results						18.213	22.000	14.716
Percentage errors						14.14%	2.74%	4.86%

4.7.5 Development of Diagnostic Analytics to Detect Anomalies during 3D Printing

Vibration data containing acceleration and gyroscope time series stamps were acquired along x, y, and z axes. The process of acquiring data is followed from Yen *et al.* (2022), where anomalous points were manually introduced during the printing process for a certain period of time. The anomalies were introduced manually by pulling the x-axis belt, pulling and pushing the bed, slightly knocking the structure of the printer, and shaking the printer itself to record the abnormal data points (Table 4.11).

Table 4.11 describes the data set acquired for the present research work. The three datasets are for training, testing and validation. Dataset-1 is a training dataset which is a mixture of abnormal and normal data points. Dataset-2 is a testing dataset, which consists of only normal points. Dataset-3 is a validation dataset that contains both normal and abnormal points, but with a smaller number of abnormal points. The normal and abnormal signals were identified by algorithms by analysing Dataset-1 which is a combination of normal as well abnormal signals. Table 4.12 shows the range of normal and abnormal signals for the accelerometer and gyroscope. However, it should be noted that these ranges are not universal but will depend upon the printer and the acquired data.

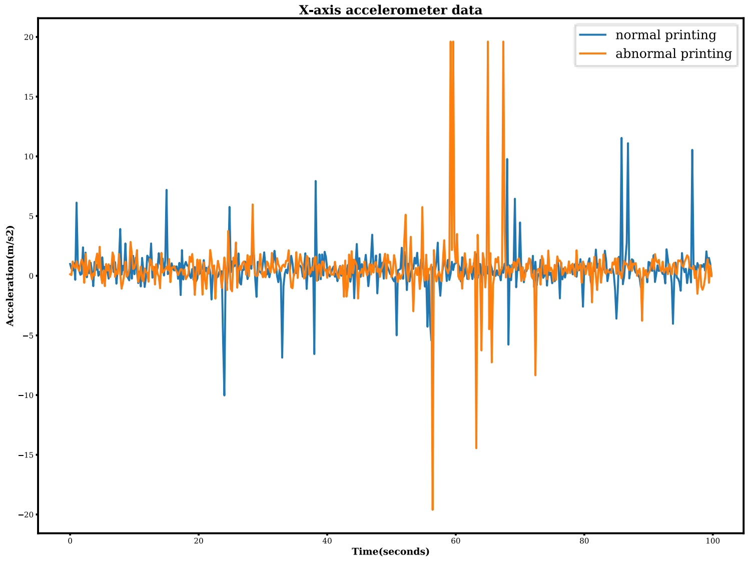
Table 4.11 Summary of the dataset

Dataset	**Abnormal points**	**Normal points**	**Total data points**
Dataset-1	2644	2922	5566
Dataset-2	0	7987	7987
Dataset-3	405	7562	7967

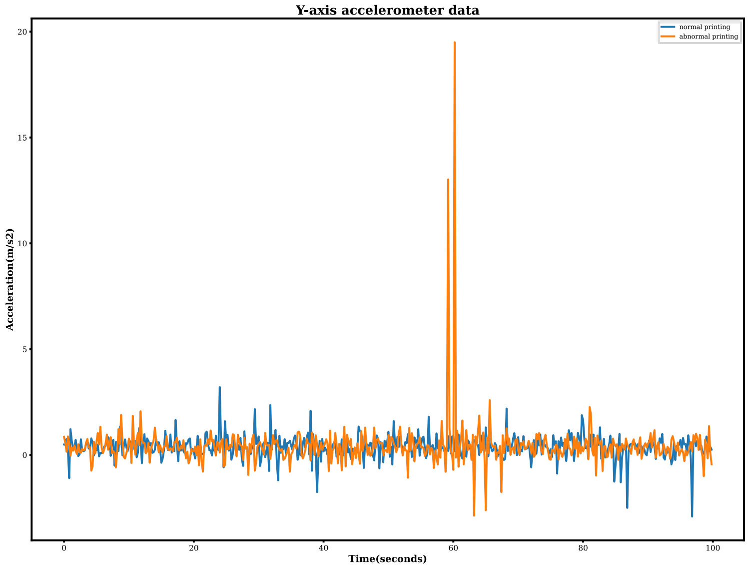
Table 4.12 Range of amplitude for normal and abnormal vibrations

Data type	**Range**	**Accelerometer**			**Gyroscope**		
		x-axis (m/s^2)	y-axis (m/s^2)	z-axis (m/s^2)	x-axis (deg/s)	y-axis (deg/s)	z-axis (deg/s)
Normal	Minimum	-13.08	-4.81	-11.25	-1.95	-25.01	-5.24
	Maximum	14.15	5.7	14.6	1.94	23.67	3.9
Abnormal	Minimum	-19.61	-5.6	-19.61	-5.5	-31.48	-32.58
	Maximum	19.61	19.50	19.61	4.58	35.19	27.04

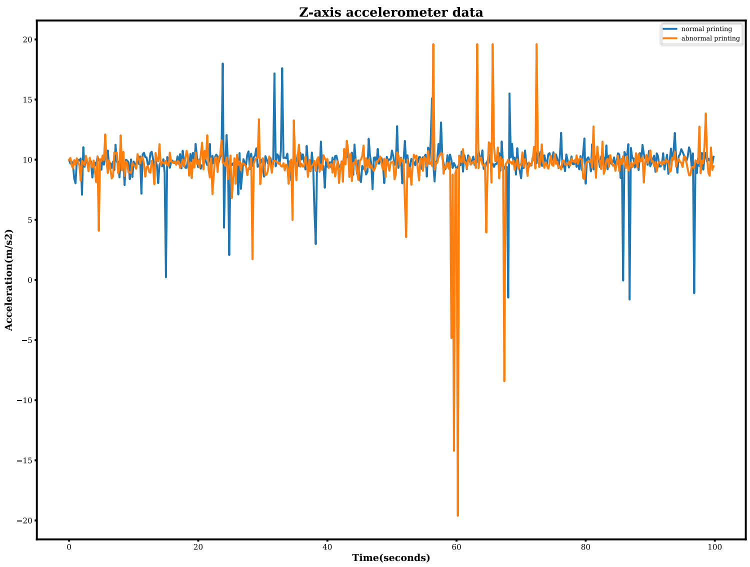
Figures 4.19 and 4.20 show samples of the accelerometer and gyroscope data, respectively along the x-, y-, z-axes during normal and abnormal printer health using blue and orange lines, respectively. These plots provide a visual representation of how the data looks in two opposite processes. Data pre-processing and denoising of raw accelerometer data were performed using python as a scripting language. Denoising of the data was performed to remove noise from the data and retain only relevant signals using PyWavelets, a wavelet transformation python package (G. Lee *et al.*, 2019). Figures 4.21 and 4.22 show samples of the denoised and noisy signals for the accelerometer and gyroscope data, respectively along the x-, y-, z-axes.



(a)

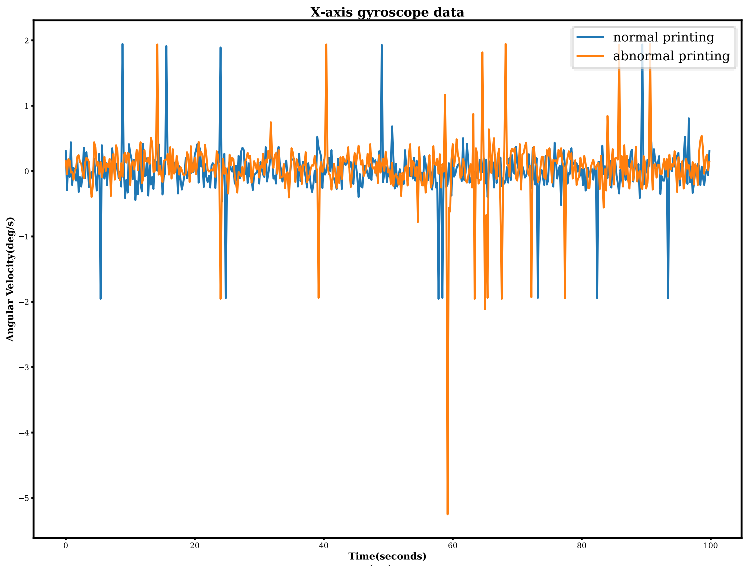


(b)

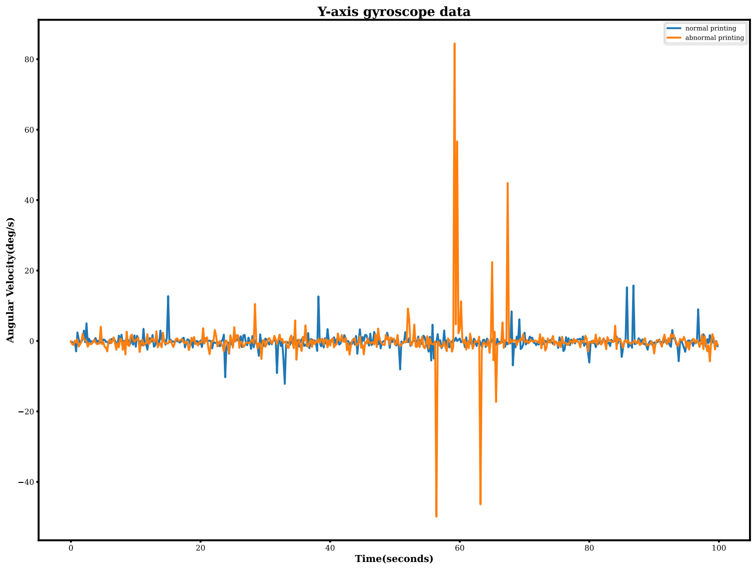


(c)

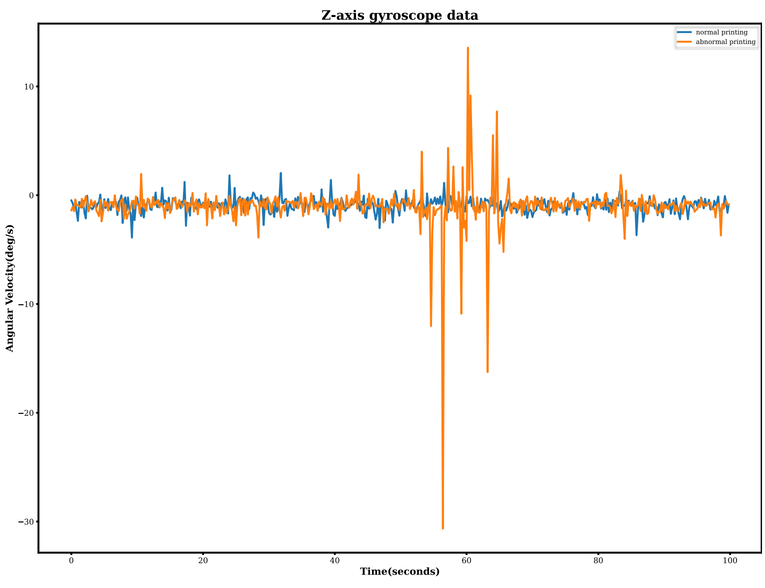
Figure 4.19 Normal and abnormal accelerometer data along x-, y-, z-axes



(a)

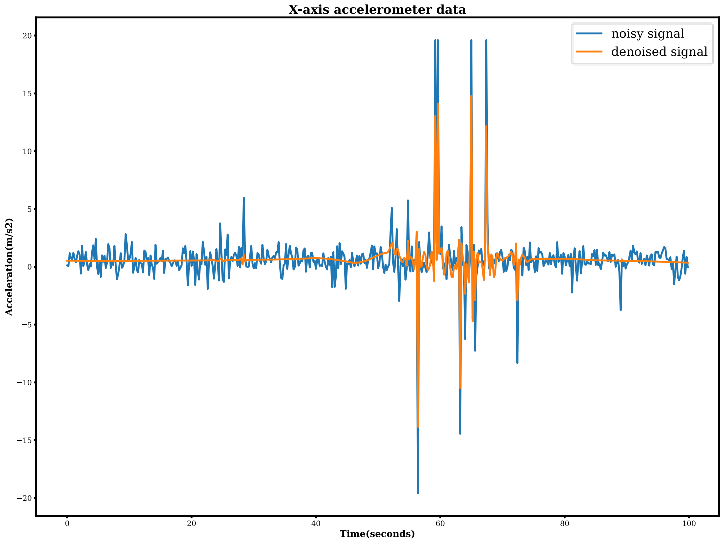


(b)

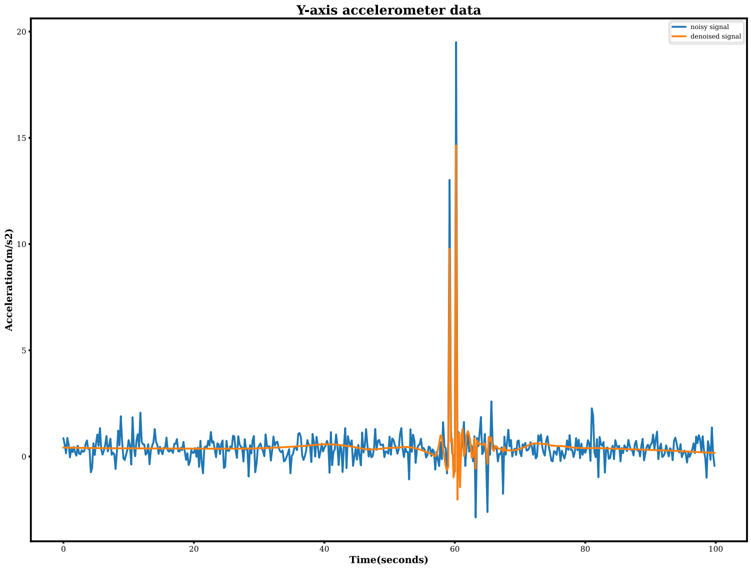


(c)

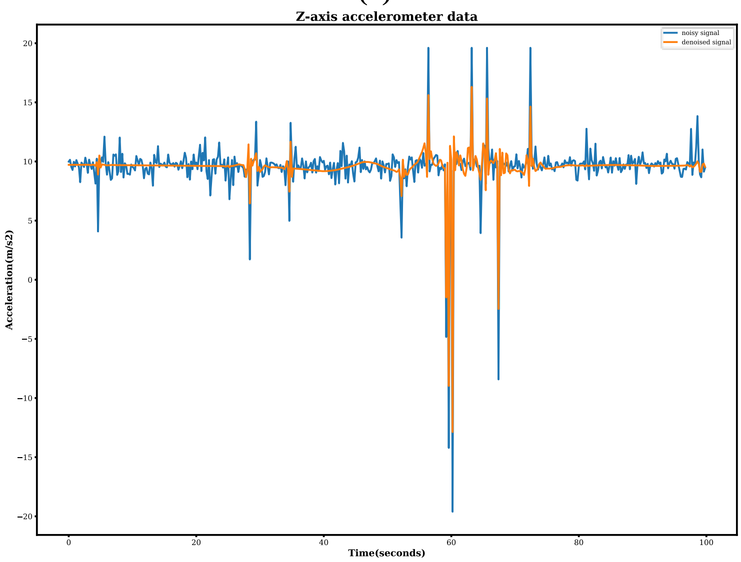
Figure 4.20 Normal and abnormal gyroscope data along x-, y-, z-axes



(a)

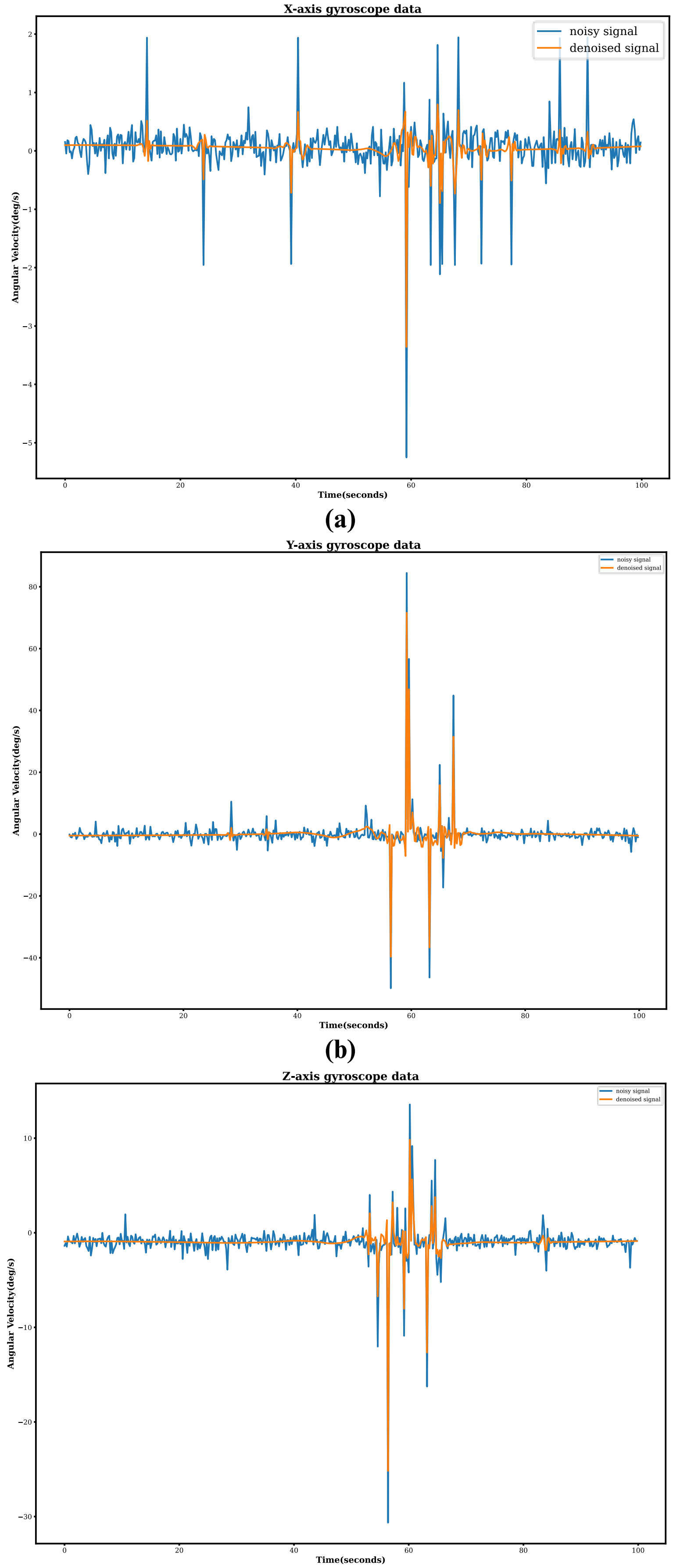


(b)



(c)

Figure 4.21 Denoised accelerometer data along x-, y-, z-axes



(a)

(b)

(c)

Figure 4.22 Denoised gyroscope data along x-, y-, z-axes

The PCA plot for denoised vibration data is shown in Figure 4.23. Principal component analysis (PCA) is a dimensional reduction method. The data were standardized, and principal component analysis (PCA) was used to reduce the feature space from six features (three axes of acceleration and three axes of gyroscope) to two feature spaces (PCA_1 and PCA_2). It shows the projection of the vibration points in these two feature spaces for easy visualization and analysis. PCA was performed using the python library – sklearn. The points were grouped automatically between 0 and 10 on the x-axis using python library. PCA enables the concentration of as much information (variance) as possible in a lower-dimensional space so that regular visualization charts can be generated (Mendia *et al.*, 2022). In this case, the point separated by 70 on the x-axis (PCA_1) and at -15 on the y-axis (PCA_2) represents maximum abnormality as this point is away from the apex and scattered.

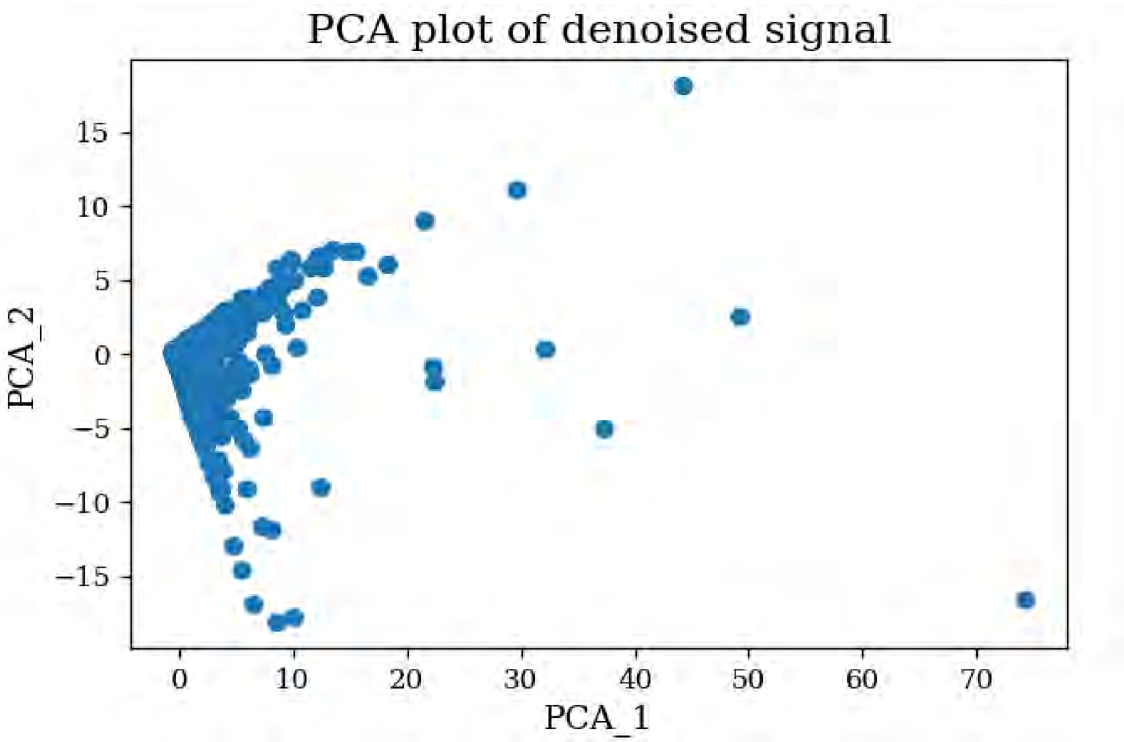
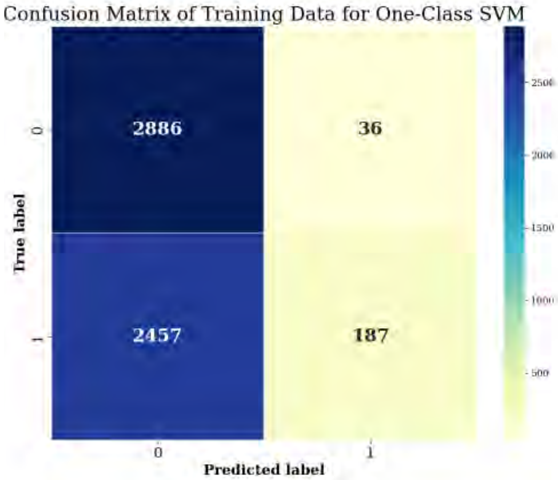


Figure 4.23 PCA plot for denoised vibration data

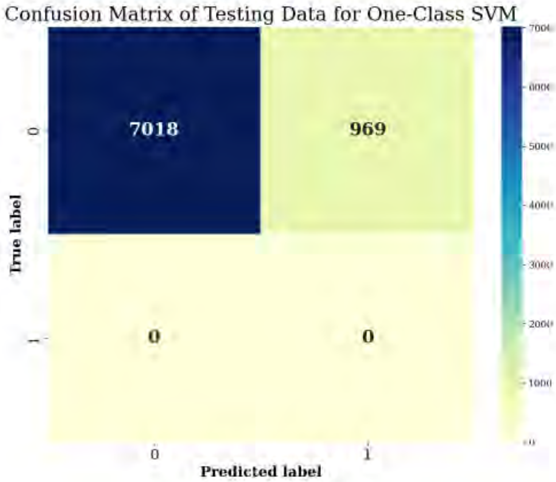
Several researchers (Mendia *et al.*, 2022; Hürkamp *et al.*, 2021; Reddy *et al.*, 2022) have used accuracy, precision, and recall as performance metrices for evaluating machine learning algorithms. Therefore, the developed algorithms were evaluated using these performance metrics. Accuracy is the ratio of all accurate predictions to the total number of predictions. Precision of a label is the ratio of accurate positive predictions of the label to the total predictions of the label. Recall of a label is the ratio of accurate positive predictions of the label to the total number of actual labels.

4.7.5.1 One-class support vector ML algorithm

One-Class SVM is a type of SVM which is an unsupervised algorithm, unlike other SVM algorithms. This is mainly used for novelty detection. i.e., classifying the new unseen data as similar or different from the data it is trained on. The developed One-Class SVM algorithm has parameter *'nu'* which tells the algorithm to assume a fraction of points to be the outlier. This value was set to 0.04, and represents that there lies only 4% of data points that are abnormal. This value has been arrived at on the basis that a printer should normally have a very small proportion of data points with abnormal values which are mostly due to sudden movements of nozzle or bed during the printing process. The '*gamma'* parameter was set to 0.01. This hyper parameter value was tuned using hit and trial method for the best prediction performance. Generally, a larger gamma value is used for complex classification and a smaller gamma value is used for simpler classification. In this case since the classification is simple in terms of normal and abnormal, therefore the value of the gamma parameter was taken as 0.01 for the best prediction performance. The One-Class SVM algorithm was trained on dataset 1, and the algorithm was tested and validated on dataset 2 and 3, respectively. In each of the three cases, the evaluation metrics of the algorithm were determined by comparing the actual labels to the predicted labels. The confusion matrices for the training, testing, and validation are shown in Figures 4.24 (a), 4.24 (b), and 4.24 (c), respectively. Here the label '0' indicates a normal data point, and the label '1' indicates an outlier or abnormal data point. The training, testing, and validation accuracy were found to be 55%, 88%, and 93%, respectively.



(a)



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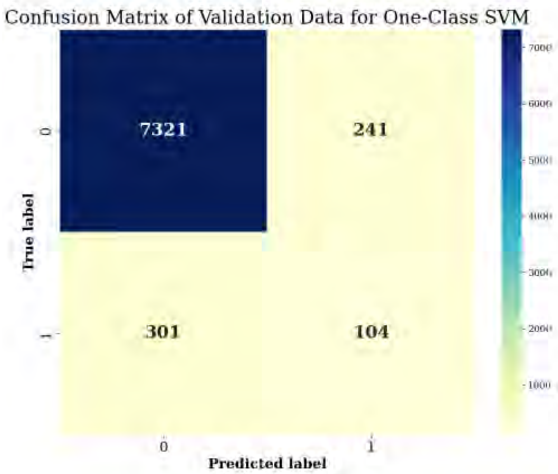


(c)

Figure 4.24 One-Class SVM algorithm confusion matrix for (a) training, (b) testing, and (c) validation

4.7.5.2 Local outlier factor (LOF) ML algorithm

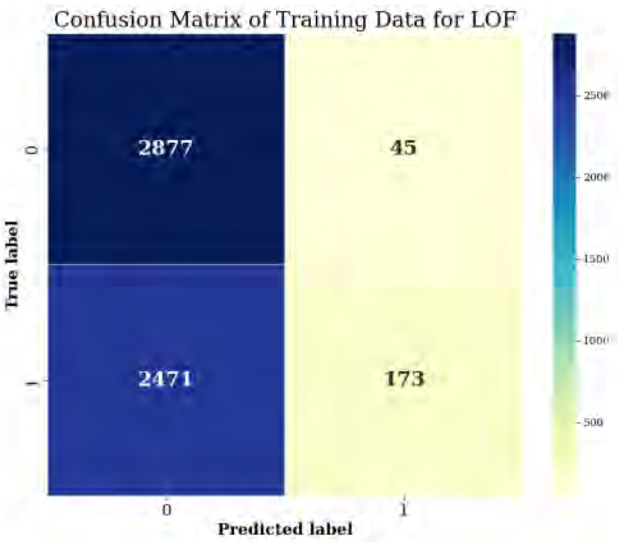
LOF algorithm is an unsupervised anomaly identification that calculates the local density deviation of a data point relative to its neighbours. It classifies points as outliers with lower density than their neighbours. The developed LOF algorithm has parameter contamination which tells the algorithm to assume a fraction of points to be an outlier. This value was set to 0.04. The '*n*_neighbors' parameter tells how many data points are to be considered as neighbors which were set to 100. The novelty parameter tells the algorithm whether novelty detection is being done which was set as true. The algorithm was trained on the denoised and pre-processed accelerometer data.

The LOF algorithm was trained, tested, and validated on dataset-1, dataset-2, and dataset-3, respectively. The confusion matrices for training, testing, and validation are shown in figures 4.25 (a), 4.25 (b), and 4.25 (c), respectively. The training testing and validation accuracy were found to be 54.79%, 77.50%, and 90.58%, respectively.

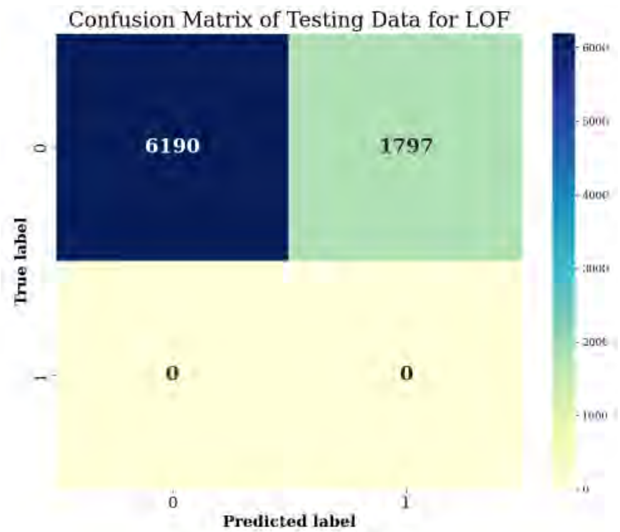
4.7.5.3 Support vector machine (SVM) ML algorithm

SVM is a supervised machine learning algorithm for classification and regression (IBM, 2023). The support vector classifier (SVC) identifies the hyperplane that maximizes the difference between two classes. Default parameter values have been used for algorithm preparation. The algorithm was trained on the denoised and pre-processed accelerometer data.

The SVM algorithm was trained, tested, and validated in a similar manner to the One-Class SVM algorithm. The confusion matrices for training, testing, and validation are shown in Figures 4.26 (a), 4.26 (b), and 4.26 (c), respectively. In this, the training, testing, and validation accuracy were found to be 89.27%, 97.60%, and 97.21%, respectively.



(a)



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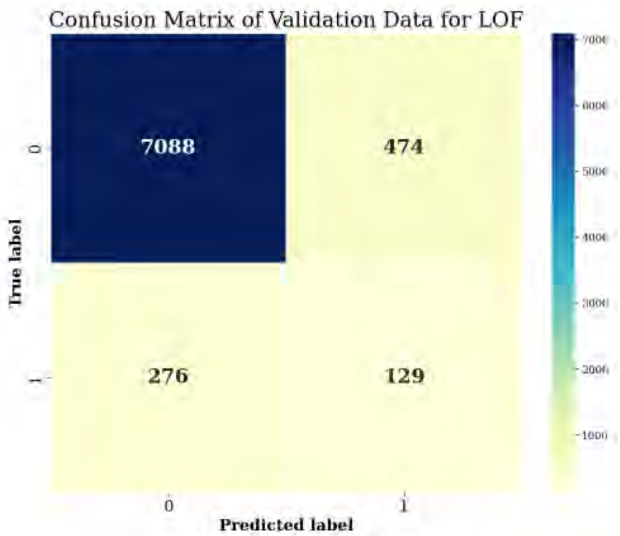
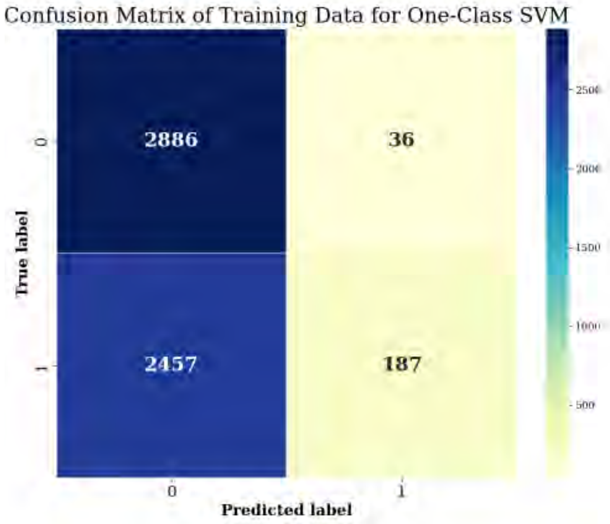
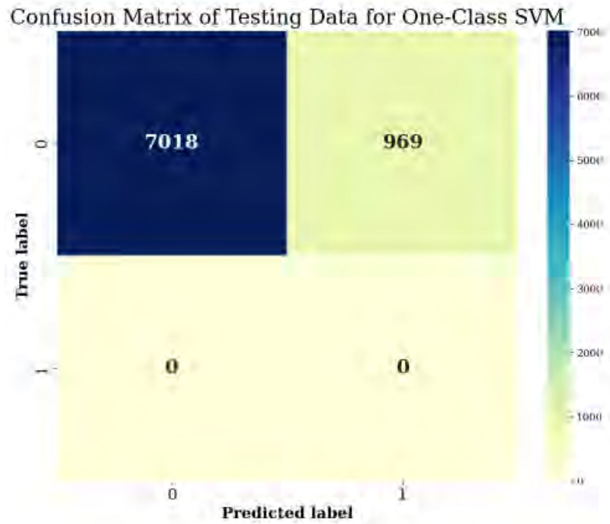


(c)

Figure 4.25 LOF algorithm confusion matrix for (a) training, (b) testing, and (c) validation



(a)



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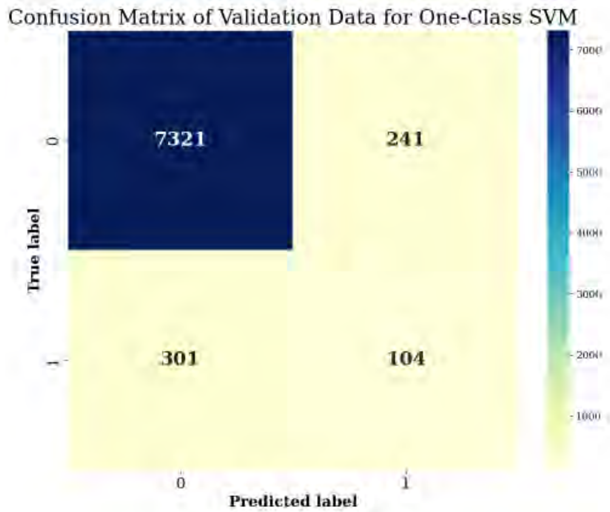


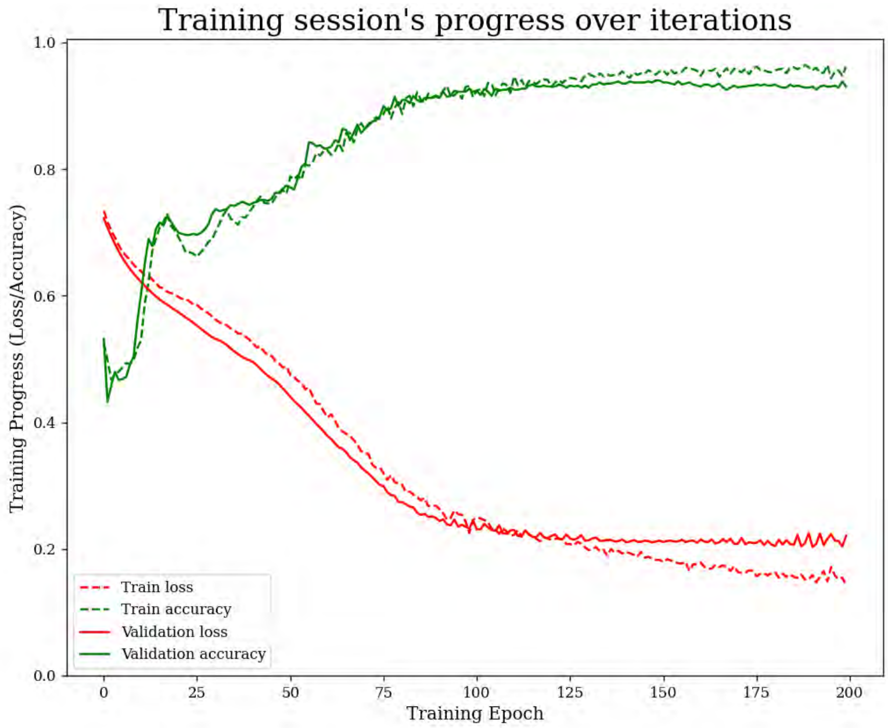
(c)

Figure 4.26 SVM algorithm confusion matrix for (a) training, (b) testing, and (c) validation

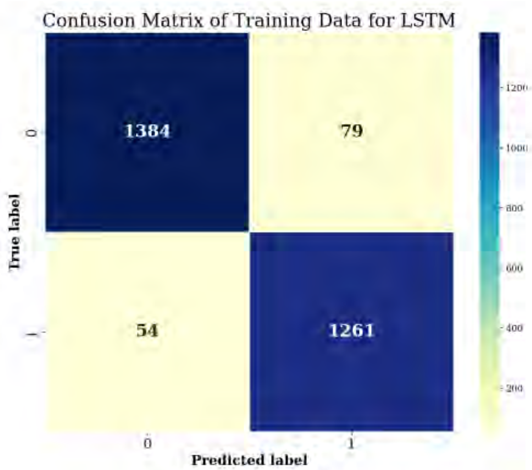
4.7.5.4 Long short-term memory (LSTM) ML algorithm

Recurring Neural Network (RNN) is a neural network design that is primarily employed for sequential or time-series data. It generates output based on the prior time-step value. LSTM is a type of RNN utilized primarily for managing time-series data. In contrast to a conventional RNN, it overcomes the issue of long-term dependency, making it ideal for this application. LSTM consists of three gates: forget gate, input gate, and output gate. Data were grouped for ten consecutive timesteps for every two timesteps. The input layer of the developed algorithm consists of an RNN layer with 128 nodes, a dropout layer with a dropout value of 0.5, a dense layer with 64 nodes, and a SoftMax layer with two nodes that indicate whether the data is normal or an outlier. The hyper-parameter values in respective layers were obtained by hyper tuning and training the developed algorithm until the best possible results were obtained.

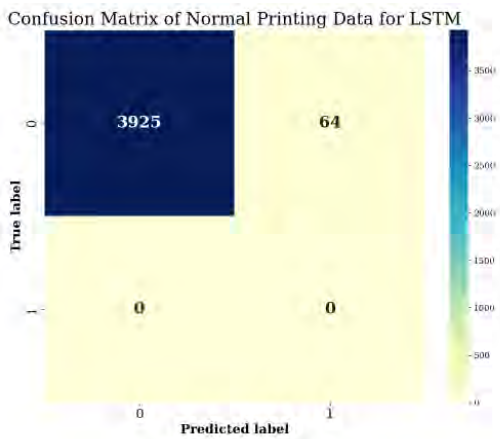
The algorithm was then trained for 200 epochs with a batch size of 2048. The trained algorithm was then used to identify anomalies in validation data. The LSTM algorithm was fitted on dataset – 1, out of which 67% of data was used for training the algorithm and the rest for testing. Datasets – 2 and – 3 were used for algorithm validation. The network was trained for 200 epochs since the validation loss did not change much, resulting in a validation accuracy of 92.14%, as shown in Figure 4.27 (a). Training loss refers to the error on the training set, whereas validation loss is the error acquired when passing the validation set through the trained LSTM. As the number of epochs increases, validation and training losses decrease. From the confusion matrices, as shown in Figures 4.27 (b), 4.27 (c), and 4.27 (d), the accuracy of the training data was found to be 94.82%; for dataset – 2, the accuracy was found to be 98.49%; and for the dataset – 3, it was found to be 97.48%. As these values are high (greater than 90%), and therefore validates the developed algorithm.

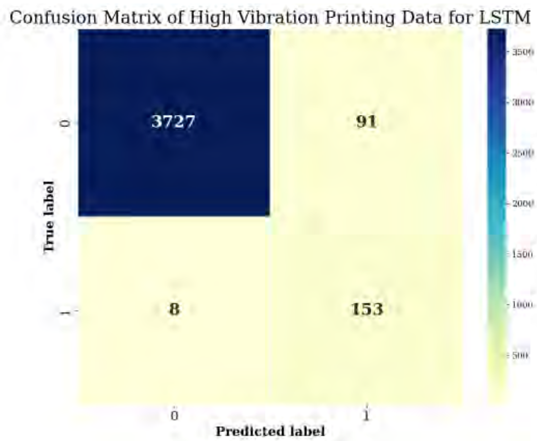


(a)



(b)





(c) **(d)**

Figure 4.27 LSTM algorithm (a) Loss curve, and confusion matrices for (b) training, (c) testing, and (d) validation

4.7.5.5 Comparison of the developed ML algorithms

Tables 4.13, 4.14, and 4.15 show the comparison of evaluation metrics of developed algorithms on datasets – 1, – 2 and – 3, respectively. It was found that LSTM (supervised machine learning) algorithm outperforms the One-Class SVM (unsupervised machine learning) in terms of better precision and recalls for abnormal data points.

The comparison of overall accuracy and computational time for anomaly detection using the proposed algorithms is shown in Table 4.16. The proposed algorithms were deployed on the Google Colab platform running on hardware specifications of Intel(R) Xeon(R) CPU @ 2.20GHz with a RAM size of 12.38 GB. Unsupervised machine learning algorithms took less computational time as compared to supervised machine learning algorithms suggesting that they are more feasible for in-situ process monitoring and anomaly detection during 3D printing, advantageous in applications where less latency is required.

The LSTM algorithm was selected for anomaly detection during 3D printing due to its highest accuracy. Although it requires more computational time, this can be reduced to sub-milliseconds with improved hardware specifications, making it feasible for in-situ process monitoring and anomaly detection during 3D printing.

Table 4.13 Evaluation metrics of algorithms for dataset-1

Label	One-Class SVM			LSTM			LOF			SVC		
	Precision	Recall	Accuracy (%)	Precision	Recall	Accuracy (%)	Precision	Recall	Accuracy (%)	Precision	Recall	Accuracy (%)
Normal (0)	0.54	0.99	55.21	0.94	0.96	94.82	0.54	0.98	54.79	0.86	0.95	89.27
Abnormal (1)	0.84	0.07		0.95	0.94		0.79	0.07		0.94	0.83	

Table 4.14 Evaluation metrics of algorithms for dataset-2

Label	One-Class SVM			LSTM			LOF			SVC		
	Precision	Recall	Accuracy (%)	Precision	Recall	Accuracy (%)	Precision	Recall	Accuracy (%)	Precision	Recall	Accuracy (%)
Normal (0)	1	0.88	87.86	1	0.98	98.49	1	0.78	77.50	1	0.98	97.60
Abnormal (1)	0	0		0	0		0	0		0	0	

Table 4.15 Evaluation metrics of algorithms for dataset-3

Label	One-Class SVM			LSTM			LOF			SVC		
	Precision	Recall	Accuracy (%)	Precision	Recall	Accuracy (%)	Precision	Recall	Accuracy (%)	Precision	Recall	Accuracy (%)
Normal (0)	0.96	0.97	93.19	1	0.98	97.48	0.96	0.94	90.58	1	0.97	97.21
Abnormal (1)	0.30	0.26		0.63	0.94		0.21	0.32		0.66	0.93	

Table 4.16 Comparison of different algorithms based on overall accuracy and computational time

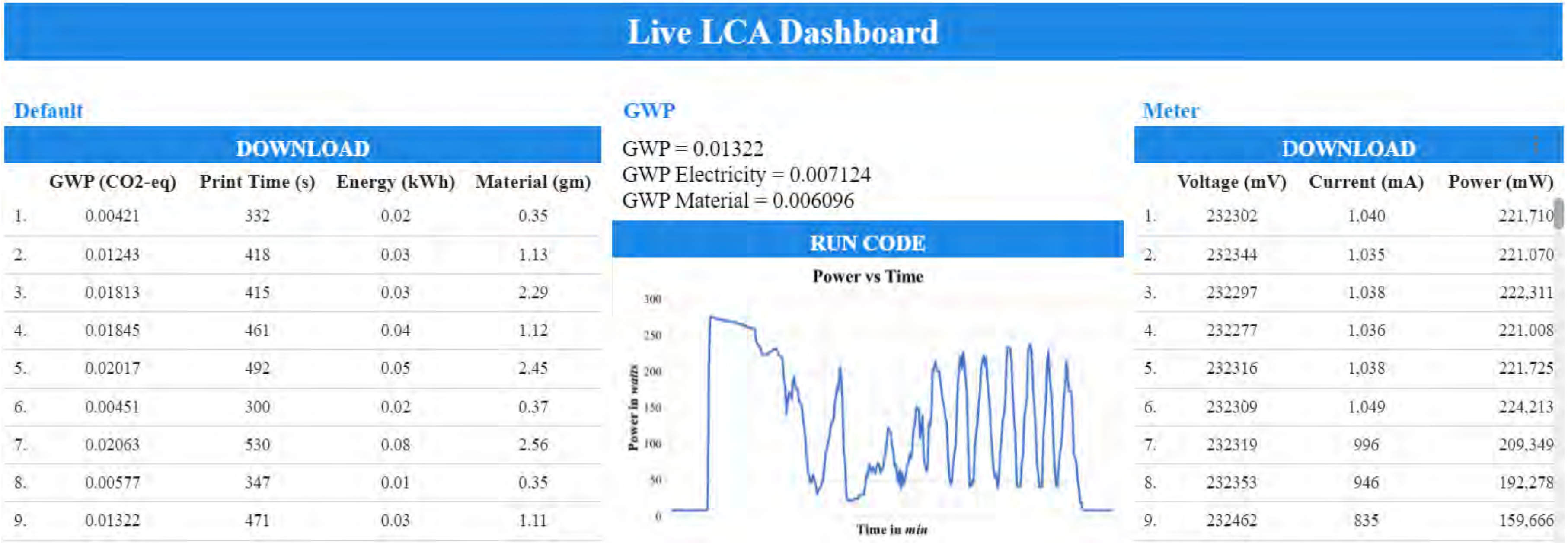
Algorithm	Overall accuracy (%)	Computational time (seconds)			
		Dataset 1	Dataset 2	Dataset 3	Average computational time
One-Class SVM	81.38	0.018	0.030	0.489	0.179
LOF	76.55	0.034	0.029	0.575	0.212
LSTM	97.17	1.159	0.742	1.178	1.026
SVC	95.30	1.180	1.292	1.086	1.186

4.8 A SMART 3D PRINTER MANAGEMENT SYSTEM

4.8.1 Decision Support, Visualization, Feedback, and Control

Appropriate and timely decisions making is a crucial solution for industries to sustain in the era of industry 4.0 (Salama & Eltawil, 2018). Data is collected, processed, and analyzed to obtain various patterns and infographics, and displayed on a dashboard to provide active decision support to a user in real-time. The decision support system is an integral element of a CPS, placed at the fourth (cognition level) out of five levels of CPS implementation architecture (J. Lee *et al.*, 2015). It is useful in obtaining additional information about performance of the shop floor or assembly line, evaluating a wide variety of scenarios for improving responses, and lastly obtaining the optimum combination of decision variables from multiple possible solutions in a comparatively short span of time. Consequently, it eases managerial tasks by providing timely, informed, and valuable insights using dashboards and alternatives for executing these decisions after evaluating different scenarios (Kellenbrink *et al.*, 2022).

The decision support system for the present research provides real-time recommendations of printing parameters depending on the managerial requirements, enabling a practitioner to override printing parameters directly on PMS, both locally and remotely. Interaction and physical actuation take place for the variables crossing the threshold values. Active decisions can be taken based on threshold limits, through alerts or instructions enabling the operator to effectively interact with the physical world. This can be performed either manually or through automated actuation. Figure 4.28 shows the PMS dashboard for online monitoring and controlling of a 3D printer, and Figure 4.29 shows the dashboard for online visualization of printing parameters using Node-Red.



	GWP (CO2-eq)	Print Time (s)	Energy (kWh)	Material (gm)
1.	0.00421	332	0.02	0.35
2.	0.01243	418	0.03	1.13
3.	0.01813	415	0.03	2.29
4.	0.01845	461	0.04	1.12
5.	0.02017	492	0.05	2.45
6.	0.00451	300	0.02	0.37
7.	0.02063	530	0.08	2.56
8.	0.00577	347	0.01	0.35
9.	0.01322	471	0.03	1.11

	Voltage (mV)	Current (mA)	Power (mW)
1.	232302	1,040	221,710
2.	232344	1,035	221,070
3.	232297	1,038	222,311
4.	232277	1,036	221,008
5.	232316	1,038	221,725
6.	232309	1,049	224,213
7.	232319	996	209,349
8.	232353	946	192,278
9.	232462	835	159,666

Figure 4.28 Dashboard for online visualization of GWP for a 3D printed product

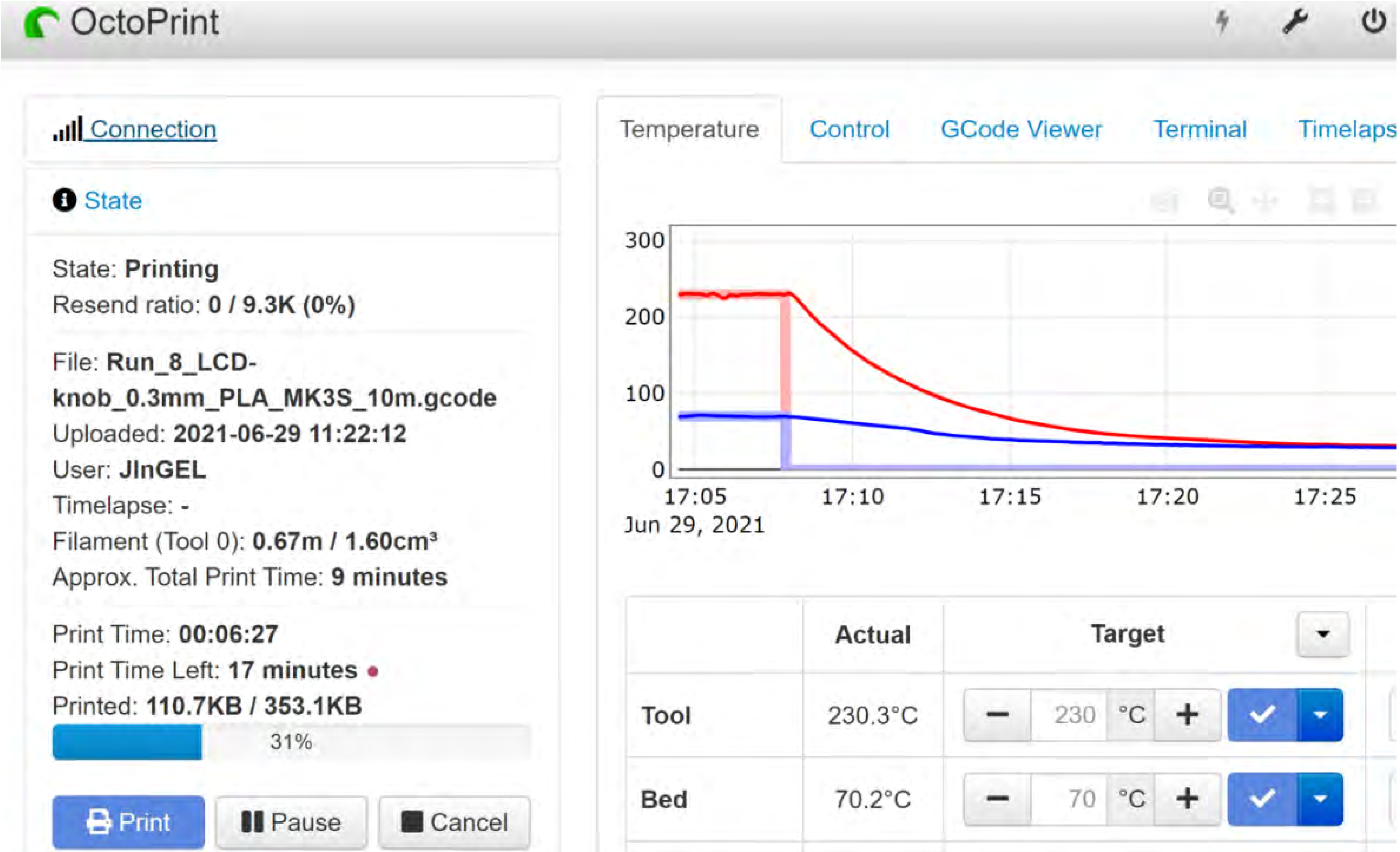
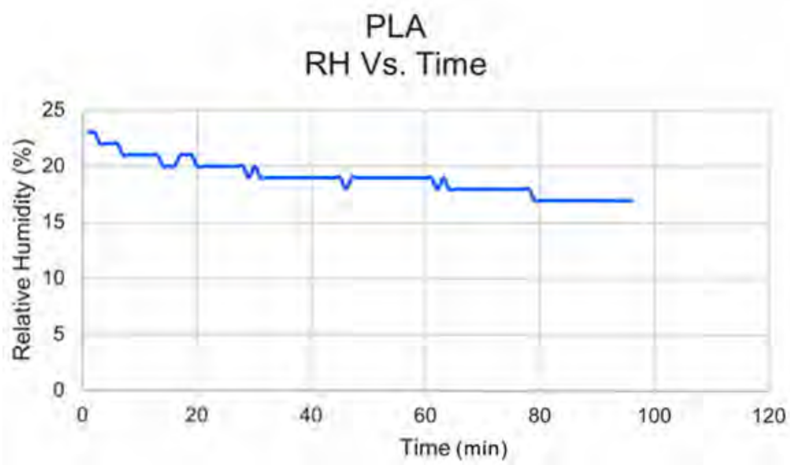


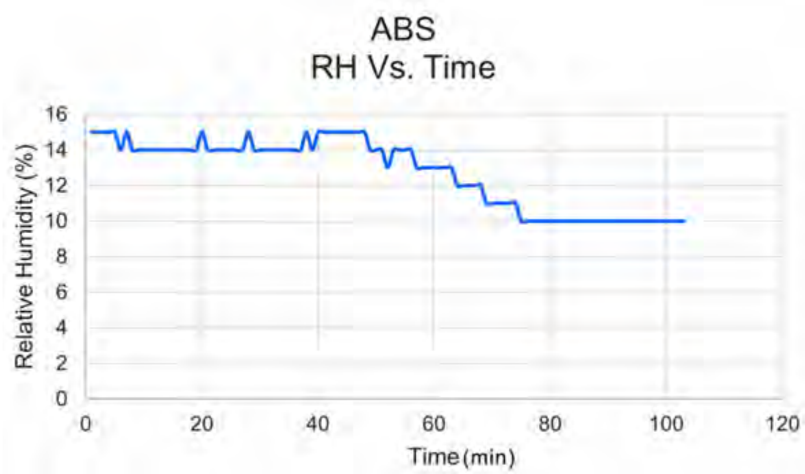
Figure 4.29 Live dashboard for 3D printer management system

4.8.2 Real-time Monitoring of Relative Humidity

Humidity-time plots for PLA, ABS, and PETG filament materials are shown in Figure 4.30.



(a)



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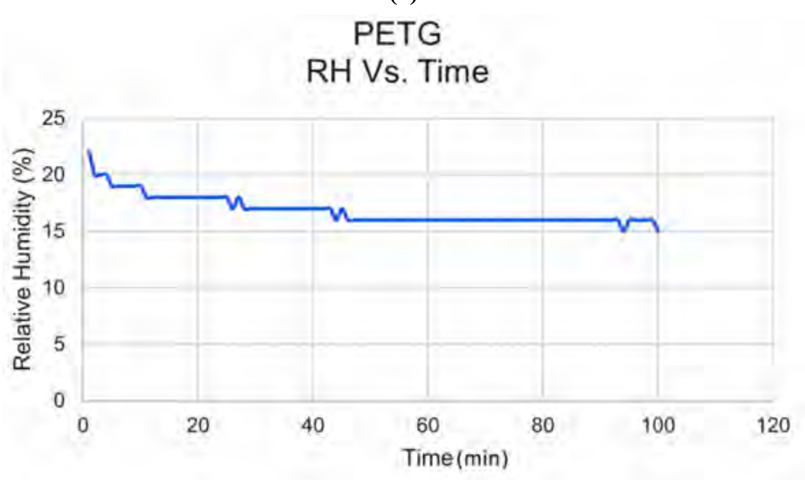


(c)

Figure 4.30 Relative humidity values with respect to time for (a) PLA, (b) ABS, and (c) PETG filament materials

It can be observed that relative humidity in the enclosed chamber keeps on decreasing until it reaches the saturation state. The saturation value depends on the filament material being used and therefore governs the quality of the finished parts. Filament materials like nylon have high moisture absorbing tendency from atmosphere and can lead to clogging of the nozzle. This can be prevented using real-time monitoring of humidity values and employing active mechanisms such as dehumidifier.

4.8.3 Real-time Monitoring of Ambient Temperature

Figure 4.31 illustrates variation of ambient temperature of the 3D printer enclosure with respect to time for PLA, ABS, and PETG filament materials.

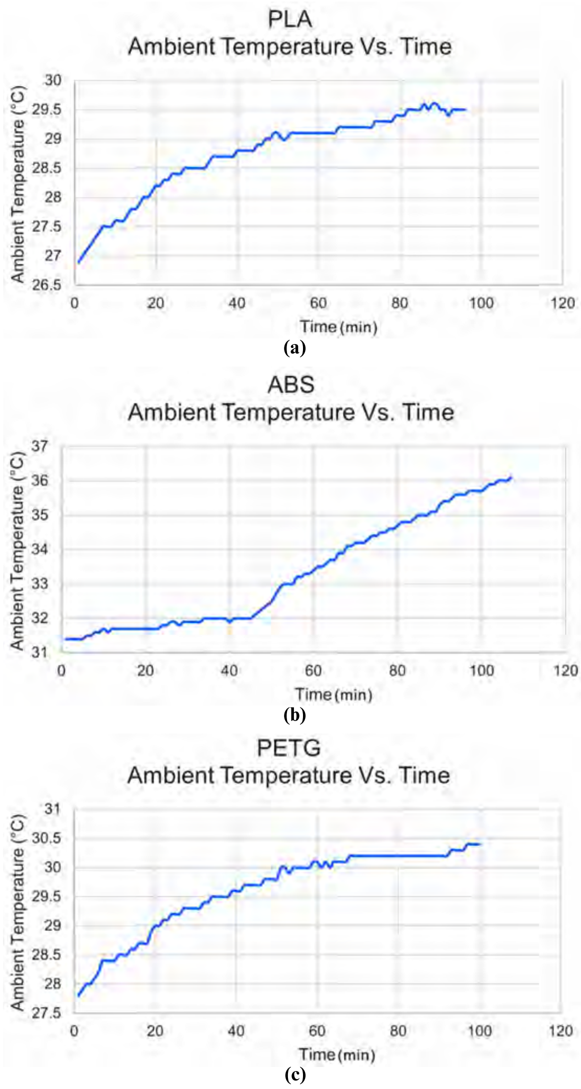


Figure 4.31 Ambient temperature values with respect to time for (a) PLA, (b) ABS, and (c) PETG filament materials

There is a steady increase in the ambient temperature of the enclosure due to the heat produced by the heated bed and nozzle. The ambient temperature is found to be highest for ABS since it prints at higher temperatures. A commonly known behaviour for ABS is that it warps very easily when not printed at adequate ambient temperature. To prevent printing failure from warping, it is essential to monitor the ambient temperature along with active control for the best results.

4.8.4 Real-time Monitoring of Environmental Emissions

Thermal degradation of thermoplastics generates airborne emissions with a wide collection of additives, free monomers, carcinogens, and respiratory sensitizers that are hazardous to human health (Unwin *et al.*, 2013). Real-time monitoring of environmental emissions (like VOCs and PM) during the 3D printing is significant for assessing potentially harmful exposure to a user on the shop floor, and useful in understanding the thermal degradation process of thermoplastics (Wojnowski *et al.*, 2022).

Real-time monitoring with adaptive control, such as proper ventilation, optimum process temperature, has great potential in dynamically controlling the risk associated with the airborne emissions. Figure 4.32 illustrates the VOC values with respect to time for (a) PLA, (b) ABS, (c) PETG filament materials.

It can be observed that the values end up saturating to a certain number of VOC particles which is generally around 28000 ppm. For the given experimental conditions, Figures 4.32 (d), (e), and (f) show the PM values with respect to time for PLA, ABS, and PETG filament materials, respectively obtained using SPS30 PM sensor. It can be inferred that the typical PM size of the given environment was around 0.55 for all the three filaments.

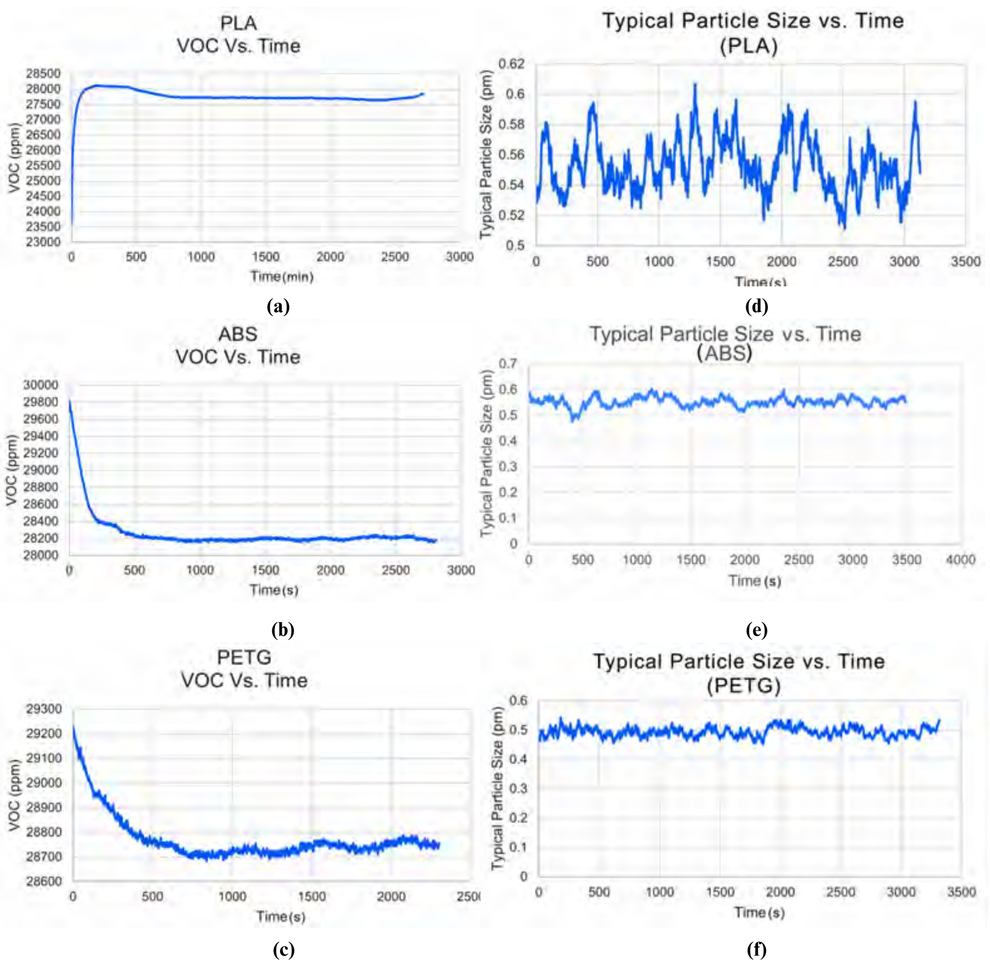
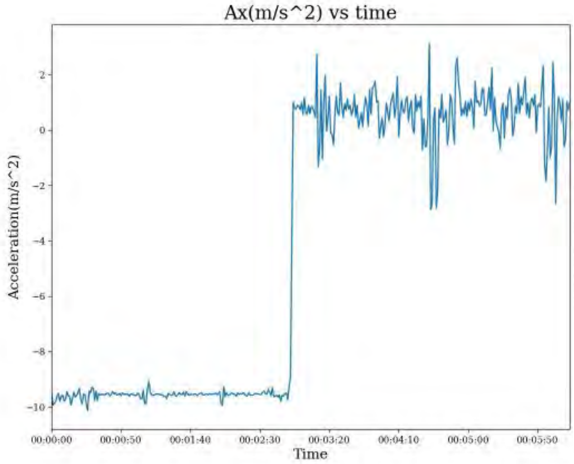


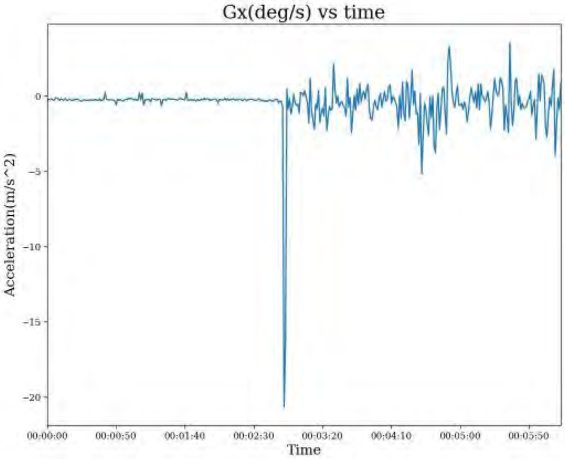
Figure 4.32 VOC values with respect to time for (a) PLA, (b) ABS, and (c) PETG filament materials, PM values with respect to time for (d) PLA, (e) ABS, and (f) PETG filament materials

4.8.5 Real-time Monitoring of Acceleration and Orientation

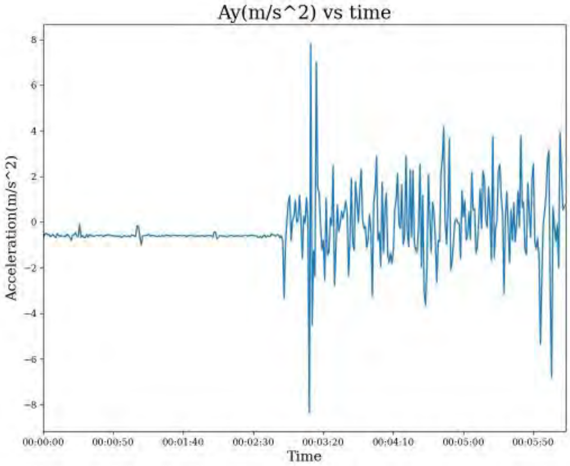
Acceleration and orientation data acquired during 3D printing with PLA filament is shown in Figure 4.33. This holds a lot of potential for condition monitoring. The captured data of the three filament materials can help in solving printing problems of ghosting or ringing. The gyroscope measured orientation can help in calibrating the maximum allowable accelerations of the 3D Printer for countering ghosting while decreasing print time.



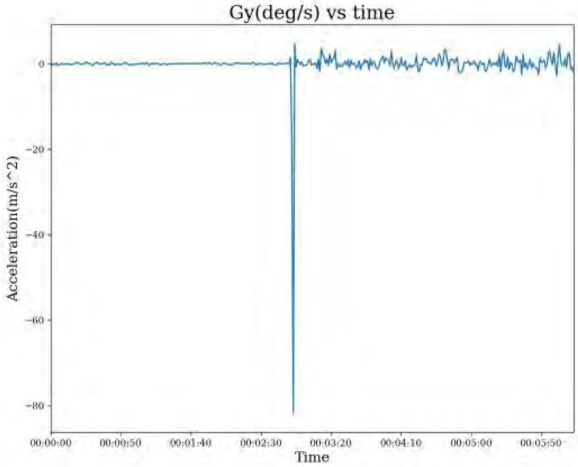
(a)



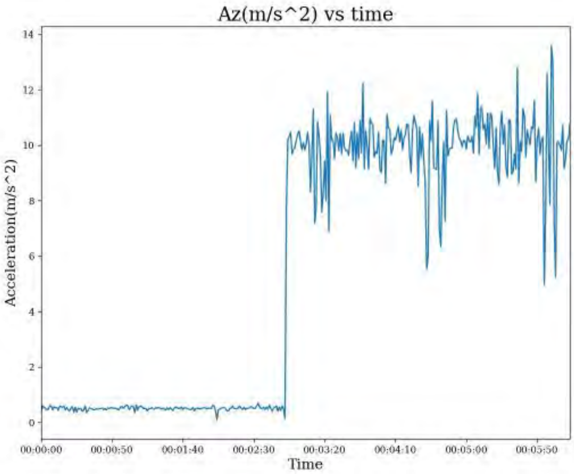
(d)



(b)



(e)



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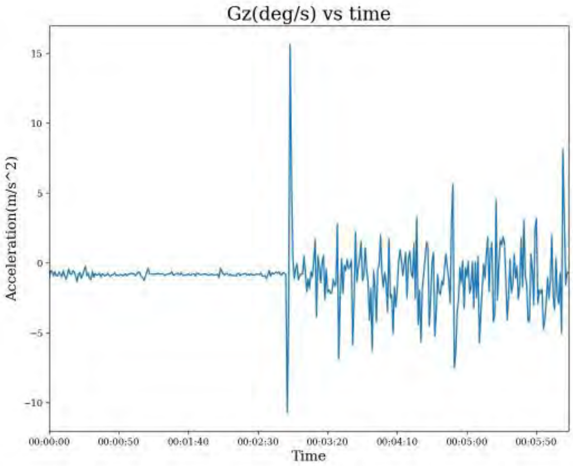


(f)

Figure 4.33 Acceleration with respect to time during 3D printing with PLA filament material along (a) x-axis, (b) y-axis, (c) z-axis; and orientation along (d) x-axis, (e) y-axis, (f) z-axis

4.8.6 Machine Vision based Online Monitoring, Identification, and Control of Defects

Machine vision is used to monitor, identify, and control defects during 3D printing process using image processing algorithms on edge. A Camera and a Raspberry Pi were wired together with python scripts and local edge servers for deploying defect identification and control module on Node-Red; an open source, flow-based development tool for visual programming.

Figure 4.34 illustrates the process flow diagram for online monitoring, identification, and control of defects during 3D printing. A machine vision camera attached to the raspberry pi is used to take regular snapshots after printing of each layer as shown in Figure 4.35 (a). These snapshots are imported sequentially with height information, turned to grayscale, and blurred before finding the outer edge of the printed specimen. The logic behind the identification, and control of defects is provided using image processing algorithm programmed using python language. Modelling consists of digital image processing using OpenCV for implementing real-time machine vision system. The specimen image is transformed into numerical features to identify printing deviations as compared to the CAD data and assigned dimensional tolerances. This is followed by image warping, where the length and interval of the coordinate arrays are restructured into equal length and interval. The contour arrays of the detected edge and CAD are compared in a sorted sequence for the given height. Comparison is made in terms of absolute distance between corresponding pixels. The output is then generated as a two-dimensional graphical representation along with quantitative value notification to the dashboard as shown in Figure 4.35 (b). The product is continuously 3D printed until any defect is detected. Under faulty circumstances, printing is paused, and a notification is sent to the dashboard for the user to confirm. A relay module is also used as an edge device. A small voltage signal via the relay module energizes the electromagnets and thus opens the switch and vice versa. It is programmed to turn off the 3D Printer when anything goes beyond the nominal values like high VOC values in the enclosure, which can suggest unsafe working conditions and therefore automatically pause the 3D Printer. Alert messages are generated and sent to the manager using Gmail API and Google cloud console. A common cause of print failure is the printer running out of filament. If the printer being used does not have the capability to detect and pause filament runaway, then the entire print is wasted since the nozzle will continue to trace its path without depositing any filament material. To prevent this failure, a filament sensor is used to detect the filament availability for the subsequent printing. Filament sensor is hosted on edge computing for active feedback and control with reduced latency and response time. If the filament sensor detects no filament, it automatically pauses the print and lifts nozzle to a safe location so the user change filament or resolve the issue manually.

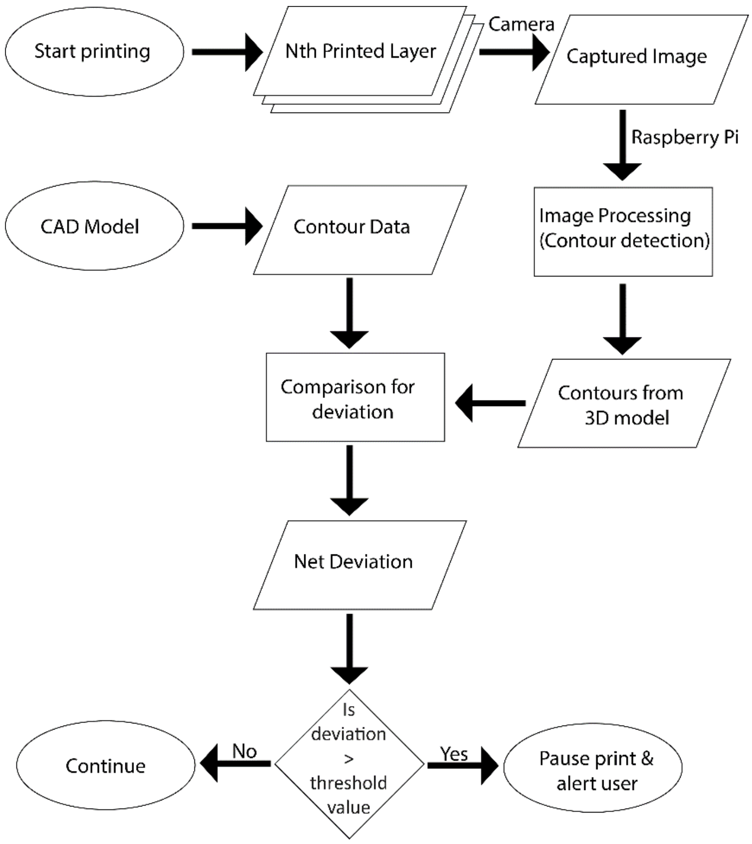


Figure 4.34 Process flow diagram for online monitoring, identification, and control of defects during 3D printing

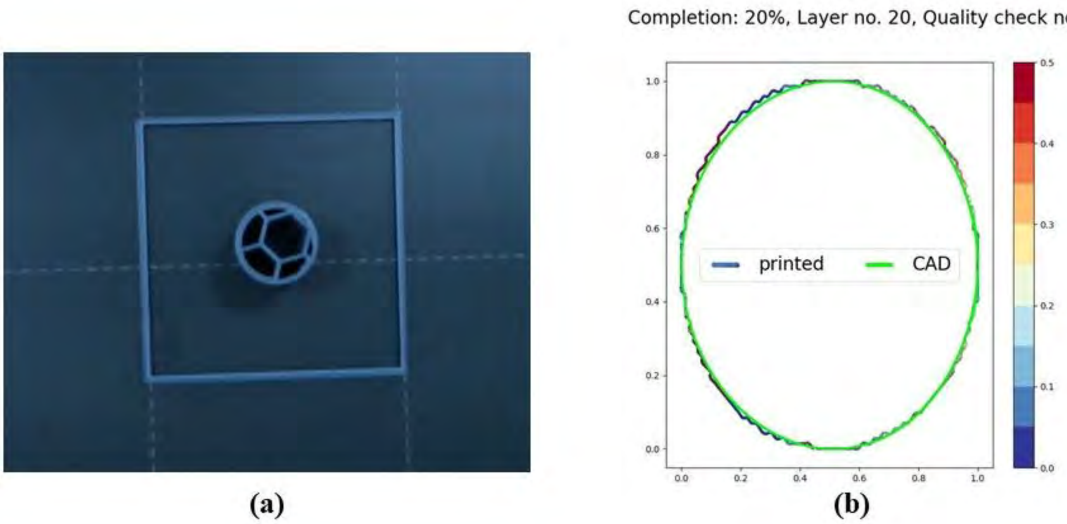
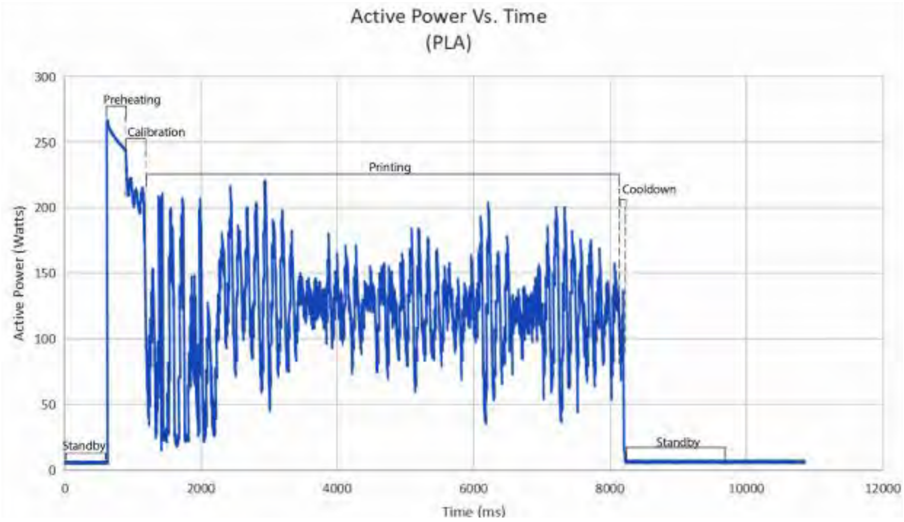


Figure 4.35 Snapshot of (a) 3D printed product, (b) comparison with CAD model

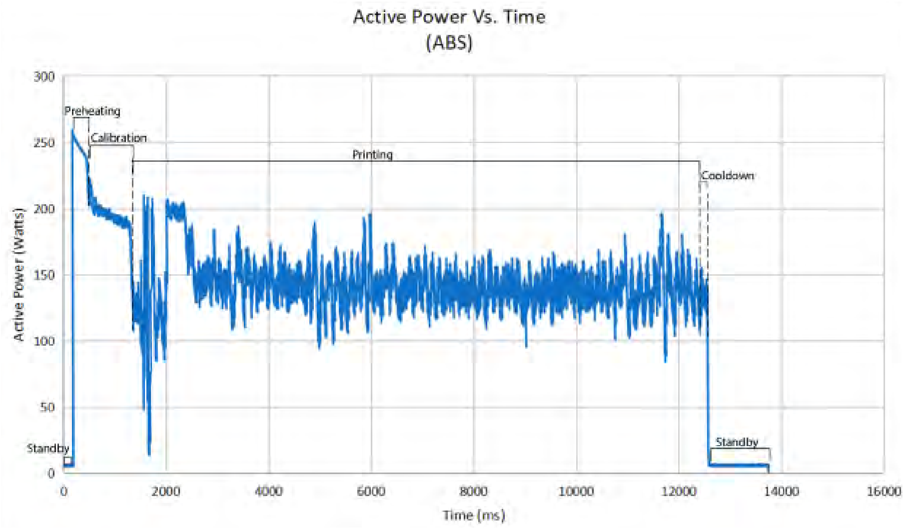
4.8.7 Real-time Monitoring and Control of Energy Consumption

Energy consumption data during 3D printing process can be acquired and recorded as timestamps using inexpensive energy monitoring systems. It can be further processed and analyzed to get a better understanding of the process. A smart energy meter is used for monitoring and recording power consumed during standby, preheating, calibration, printing, and cooldown as shown in Figure 4.36.

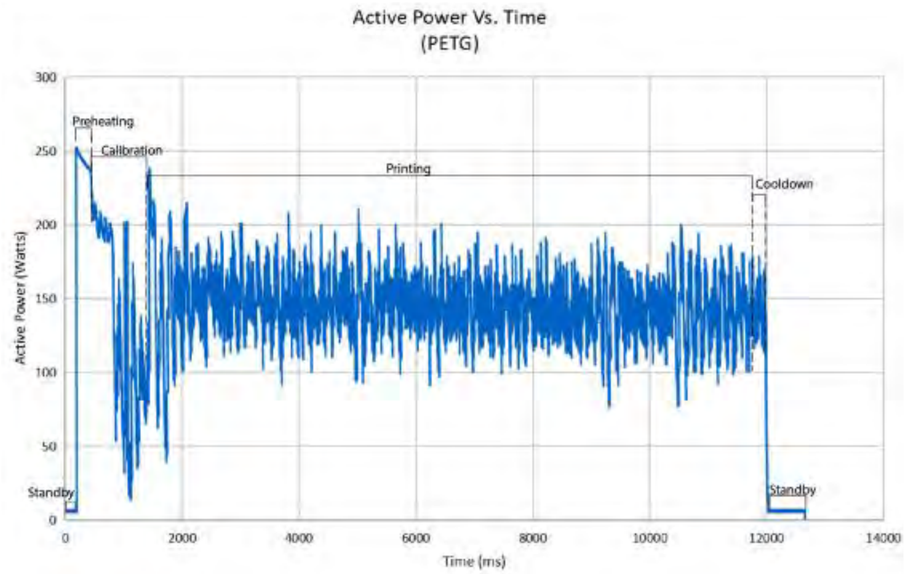
During the standby phase, the printer is powered on but is not handling any active job. Due to its idle state, printer consumes minimum power to keep itself alive and ready to receive instructions from user while displaying the current status. During preheating, energy is used up to pull nozzle and bed temperatures to the required values for printing the specified filament material. During the calibration process, power is consumed as most of the actuators are functioning. During the actual printing, the power consumption profile is dependent on the model being printed. Abrupt motions in printing lead to sudden curve changes and spike formations. The longer the print time, the greater is the power consumption. Lastly, during cool-down sequence, power consumption drop is noticed since nozzle and heated thermistor reduce drawing of power and the temperatures start falling. Motors are also turned off during cool-down sequence. After cool-down, printer again enters standby phase, until turned off, waiting for next job.



(a)



(b)



(c)

Figure 4.36 Power consumption profiles with respect to time for (a) PLA, (b) ABS, and (c) PETG filament materials

Energy consumption depends on several variables such as infill, layer height, filament material, bed temperature, nozzle temperature, printing time, *etc.* Table 4.17 compares the energy consumption for PLA, ABS, and PETG filament materials under similar conditions except bed and nozzle temperature settings. ABS filament material consumes the highest power while printing almost the same weight as PLA and PETG filament materials. Moreover, live data such as filament material consumption can be acquired from PMS, along with the live energy data from smart energy meter to estimate the carbon footprint instantaneously. This will enable a user to dynamically monitor and assess the performance measures values and provide prompt decision support.

Table 4.17 Energy consumption for PLA, ABS, and PETG filament materials

<table>
<tr><th rowspan="2">Material</th><th colspan="2">Parameter settings</th><th rowspan="2">Bed temperature (°C)</th><th rowspan="2">Extruder temperature (°C)</th><th rowspan="2">Energy consumption (kWh)</th></tr>
<tr><td>Infill (%)</td><td>Layer height (mm)</td></tr>
<tr><td>PLA</td><td rowspan="3">10</td><td rowspan="3">0.2</td><td>215</td><td>60</td><td>0.07</td></tr>
<tr><td>ABS</td><td>255</td><td>110</td><td>0.15</td></tr>
<tr><td>PETG</td><td>250</td><td>90</td><td>0.13</td></tr>
</table>

4.9 COST ANALYSIS

The total cost of hardware is approximately 260 USD, excluding the 3D printer. Open-source software was used so no cost is involved for the software. Cloud computing platform does not cost up to a certain limit in free tier subscription. Therefore, there is zero cost involved in usage of cloud computing platforms for the present use case. The raspberry pi, smart energy plug, VOC sensor, PM sensor, webcam cost USD 75, USD 45, USD 24, USD 63, USD 24, respectively. Gyroscope, NodeMCU, filament sensor, relay module, and a few auxiliary hardware required to set up local network connectivity, *etc.* costed around USD 30. The low-cost solutions become significant for the adoption of these systems in micro, small and medium enterprises (MSMEs). Secondly, the MSMEs do not have enough funds to buy new Industry 4.0 compliant or smart systems/equipment to realize the benefits of Industry 4.0 adoption. The proposed low-cost system can be used with the existing equipment to get higher productivity, greater reliability, improved uptime, and enhanced quality benefits of Industry 4.0.

4.10 SUMMARY

This chapter presents a CPPS framework for smart 3D printing analytics and management. Further, the following models have been developed to demonstrate the usefulness of the proposed CPPS framework:

- Real-time monitoring, visualization and control using computing technologies
- Real-time monitoring and control of defects during 3D printing using a machine vision system and edge computing
- Live demonstration of energy consumption and carbon footprint during 3D printing
- Development of machine learning algorithm to predict RUL of a 3D printer nozzle
- Development of machine learning algorithm for real-time anomaly detection using vibration data
- Development of a live dashboard for the real-time visualization and control
- Development of a prescriptive model to prescribe optimal printing parameters for minimizing carbon footprint and printing time at targeted surface finish.

The conclusions and the practical significance are as follows:

- Cloud computing platform was found better to store data for temperature, humidity, and energy consumption as these variables require high storage volumes, remote and easy accessibility, scalability, and redundancy. Fog computing platform was used to store data on VOC, acceleration, particulate matter, and orientation for the closer proximity of data source as these parameters require resource intensive processing, medium storage volumes, low latency, and easy accessibility. Edge computing platform was used to automatically detect defects, filament runout, filament breakage, and smoke at its source as these parameters require faster insights, very low latency, autonomous and prompt decision making, and instant actuation without demanding resource intensive processing and higher storage.

- The proposed LSTM machine learning algorithm for descriptive analytics characterizes and estimates energy consumption during various stages of 3D printing and for different materials (PLA, ABS, PETG) with high prediction accuracy. This would be helpful in understanding of the energy consumption in each stage of the 3D printing process.
- The proposed computational model for descriptive analytics enables live estimation of environmental impact for the 3D printed products with varying combinations of printing parameters. It offers different stakeholders (operator, manager, manufacturer) the results of life cycle assessment for prompt interventions. Furthermore, it enables environmentally conscious consumers to make well-informed purchasing decisions through enhanced transparency and visibility.
- The proposed prognostic model, developed by using autoregressive machine learning algorithm, is valuable to monitor the nozzle health, which helps to improve the printer uptime, reliability, and energy efficiency; and product quality. It also prevents abnormal power usage and facilitates proactive planning of maintenance schedule and sequence of orders.
- Prescriptive analytics enabled to understand the relationship among 3D printer performance measures. It prescribed optimal printing parameters, providing decision

support to practitioners in overriding the parameters online for the simultaneous optimization of environmental, economic, and technological performance characteristics. This is also useful at the computer-aided process planning stages in the design optimization and the production of high-quality goods with tight tolerances demanded by a customer.

- The proposed diagnostic model developed by using machine learning algorithms detected anomalies due to mechanical or structural failure of the 3D printer. The developed supervised LSTM algorithm has an overall accuracy of 97.17%, outperforming other supervised (SVM), and unsupervised (One-Class SVM, LOF) machine learning algorithms. Unsupervised machine learning algorithms were found to have higher computational speed than supervised machine learning algorithms for detecting anomalies during 3D printing. The significance of timely detection of anomalies lies in its ability to achieve error-free 3D printing, resulting in less material waste, reduced human intervention & costs, and improved product quality by detecting potential anomalies during printing and terminating the printing process.

CHAPTER 5

DEVELOPMENT OF A CPPS FRAMEWORK FOR SMART TOOL HEALTH ANALYTICS AND MANAGEMENT

More and more organizations are trying to install tool health analytics dashboards for CNC machines to avoid unexpected failures, maintain machining accuracy, and optimize tool change. This chapter aims at developing a CPPS framework for a smart tool health management system to prescribe the optimum cutting parameters to managers/operators for optimizing the remaining useful life and/or material removal rate, and/or active power consumption (either separately or simultaneously) at a predefined surface finish.

5.1 INTRODUCTION

Metal cutting is an essential process of removing unwanted material from the workpiece to obtain the desired shape and size. The frequent replacement of tools during machining adds to tooling cost as well as lowers productivity. Generally, the tool life is pre-determined at laboratory conditions for a tool-workpiece material pair for a range of operating conditions. However, the workpiece properties, particularly near the surface of the workpiece may be different when produced under actual working conditions. This leads to either inefficient use of a tool (tool changed before the end of life) or premature tool failure leading to poor surface finish, dimensional accuracy, surface texture, *etc.* The literature suggests a downtime up to 20% (Kurada & Bradley, 1997) and productivity loss of 7-20 % (Kegg, 1984) for the inefficient use of tools. This becomes more challenging when working with hard materials and superalloys, known as difficult to machine materials. One such difficult to machine material is AISI H13 tool steel with hardness greater than 30 HRC. H13 tool steel is widely used in aerospace, automotive, and tooling (moulds and dies) industries. This research used H13 tool steel workpiece material and coated carbide tool (AlTiN). An optimized tool change will also assist managers in developing efficient production plans and tool purchase schedules. The benefits become profound for autonomous manufacturing under industry 4.0 environment. Therefore, this study uses machine learning algorithms on the real-time data to predict the remaining useful life of the tool in real-time and prescribes the optimum cutting variables to achieve the organizational objectives of optimum RUL and/or material removal rate (MRR) at a predefined surface finish.

Most of the existing research on tool health analysis provides proof of concept as happens with any new research. It means that remaining useful life is predicted based on the data at specific cutting conditions for a tool/workpiece material combination. Few researchers (Drouillet *et al.*, 2016; Malakizadi *et al.*, 2020; Corne *et al.*, 2017; Zhou *et al.*, 2022) have varied one of the cutting parameters to predict the RUL without incorporating standard design of experiments (DOE) methodologies. This has limited use in industrial applications as the cutting parameters in industry are variables, and RUL may be different from the predicted value at the specific cutting parameters. Therefore, a proper design of experiments is required so that the RUL can be predicted to include the effects of cutting parameters on it. The predicted RUL under these statistically significant conditions can be further optimized to provide a set of cutting parameters for optimum/maximum RUL. The surface finish for a machining job is known as *a priori* (Kant & Sangwan, 2014), therefore optimization of RUL without the prescribed surface finish hardly has any practical significance. The proposed research methodology can also prescribe the cutting parameters for maximum MRR and the corresponding RUL at the targeted surface finish as required by the industry. The proposed model takes into consideration the productivity, cost, and quality into consideration to prescribe the cutting parameters for a milling operation.

The prognostic and prescriptive analyses work well with normal working conditions considering wear and tear. But a diagnostic analysis is necessary to detect anomalous behaviour of a system. An anomaly is defined as the occurrence of events/items/data points/observations that are distinct (abrupt or gradual) from what is standard, normal, or expected (Saez *et al.*, 2017). There can be multiple reasons for anomalous behaviour in machining operations. There may be failure events during the useful life of a tool due to several reasons such as improper fixing of either tool or workpiece, presence of irregularities on the workpiece, *etc.* Anomalous behaviour detection in real-time can facilitate timely actions, to prevent machining faults, through automated actuation or operator intervention (Nouri *et al.*, 2015). Diagnosis could detect tool wear stages and anomalies and prevent dynamic breakdown of cutting tools to maintain product quality, reduce downtime, and improve the reliability during smart manufacturing (Wei *et al.*, 2022; F. Zhang *et al.*, 2020). Unmanned running of machine tools, as envisioned under industry 4.0, under abnormal conditions may lead not only the high rejections and poor surface finish but may also damage the machine tools and sensors. Diagnostic analysis should be offered complementary with the prognostic and prescriptive analyses to avoid costly damage and runouts as well as to imbibe confidence in the managers and operators under industry 4.0 environment. Proper diagnostic could prevent product rejections and premature tool failures thereby saving time, money, and energy (Cooper *et al.*, 2020).

CPPS based approach has been used to retrofit and upgrade traditional CNC machines into smart machines with the integration of various hardware and software components by enabling 3Cs (computation, communication, and control) with real-time capabilities, modularity, and reconfigurability (Lins *et al.*, 2020). There have been a few attempts (Lins *et al.*, 2020; Y. Zhang *et al.*, 2020) to integrate CPPS approach with the tool health analytics. This chapter develops a cyber physical production system framework for tool health analysis combining diagnostic, prognostic, and prescriptive analytics, along with the development of a knowledge-based system.

Knowledge-based system (KBS) aims to store relevant acquired data, information, and intelligence to be shared among stakeholders (Wan *et al.*, 2019). In a smart factory, KBS has become an essential component for enabling strategic and operational functions by continuously supporting value creation and facilitating the development and protection of human-machine collective intelligence (Ansari, 2019a). Further, KBS has demonstrated promising results in increasing overall equipment efficiency (OEE) by approximately 5% in the automotive industry by predicting early downtime, recommending text for documentation, and selecting the best-suited maintenance technician (Ansari *et al.*, 2021). This chapter also presents a novel knowledge-based system that updates knowledge and information about the chip colour at the different health conditions of a tool. The KBS also draws the tool life curve of the cutting tool and the energy consumption pattern across the tool life. The KBS will help the managers and even less skilled employees to take better decisions for the selection of cutting parameters and tool change. This chapter proposes machine learning algorithms (gaussian mixture model integrated with hidden Markov model for classification and autoregressive model for prediction) to predict the RUL of the cutting tool; regression models to prescribe optimum cutting parameters; a machine learning algorithm (random forest) for anomaly detection; and a knowledge-based system for chip conditions and tool life curves.

The chapter is structured as follows. Section 5.2 presents the research background focusing on modelling techniques and analytics used for tool health analysis. Section 5.3 presents the research methodology and proposes a CPPS framework for smart tool health analytics and management. Sections 5.4, 5.5, 5.6, 5.7 discuss the experimental planning, physical world, data acquisition system, and cyber world respectively. Section 5.8

discusses the smart tool health management system. Section 5.9 presents a knowledge-based system. Finally, section 5.10 summarizes the chapter and highlights the major contribution of the present work.

5.2 BACKGROUND

5.2.1 Tool Health Modelling Techniques

The tools and techniques adopted for tool health analysis can be broadly divided into five categories: namely, analytical models, physics-based models, mathematical/empirical models, data-driven models, and hybrid models.

Researchers have developed numerous analytical/mechanistic models by extending the basic Taylor's tool life equation for predictive assessment of tool-wear and tool-life (Marksberry & Jawahir, 2008). However, these models are unsuitable for industrial applications for not considering the underlying uncertainty in tool wear. Moreover, these models also require a large number of experiments to determine the empirical constants using sophisticated equipment (dynamometers to calculate forces) that increase the experimental efforts, time, material, and costs (Marksberry & Jawahir, 2008; Drouillet *et al.*, 2016).

Physics-based models have been developed by researchers to correlate tool degradation with sensor signals for force, power, current, vibration, *etc.* These models consider various assumptions or simplifications and can solve the complexities of tool wear prediction with reduced experimental efforts, time, material, and costs (Malakizadi *et al.*, 2020; J. Wang *et al.*, 2020) but require an in-depth understanding of the system behaviour (Wu *et al.*, 2017a). However, limitations such as non-availability of in-depth prior knowledge of system behaviour and inability of being updated with the dynamic changes in physical parameters result in lower accuracies, effectiveness, and flexibilities of these models (Wu *et al.*, 2017a; Wang *et al.*, 2019; Zhao *et al.*, 2019).

Mathematical/empirical modelling is the conversion of a real-life scenario into a mathematical equation (Dundar *et al.*, 2012). Several studies have been carried out by researchers (Zoghipour *et al.*, 2021; Hanafi *et al.*, 2012; Kant & Sangwan, 2014; Q. Wang *et al.*, 2014; Camposeco-Negrete, 2015; Li *et al.*, 2017; Wang *et al.*, 2019) to develop mathematical equations using statistical techniques to investigate, evaluate, predict, and optimize a variety of responses such as tool life, surface roughness, machining time, energy consumption, *etc.* Researchers have shown that mathematical models could effectively predict the tool wear with a good correlation between the predicted and the measured values (Choudhury & Srinivas, 2004). However, large number of experiments required to develop mathematical models can be challenging and time consuming. Moreover, oversimplification of the real problem without considering all influencing parameters can result in inaccuracies and impractical solutions for industrial applications (Denkena *et al.*, 2020).

Data-driven models are of two types: one, batch processing of the recorded process data to develop a model and then dynamically update the developed model with the new data; two, real-time or near real-time data mining and processing the live data for the real-time decision making. Real-time data processing is very challenging and requires fast response time and low processing time (Dogan & Birant, 2021). The recent developments in digitalization have generated a huge amount of data in industries. Stored or real-time data are analyzed using machine learning algorithms to discover useful insights and support decision making (Zhao *et al.*, 2019; F. Zhang *et al.*, 2020). Several machine learning algorithms are used to process sensor data, which can be trained to learn from its past behaviour or trend and can use the learning to make future predictions of tool life (Drouillet *et al.*, 2016). Machine learning models have several benefits: convenient (low entrance barrier), automatable (fully computational), fast (online operations possible), and provide better insight for knowledge driven continuous process improvement (Thiede *et al.*, 2020). Machine learning algorithms have been used by researchers for tool wear prediction (Ma *et al.*, 2021; Y. Li *et al.*, 2019; Duan *et al.*, 2022) and tool condition monitoring (Wang *et al.*, 2014) with good accuracies.

Hybrid models combine different types of models (physics-based models, mathematical models, data-driven models). Currently, there is an increasing trend among researchers to apply hybrid models for tool wear prediction (Rai & Sahu, 2020). Yang *et al.* (2022) proposed a hybrid model combining physics-based model with machine learning models for detecting anomalies during milling operations. The model was able to reduce false alarms significantly with the ability to detect online tool wear with good accuracy. Hybrid models have been used for predicting tool life (Zhu & Zhang, 2019), and tool wear in different stages (initial, normal, and severe) of tool life (Li *et al.*, 2022).

5.2.2 Tool Health Analytics

Relevant literature on tool health analysis has been reviewed in terms of modelling techniques, state variables, machining process, algorithms, and workpiece materials used.

Pimenov *et al.* (2022) reviewed artificial intelligence techniques for monitoring tool wear in machining and the effective use of modern sensors (dynamometers, accelerometers, acoustic emission sensors, current and power sensors, image sensors, *etc.*) for automating and modelling technological parameters of turning, milling, drilling, and grinding processes. Watanabe *et al.* (2020) proposed a data-driven technique using Mahalanobis-Taguchi algorithm to detect anomalies due to chip biting and tool vibration using motor current during the turning of stainless steel. Similarly, Cooper *et al.* (2020) proposed a generative adversarial network algorithm (a data-driven technique) to detect tool failure using acoustic signals while milling AISI 1018 steel. Lins *et al.* (2020) modelled images using Petri Net algorithm, a data-driven technique, to monitor tool wear and provide alerts for the tool change. Wei *et al.* (2022) acquired force data to develop a data-driven technique based on optimal path forest to classify different tool wear states in a milling process. Zhou *et al.* (2020) modelled vibration signals using SVM algorithm to identify transition points for a tool change during the milling of titanium alloys. Zhou *et* *al.* (2022) proposed a two-layer angle kernel extreme learning machine algorithm to monitor tool wear conditions using acoustic sensor signals during the milling of AISI 1045 steel. R. Liu (2022) proposed a calibration-based algorithm that uses similarity analysis to monitor tool wear and used edge computing close to the data source to reduce latency.

Aramesh *et al.* (2016) proposed an empirical model to estimate the RUL of turning tools using survival analysis techniques based on the proportional hazard model. Tool wear under variable cutting speed and feed but with constant depth of cut were measured at the second transition point and taken as a failure criterion (baseline) to estimate the RUL of cutting tools. Y. Zhang *et al.* (2020) predicted tool failure based on vibration variable and gradient boosting decision tree algorithm for a milling process. Corne *et al.* (2017) predicted tool wear using spindle power and neural network model during the drilling of Inconel alloy. Li *et al.* (2022) proposed a hybrid (physics and data-driven) model to predict tool wear in three different stages (initial, normal, and severe) based on the force and vibration variables and using the meta-learning algorithm for a milling process. Wu *et al.* (2017a) predicted the RUL of a tool using current and voltage variables based on random forest algorithm during the milling of stainless steel. Malakizadi *et al.* (2020) proposed a physics-based technique based on neural networks to predict tool wear occurring due to dissolution and diffusion phenomena during turning of C50 steel. Ma *et al.* (2021) modelled force variable using the convolutional neural network (CNN) – gated recurrent unit (GRU) algorithm, a deep learning data-driven technique, to predict tool wear during the milling of a titanium alloy (TC18). Drouillet *et al.* (2016), modelled spindle power to predict the RUL of a cutting tool with high accuracy and significantly less computational time using neural networks during the milling of stainless steel. Li *et al.* (2019) acquired both power and current data to develop a data-driven technique based on meta-learning to predict tool wear during the milling of a titanium alloy. Jinsong *et al.* (2017) predicted the RUL of a cutting tool with improvements in cycle time, machining efficiency, and product quality using neural network and spindle load data during the milling of titanium alloy.

Zhu & Zhang (2019) proposed a hybrid (empirical and analytical) technique based on neural networks to predict tool life using force data during the milling of Inconel alloy. Cheng *et al.* (2022) acquired force data for simultaneous monitoring and prediction of tool wear during the milling of superalloy (Haynes 230) based on the CNN-BiLSTM algorithm. Ferreira & Gonçalves (2022) reviewed the literature for RUL prediction using machine learning algorithms and explored the potential of predicting the RUL and integrating it with production planning and maintenance systems to reduce downtimes, improve maintenance plans and production schedules, and minimize defects, which can lead to higher profits and customer satisfaction. He *et al.* (2022) proposed a cross-domain adaptation network based on attention mechanism to predict tool wear during milling of AISI 1045 steel using vibration signals datasets. X. Liu *et al.* (2022) proposed a customized DenseNet and GRU integrated model to predict tool wear based on multi-sensor feature fusion of force, vibration, and acoustic data during the milling of stainless steel. The proposed model performed better in terms of accuracy than the other previously developed models for the PHM 2010 benchmark data set. However, the proposed model was developed under constant cutting parameters.

All studies, except Kene & Choudhury (2019) provide only prognostic analytics of tool health. Kene & Choudhury (2019) developed an analytical model based on sensor fusion function to predict tool wear and prescribed optimal cutting parameters during a turning process. This chapter proposes a prescriptive analytics model for the milling process. The current study proposes a hybrid technique for prescribing the optimum cutting parameters to managers/operators to optimize the remaining useful life and/or material removal rate, and/or active power consumption (either separately or simultaneously) at a predefined surface finish.

Table 5.1 presents an overview of reviewed literature with respect to their objective(s)/purpose, employed methods/modeling techniques, machining process, data types, algorithms, materials, and technology readiness level (TRL).

Table 5.1 An overview of reviewed literature in the domain of tool health analytics

Objective(s)	**Author(s)**	**Modelling Technique**	**Machining process**	**Data types**	**Algorithm(s)**	**Material**	**Technology readiness level (TRL)**
Diagnostic analytics	Watanabe *et al.* (2020)	Data-driven	Turning	Motor current	Mahalanobis-Taguchi	Stainless-steel	Method development
	Cooper *et al.* (2020)	Data-driven	Milling	Acoustic signals	Generative adversarial networks	AISI 1018 steel	Method development
	Lins *et al.* (2020)	Data-driven	Drilling	Images	Petri Net	-	Architecture development with proof-of-concept demonstration
	Wei *et al.* (2022)	Data-driven	Milling	Force	Optimal path forest	-	Method development
	Zhou *et al.* (2020)	Data-driven	Milling	Vibration	Support vector machine	Titanium alloy (Ti-6Al-4V)	Method development
	Zhou *et al.* (2022)	Data-driven	Milling	Acoustic signals	Two-layer angle kernel extreme learning	AISI 1045 steel	Method development and experimental investigations
	R. Liu (2022)	Data-driven	Milling	Spindle torque signals	Calibration-based algorithm	AISI 1018 steel	Method development with proof-of-concept demonstration
Prognostic analytics	Aramesh *et al.* (2016)	Empirical	Turning	-	Proportional hazard model	Ti-MMCs	Experimental research
	Y. Zhang *et al.* (2020)	Data-driven	Milling	Vibration	Integrated dynamic principal component analysis and gradient boosting decision trees	-	Framework development with proof-of-concept demonstration

Table 5.1 An overview of reviewed literature in the domain of tool health analytics (contd…)

Objective(s)	**Author(s)**	**Modelling Technique**	**Machining process**	**Data types**	**Algorithm(s)**	**Material**	**Technology readiness level (TRL)**
Prognostic analytics	Corne *et al.* (2017)	Data-driven	Drilling	Spindle power, force	Neural network	Inconel 625	Method development and experimental investigations
	Li *et al.* (2022)	Hybrid (physics and data driven)	Milling	Force, vibration	Meta learning	-	Method development, experimental and performance comparison
	Wu *et al.* (2017)	Data-driven	Milling	Current, voltage	Random forest	Stainless steel	Method development, experimental and performance comparison
	Malakizadi *et al.* (2020)	Physics-based	Turning	Temperature	Neural network	C50 steel	Method development
	Ma *et al.* (2021)	Data-driven	Milling	Force	CNN-GRU	Titanium alloy (TC18)	Method development and experimental investigations
	Drouillet *et al.* (2016)	Data-driven	Milling	Spindle power	Neural network	Stainless-steel	Method development and experimental investigations
	Li *et al.* (2019)	Data-driven	Milling	Power, current	Meta learning	Titanium alloy	Method development and experimental investigations
	Jinsong *et al.* (2017)	Data driven	Milling	Spindle load	Neural network	Titanium alloy	Method development and experimental investigations
	Zhu & Zhang (2019)	Hybrid (empirical and analytical)	Milling	Force	Neural network	Inconel alloy 718	Method development and experimental investigations
	Cheng *et al.* (2022)	Data-driven	Milling	Force	CNN-BiLSTM	Superalloy (Haynes 230)	Method development and experimental investigations

Table 5.1 An overview of reviewed literature in the domain of tool health analytics (contd…)

Objective(s)	**Author(s)**	**Modelling Technique**	**Machining process**	**Data types**	**Algorithm(s)**	**Material**	**Technology readiness level (TRL)**
	He *et al.* (2022)	Data-driven	Milling	Vibration	Cross-domain adaptation network based on attention mechanism (CDATT)	AISI 1045 steel	Method development and experimental investigations
	X. Liu *et al.* (2022)	Data-driven	Milling	Force, vibration, acoustic	Integrated DenseNet and GRU model	Stainless steel	Method development and performance comparison
Prescriptive analytics	Kene & Choudhury (2019)	Analytical	Turning	Force, vibration, surface roughness	-	E24 grade steel	Method development and experimental investigations
Diagnostic + Prescriptive analytics	This chapter	Hybrid	Milling	Force, power, surface roughness	Auto-regression, GMM-HMM, random forest, RSM	AISI H13 tool steel	Framework development with proof-of-concept demonstration

Literature review shows that tool health analysis has been employed for single point (turning) as well as multi-point (milling and drilling) cutting tools, but more attention has been given to the milling process. It may be attributed to the complex and dynamic nature of cutting in milling, higher cost of milling cutters, and higher costs and lower productivity associated with tool failures and replacements in a milling process. Yan *et al.* (1999) has also mentioned that, in tool health analytics, more significance has been given to milling process analytics due to higher complexities involved in milling, and a semi-intermittent process that generates discontinuous signals during intermittent engagement and disengagement of the inserts. More tool health analysis studies have been performed for difficult to machine workpiece materials due to faster tool wear rate thereby affecting the product quality, energy consumption and productivity because of frequent tool replacements.

Wan *et al.* (2019) proposed a knowledge-based system using case-based reasoning for planning maintenance activities thereby improving the efficiency and effectiveness of machine tool maintenance. Francalanza *et al.* (2017) proposed a knowledge-based tool for CPPS-based digital factories to support decision-making and minimize disruptions.

The objectives of this chapter are (i) to develop a CPPS framework for a smart tool health analysis combining diagnostic and prescriptive analytics, and (ii) to develop a knowledge-based system for tool health monitoring. The objectives are achieved by developing the following models:

- Development of a machine learning algorithm to predict RUL of a tool (prognostic analytics)
- Development of regression models to prescribe optimum cutting parameters to optimize RUL in conjunction with MRR and APT (prescriptive analytics)

- Development of a machine learning based methodology for anomaly detection (diagnostic analytics)
- Development of a knowledge-based system to update the learning from the machine learning algorithms; and to update the tool life curve and chip conditions at different phases of a tool life.

5.3 RESEARCH METHODOLOGY

The research methodology for the present work is based on a cyber-physical production system framework. It consists of four fundamental elements: physical world, data acquisition system, cyber world, and decision support system. In addition to these four fundamental elements, two extension elements are also proposed, namely design of experiments and knowledge base development, as shown in Figure 5.1.

The first step is to plan the experiments by selecting the appropriate cutting parameters, workpiece, cutting tool, and workpiece preparation. The experiments were then designed using the Taguchi L27 orthogonal array, which provides a robust design for acquiring a broad range of data with fewer experiments and at a reduced cost.

The second step is to set up the physical world through the integration of various hardware, such as energy meter, dynamometer, XDK sensor, and software such as LabVIEW, Node-RED, DynoWare with the CNC machine. In the third step, experiments were performed to acquire online data related to power & force from CNC machine. Subsequently, offline data related to tool wear, surface roughness, and chips texture were acquired from the cutting tool, machined workpiece, and chips, respectively. Next step is the development of cyber world wherein data was processed into meaning information for generating prognostic, prescriptive and diagnostic analyses using machine learning algorithms and regression models.

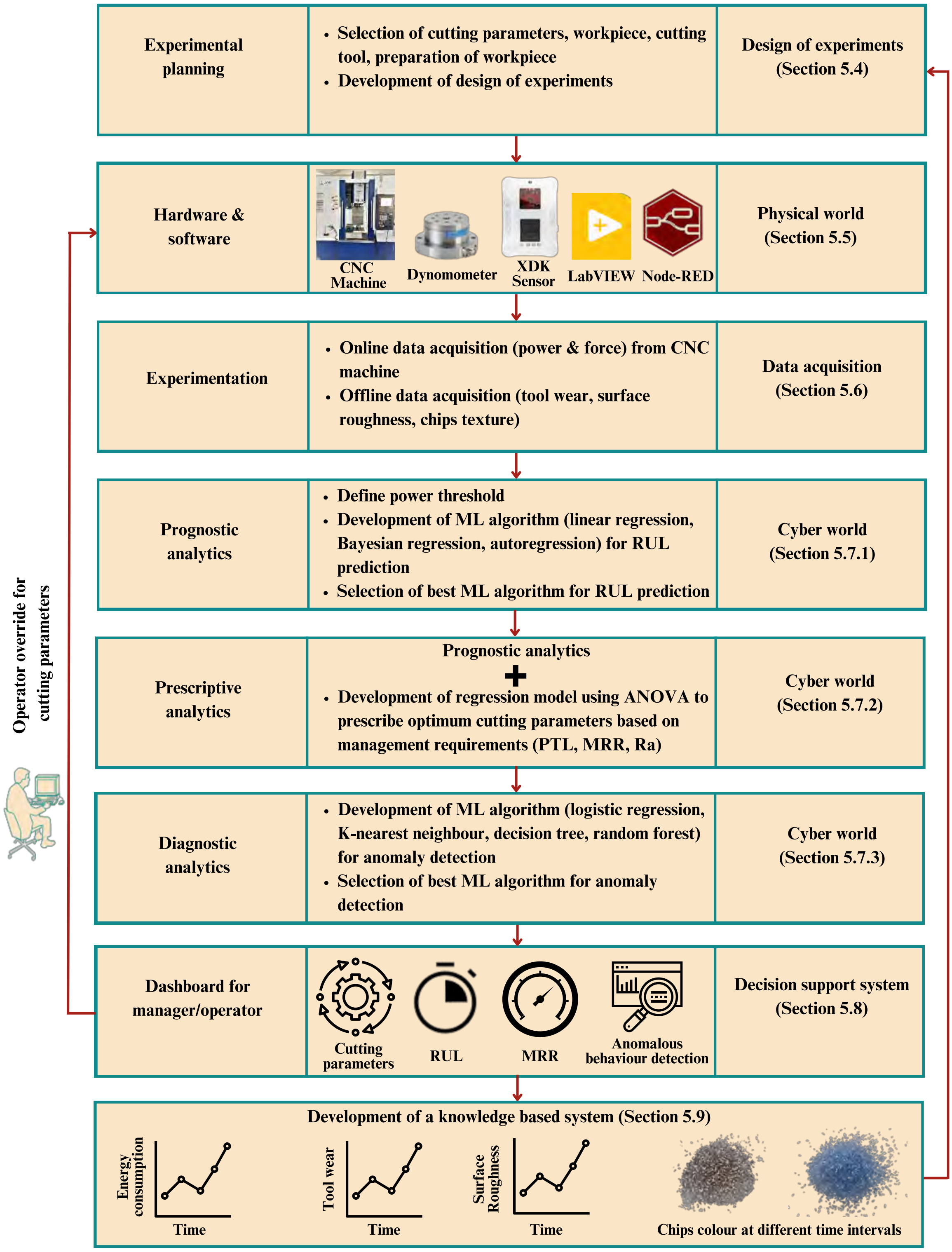


Figure 5.1 Research methodology for the development of a CPPS framework for smart tool health management system

Next step involves the development of a decision support system, in which dashboards were developed for monitoring cutting parameters, RUL, MRR, and anomalous behaviour to support decisions regarding control actions to be taken by an operator based on organizational requirements. The last step involves the development of a knowledge-based system that updates knowledge and information about the chip colour at different health conditions of a tool and various curves (tool life, energy consumption, and surface roughness).

CPPS framework would enable networked physical components and computational processes, where ‘cyber’ and ‘physical’ parts are tightly coupled in a feedback relation, continuously affecting one another leading to analyzable and predictable systems, while promoting learning and analysis on live data. The arrows in Figure 5.1 represent the flow of data from one element to another. The loop is closed with the human at the center to provide simple (the lesser, the better) overrides depending on the condition of the machine. CPPS framework has the potential to take decisions based on the algorithmic monitoring system with minimum operator intervention, and expert knowledge of various tools and techniques of decision-making process (Teti *et al.*, 2010).

5.4 EXPERIMENTAL PLANNING (MATERIALS AND METHODS)

Experiments were performed to acquire data for tool health prescriptive analytics. Three axes CNC vertical milling center of make LMW JV 40 (spindle motor capacity of 7.5 KW, maximum spindle speed of 8000 RPM), is used to perform end milling on AISI H13 tool steel using coated carbide cutting tool. The hardness of the workpiece is 45 HRC. The size of the workpiece was 50×50×50 mm^3. The cutting tool is AlTiN coated cemented carbides end mill cutter of 12 mm diameter with four flutes. Carbide tools are widely used for machining difficult-to-machine materials due to their performance and price (Shokrani *et al.*, 2012).

Experiments were designed using Taguchi L-27 orthogonal array approach, which is a systematic way to design, conduct, and analyse experiments. This results in obtaining maximum quantitative information from a lesser number of experimental trials which reduces the experimental cost & machining time and improves the quality & robustness (Gokulachandran & Mohandas, 2015). Table 5.2 lists the machining parameters with three levels that were chosen to cover critical values observed during preliminary experimentation. The machine capability and recommendation from insert manufacturer were also considered during the design of experiments.

Each experiment was performed using a fresh tool to acquire twenty-seven time series data sets. The cycle time for each experiment was 800 seconds. The material removal takes place for about 600 seconds excluding the air cutting time. Each workpiece was prepared by rough milling, before the experiment, to remove the oxidized layer present on the surface. The experiments were performed in a controlled environment. Real-time data of ambient temperature and relative humidity were acquired using XDK sensor node and monitored online and wirelessly through MQTT protocol on Node-Red dashboard. Ambient temperature varied between 25°C and 30°C whereas relative humidity was in the range of 40% to 60%.

Table 5.2 Machining parameters and their values based on Taguchi L-27 orthogonal array

Sl. No.	**Parameters**	**Unit**	**Symbol**	**Level 1**	**Level 2**	**Level 3**
1	Cutting speed	m/min	v	120	150	180
2	Feed	mm/rev	f	0.2	0.3	0.4
3	Axial depth of cut	mm	d	0.2	0.5	0.8

5.5 PHYSICAL WORLD (HARDWARE AND SOFTWARE USED)

Figure 5.2 illustrates the physical world comprising of a CNC vertical milling center with integrated sensor networks and devices, flows. Machining processes were performed on the workpiece to get the desired shape and size of the final product with or without coolant in a controlled manner. Machining process also results in worn-out tools, by-products such as unwanted materials in the form of chips, polluted coolant, *etc.* Various sensors and devices were integrated with the CNC machine to acquire data or monitor the parameters of temperature and humidity.

Figure 5.2 Physical world comprising of CNC vertical milling center with integrated sensor networks and devices; energy and material flow

5.6 DATA ACQUISITION SYSTEM

Generally, data acquired from the physical world can be broadly categorized into product, process, and external data (Thiede *et al.*, 2020). Data from the physical world resulting from the CNC machining center, and other external sensors/devices are listed in Table 5.3. The data was acquired from sensors and measuring devices in hybrid mode –

online measurements for acquiring power consumption and force data, whereas tool wear and workpiece surface roughness were measured offline.

Table 5.3 Sensors and devices with their applications and measurement techniques

Sensor/Device	**Application**	**Measurement Technique**
NI DAQ	Power data	Indirect
Kistler dynamometer	Force data	Indirect
Mitutoyo quick scope microscope	Tool wear measurement	Direct
Mitutoyo SJ-410 Surface roughness tester	Workpiece surface roughness	Direct
XDK	Temperature and humidity	Indirect

Figure 5.3 shows different online and offline data acquisition dashboards for (a) surface roughness measurement, (b) inbuilt power measurement, (c) tool wear measurement, (d) acquisition of force, power, and XDK sensor data.

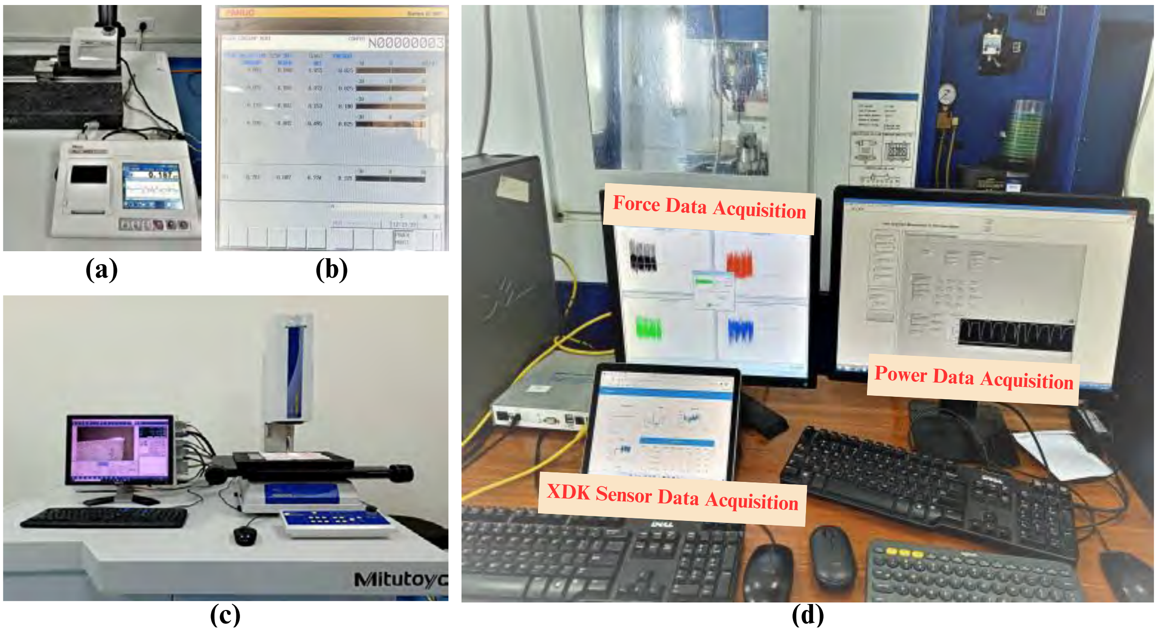


Figure 5.3 Data acquisition dashboards for (a) surface roughness measurement, (b) power monitor, (c) tool wear measurement, (d) acquisition of force data, power data, and XDK sensor data

5.7 CYBER WORLD

This section presents the development of machine learning algorithms that can be deployed in the cyber world facilitating real-time monitoring, diagnosis, and prognosis during the milling process. Historical time series data obtained from different sensors and devices were used to develop machine learning models for characterization of stages, prediction of tool's RUL, and detection of anomaly during the milling process.

5.7.1 Development of a ML Algorithm for RUL Prediction of a Cutting Tool (Prognostic Analytics)

The power data was acquired and stored using the power module of the NI DAQ system running on the LabVIEW environment during the experimentation step. Sensor data in the raw form may contain missing values, noises, and unfeasible format, therefore, needs to be pre-processed (filtered, cleaned, normalized, smoothed, and formatted) to make it suitable for machine learning models. The first step was to characterize different stages during the machining so that power consumed only during the metal cutting stage is considered as tool wear occurs when the cutting tool is in contact with the workpiece. This has been done using the GMM-HMM algorithm, an unsupervised machine learning algorithm. The main objective of characterization is to automatically classify material removal for extracting power consumption during the material removal stages only. The extracted power values are then split into training and testing sets. Different algorithms are then trained and tested to select the best algorithm until the model predicts the remaining useful life for the set threshold. The model is validated using the confirmation test.

Characterization of stages is significant in identifying the value-added (material removal), non-value added (standby), and non-value added but necessary stages (automatic tool change, air cutting, spindle on, axes movement after each layer of cut, spindle acceleration and deceleration). The energy consumption for these stages can be estimated and monitored under the industry 4.0 environment to take corrective measures if abnormal trends are observed in the computed KPIs.

Figure 5.4 shows the power profile for the milling operation, showing different observed stages. Here, the standby stage means that the spindle is not rotating. Spindle acceleration stage is when the spindle just switches on and experiences a jerk. The stage when the tool moves from the end of the current layer machining to the start of the next layer in a multi-layer milling operation is the layer change stage. Spindle deceleration stage is when the spindle turns off and moves back to the original position.

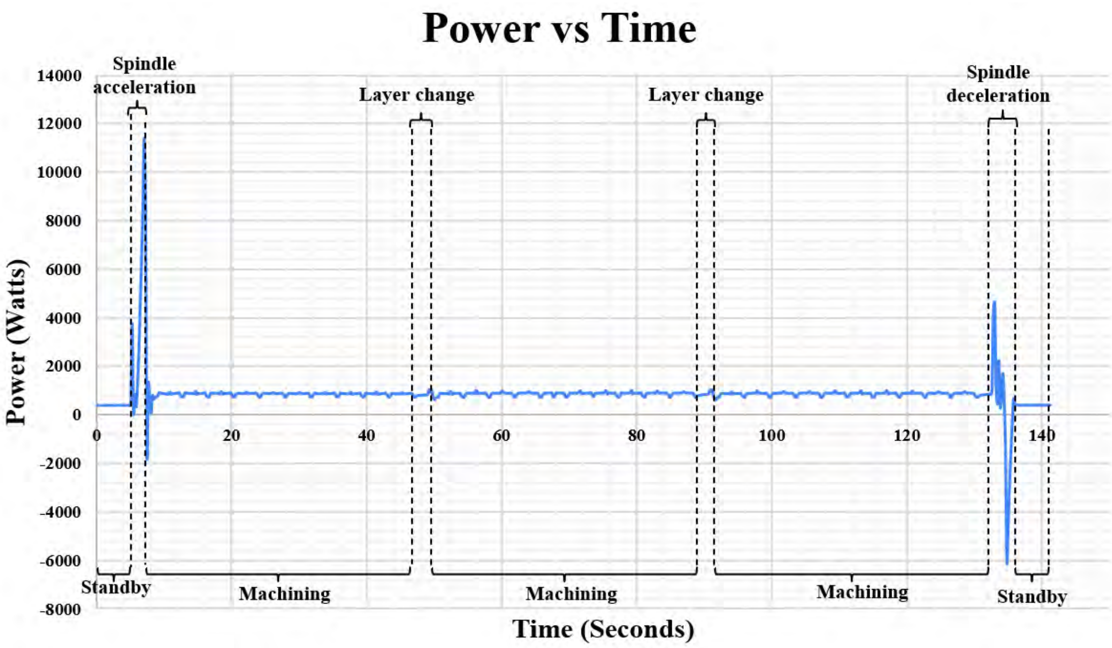
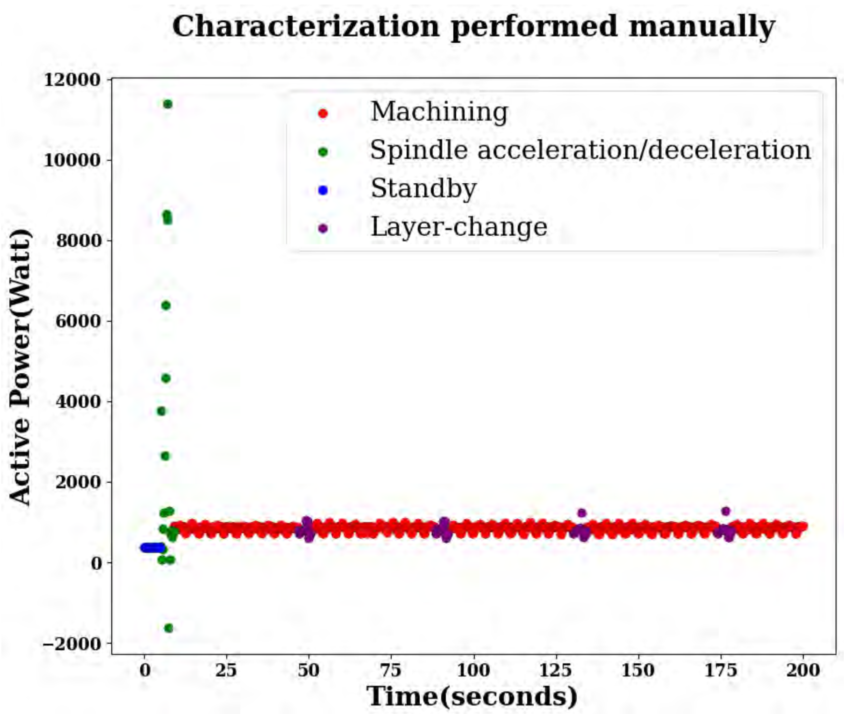


Figure 5.4 Power profile for the milling operation

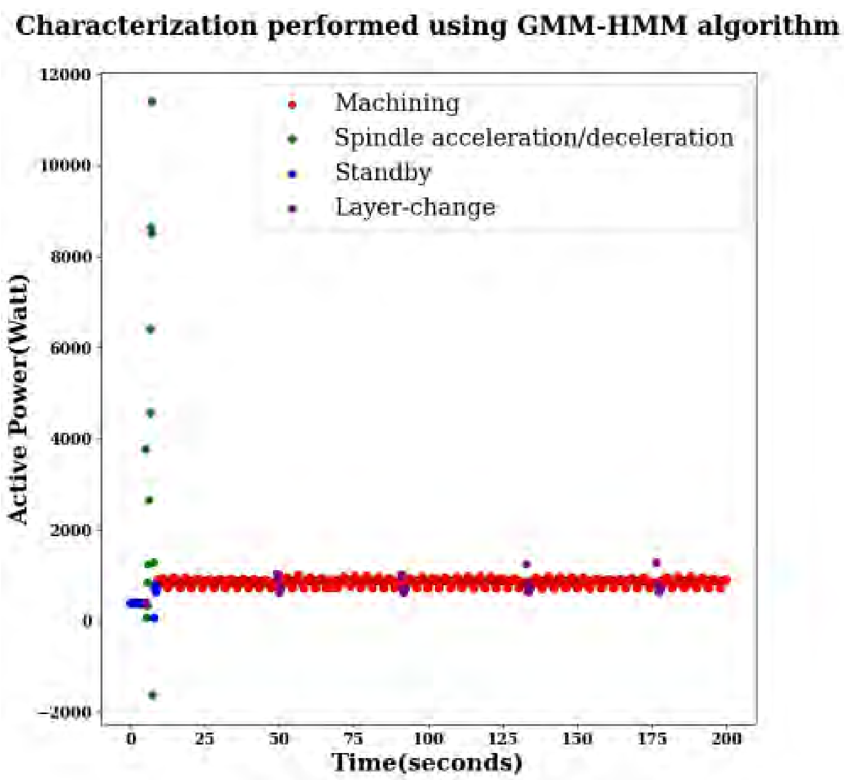
Characterization of stages is modelled using GMM-HMM algorithm that utilizes multiple Gaussian density functions for fitting continuous time series data with complex patterns. The reason for selecting GMM-HMM algorithm for characterization is its demonstrated ability to classify time series data with high performance in applications, such as human activity recognition (Cheng *et al.*, 2021), optical fiber signal transmission (Tian *et al.*, 2020), spindle health condition evaluation (Yang *et al.*, 2023), *etc.* The main advantages of GMM-HMM are high accuracy and robustness (Cheng *et al.*, 2021) with reduced computational complexity (Tian *et al.*, 2020). The GMM-HMM algorithm demonstrated higher accuracy in classifying various spindle health conditions of a CNC machine compared to other combined methods, such as PSO-SVM and GA-ELM (Yang *et al.*, 2023). Moreover, as an unsupervised machine learning algorithm, it can be trained and deployed efficiently on a smaller training dataset to automatically classify various states (Hiruta *et al.*, 2021).

The present work utilizes the acquired machine tool power data to characterize the four different stages: namely machining or material removal stage, spindle on or off stage, standby stage, and layer change stage. Figures 5.5 (a) and 5.5 (b) show the characterization of different stages performed for a sample machining run (run 26 of table 5.4) using manual labelling and GMM-HMM algorithm, respectively for 200 seconds.

Figure 5.6 illustrates the confusion matrix to validate the performance of the developed model for the characterization. The developed model can classify around 3742 points out of 4001 points correctly with an accuracy of 93.52%. However, there are some misclassifications too, mostly occurring for the layer change stage since there is not much difference between the magnitude of power from machining stage to layer change stage and layer change stage to machining stage.



(a)



(b)

Figure 5.5 Characterization of stages using (a) manual labelling and (b) GMM-HMM algorithm

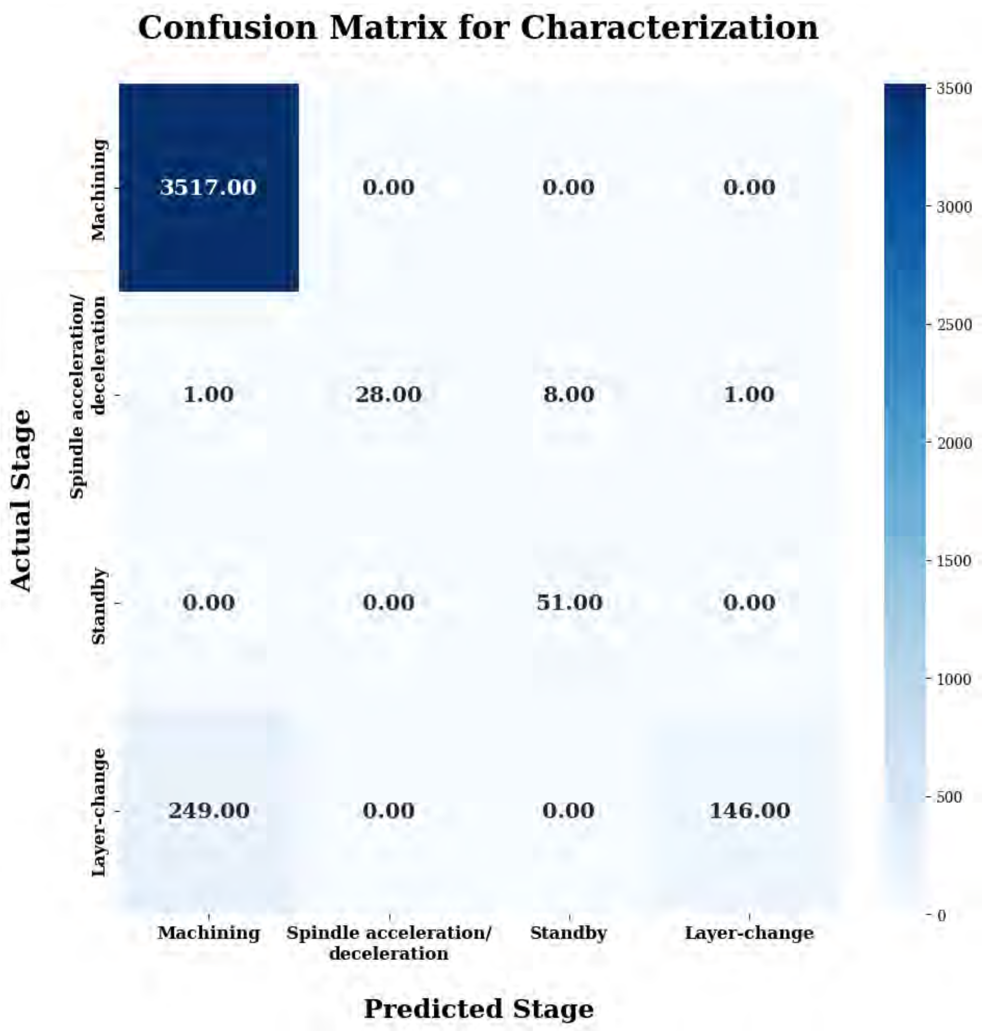
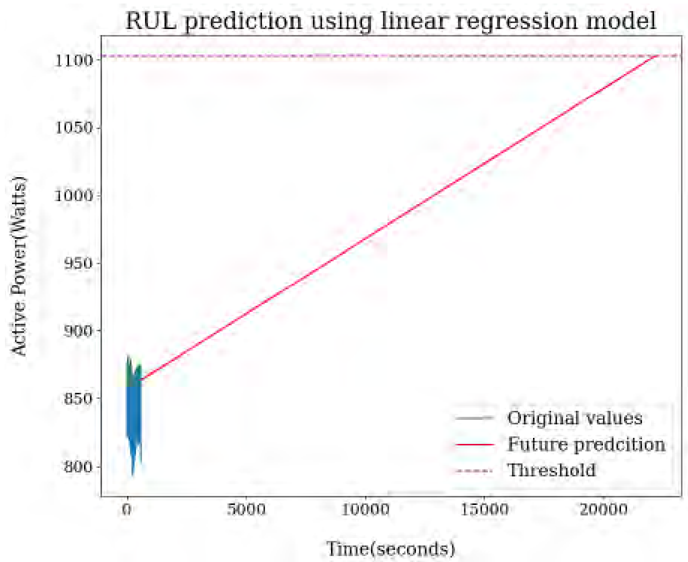


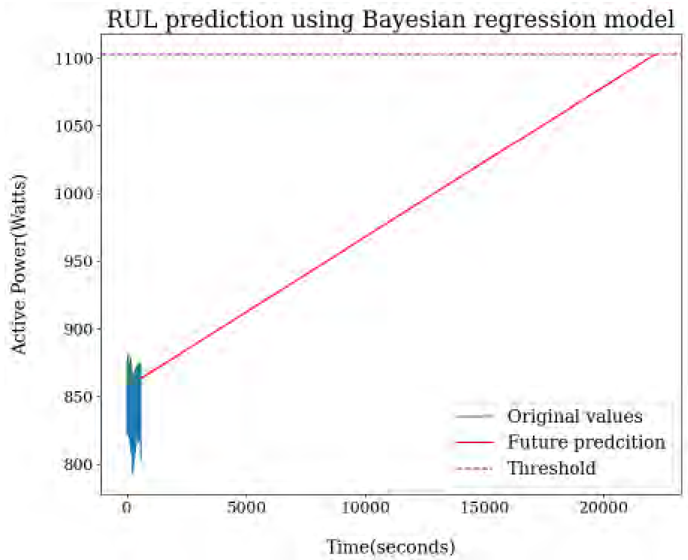
Figure 5.6 Confusion matrix for characterization of stages using GMM-HMM algorithm

Power consumption increases with time, indicating a positive correlation between these two variables. Various regression algorithms such as linear, Bayesian, and autoregressive were trained and tested to find the most suitable algorithm that predicts RUL with minimum percentage error or deviation as compared to the actual tool life. RMSE values are almost the same for all the three models. It was found that the predicted percentage error as compared to the actual tool life obtained during experimentation is minimum (around 5.38 %) for the autoregressive model. Therefore, autoregressive model was selected for predicting RUL. An autoregressive model is a time series model that uses observations from the previous time steps as input to predict the value in the next time step. This type of model is widely used when either a positive or negative correlation exists between values in time series. The lag value for the autoregressive model is four which means that the model is looking back four time periods to predict the fifth time period value. The rationale behind autoregressive model outperforming linear and bayesian regression models in predicting RUL of the cutting tool can be attributed to complex non-linear relationships existing between the variables (*i.e.,* power and time). Autoregressive models can be used to model the complex relationship between variables as they are based on stochastic process theory and mathematical statistics (Song *et al.*, 2017). On the other hand, linear regression models assume a linear association between the dependent variable and the independent variables (Bergh *et al.*, 2021). While Bayesian regression models provide a slight improvement in prediction performance over linear regression models, they, too, fail to accurately predict RUL.

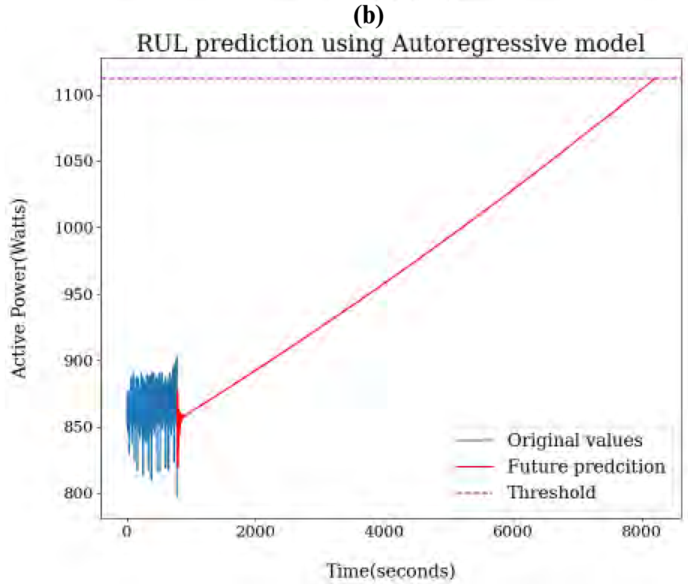
Figure 5.7 illustrates the graphical representation of the predicted RUL using the linear regression, Bayesian regression, and autoregressive models for run 26. The sky-blue colored shape represents the material removal data for 600 seconds. The pink colored line represents the threshold value. An active power threshold is automatically set in the model at 130 % of the average power value for 600 seconds. The active power threshold for the run 26 is 1112.15 Watts. Lastly, the red colored line represents the predicted power values over time. The power value reached the threshold at 27785 seconds (around 463 minutes), 2771 seconds (around 462 minutes), and 8235 seconds (around 137 minutes) using linear regression, Bayesian regression, and autoregressive models.



(a)



(b)



(c)

Figure 5.7 Graphical representation of predicted RUL using the (a) linear regression, (b) Bayesian regression, and (c) autoregressive models

Table 5.4 lists the obtained results for active power threshold, predicted tool life, and total material removed using the proposed model.

Table 5.4 Results for active power threshold (APT), predicted tool life (PTL), material removal rate (MRR), and surface roughness (Ra) at different L27 array conditions

Run No.	v(m/min)	f(mm/rev)	d(mm)	APT (W)	PTL (minutes)	MRR (mm^3/min)	R_a (µm)
1	120	0.2	0.2	832.72	309	305.568	0.308
2	120	0.2	0.5	852.96	152	763.920	0.188
3	120	0.2	0.8	855.22	124	1222.272	0.233
4	120	0.3	0.2	845.14	305	458.352	0.486
5	120	0.3	0.5	878.59	127	1145.880	0.395
6	120	0.3	0.8	890.30	120	1833.408	0.311
7	120	0.4	0.2	860.31	128	611.136	0.502
8	120	0.4	0.5	902.31	109	1527.840	0.373
9	120	0.4	0.8	1035.57	137	2444.544	0.535
10	150	0.2	0.2	859.93	223	381.888	0.581
11	150	0.2	0.5	878.69	148	954.720	0.183
12	150	0.2	0.8	885.59	130	1527.552	0.228
13	150	0.3	0.2	868.65	357	572.832	0.383
14	150	0.3	0.5	921.92	262	1432.080	0.320
15	150	0.3	0.8	979.66	140	2291.328	0.348
16	150	0.4	0.2	920.47	279	763.776	0.292
17	150	0.4	0.5	1014.93	105	1909.440	0.307
18	150	0.4	0.8	1102.40	199	3055.104	0.586
19	180	0.2	0.2	969.32	213	458.304	0.341
20	180	0.2	0.5	985.18	168	1145.760	0.218
21	180	0.2	0.8	1034.50	68	1833.216	0.250
22	180	0.3	0.2	980.54	393	687.456	0.372
23	180	0.3	0.5	1013.71	127	1718.640	0.292
24	180	0.3	0.8	1044.59	65	2749.824	0.368
25	180	0.4	0.2	1015.34	95	916.608	0.256
26	180	0.4	0.5	1112.15	137	2291.520	0.230
27	180	0.4	0.8	1109.91	69	3666.432	0.346

The predicted tool life is the sum of initial machining time (ten minutes required to display trend in the acquired power data) and the remaining useful life of the tool predicted using the developed model. The computation time for deploying the complete model (characterization with RUL prediction model) varies between 0.829 seconds to 9.783 seconds when performed on Intel i5-6300HQ processor with dynamic random-access memory (RAM) allocation of 7.516 GB out of 8 GB.

5.7.2 Prescriptive Analytics to Prescribe Optimum Cutting Parameters

In this study, prescriptive analytics considers the prior knowledge of a specific range of cutting parameters, namely cutting speed, feed rate, and depth of cut, based on the machine's capability and cutting tool insert manufacturer recommendations. In addition, it considers the prior knowledge of the developed predictive model for performance characteristics, such as predicted tool life (PTL), active power threshold (APT), material removal rate (MRR), and surface roughness (Ra), as well as their complex relationship to the cutting parameters.

Prescription of optimum cutting parameters can be performed using various modelling techniques, such as analytical, physics-based, regression/empirical, data-driven, or hybrid. First, a performance characteristic model is developed (*e.g.*, RUL, MRR, APT, and R_a in this study). Next, this model is optimized to prescribe optimal values using an optimization technique, such as the desirability function approach, genetic algorithm, particle swarm optimization, *etc.* (desirability function approach in this study). Regression/empirical models are practical, fast and provide direct estimation of industry-relevant parameters (Arrazola *et al.*, 2013). Therefore, regression models were developed and integrated with the desirability function approach to prescribe optimum cutting parameters in the current study. However, certain limitations are also associated with the regression/empirical models, such as the need for extensive experimentation, which can be time-consuming and costly, and the validity of the results may be limited to the specific range of experimentation (Arrazola *et al.*, 2013).

Regression models were developed using response surface methodology for active power threshold, predicted tool life, material removal rate, and surface roughness. The models were improved using backward elimination technique that starts with all potential terms in the model and removes the least significant term. Equations 5.1 to 5.4 were developed to describe the relationship between a set of cutting parameters, namely cutting speed (v), feed (f), axial depth of cut (d) for the responses of active power threshold (APT), predicted tool life (PTL), material removal rate (MRR), and surface roughness (R_a).

$$\mathrm{APT} = 1156 - 4.12v - 1230f - 136.6d + 0.0218v^2 + 2118f^2 + 940f*d \tag{5.1}$$

$$\mathrm{PTL} = -1209 + 15.18v + 3168f - 231.5d - 0.0517v^2 - 5533f^2 \tag{5.2}$$

$$\mathrm{MRR} = 1432 - 9.55v - 4773f - 2864d + 31.82v*f + 19.09v*d + 9548f*d \tag{5.3}$$

$$\mathrm{Ra} = 0.173 + 0.00426v + 1.94f - 1.897d + 1.058d^2 - 0.01828v*f + 2.600f*d \tag{5.4}$$

Analysis of variance has been performed to statistically analyse the adequacy of the developed model using F-value and p-value. The F-value determines whether the term is associated with the response or not and the p-value is the probability that measures the evidence against the null hypothesis. The process parameter whose p-value is less than or equal to significance level ($\alpha = 0.05$) is found to be statistically significant otherwise statistically insignificant at 95% confidence level. Tables from 5.5, 5.6, 5.7, and 5.8 show the analysis of variance results for active power threshold, predicted tool life, material removal rate, and surface roughness, respectively.

Table 5.5 ANOVA results for active power threshold

Source	DF	Adj SS	Adj MS	F-Value	P-Value	%Contribution
Model	6	191415	31902.4	59.03	0.000	94.65
Linear	3	176859	58953.0	109.08	0.000	87.46
V	1	95648	95647.7	176.97	0.000	47.30
F	1	46949	46948.7	86.87	0.000	23.22
D	1	34263	34262.6	63.39	0.000	16.94
Square	2	5011	2505.7	4.64	0.022	2.48
v*v	1	2319	2319.1	4.29	0.051	1.15
f*f	1	2692	2692.4	4.98	0.037	1.33
2-Way Interaction	1	9544	9544.0	17.66	0.000	4.72
f*d	1	9544	9544.0	17.66	0.000	4.72
Error	20	10809	540.5			
Total	26	202224				
Model Summary						
R-Square = 94.65%						

Table 5.6 ANOVA results for predicted tool life

Source	DF	Adj SS	Adj MS	F-Value	P-Value	% Contribution
Model	5	123983	24797	6.18	0.001	59.53
Linear	3	92639	30880	7.69	0.001	44.48
v	1	1663	1663	0.41	0.527	0.80
f	1	4171	4171	1.04	0.320	2.00
D	1	86806	86806	21.62	0.000	41.68
Square	2	31344	15672	3.90	0.036	15.05
v*v	1	12974	12974	3.23	0.087	6.23
f*f	1	18371	18371	4.58	0.044	8.82
Error	21	84299	4014			40.47
Total	26	208283				
Model Summary						
R-Square = 60.53%						

Table 5.7 ANOVA results for material removal rate

Source	DF	Adj SS	Adj MS	F-Value	P-Value	%Contribution
Model	6	20318616	3386436	2580.67	0.000	99.87
Linear	3	18870392	6290131	4793.47	0.000	92.75
V	1	1476243	1476243	1124.99	0.000	7.26
F	1	4102394	4102394	3126.28	0.000	20.16
D	1	13291756	13291756	10129.14	0.000	65.33
2-Way Interaction	3	1448224	482741	367.88	0.000	7.12
v*f	1	109351	109351	83.33	0.000	0.54
v*d	1	354298	354298	270.00	0.000	1.74
f*d	1	984574	984574	750.31	0.000	4.84
Error	20	26245	1312			0.13
Total	26	20344861				
Model Summary						
R-Square = 99.87%						

Table 5.8 ANOVA results for surface roughness

Source	DF	Adj SS	Adj MS	F-Value	P-Value	%Contribution
Model	6	0.237794	0.039632	8.26	0.000	71.24
Linear	3	0.074302	0.024767	5.16	0.008	22.26
v	1	0.024054	0.024054	5.01	0.037	7.21
f	1	0.044701	0.044701	9.31	0.006	13.39
d	1	0.005548	0.005548	1.16	0.295	1.66
Square	1	0.054404	0.054404	11.33	0.003	16.30
d*d	1	0.054404	0.054404	11.33	0.003	16.30
2-Way Interaction	2	0.109088	0.054544	11.36	0.001	32.68
v*f	1	0.036080	0.036080	7.52	0.013	10.81
f*d	1	0.073008	0.073008	15.21	0.001	21.87
Error	20	0.096008	0.004800			
Total	26	0.333802				
Model Summary						
R-Square = 71.24%						

P-value for all the three cutting parameters (cutting speed, feed, axial depth of cut) along with linear, square and interaction terms are less than 0.05 for both active power threshold and material removal rate, indicating strong influence of these parameter. In the case of predicted tool life, the p-value for only axial depth of cut is less than 0.05 indicating significant influence. The impact of feed and cutting speed are almost negligible. Linear and square terms are significant whereas interaction terms are insignificant, hence removed from the developed regression model. In case of surface roughness, the p-value for cutting speed and feed with linear, square and interaction terms is less than 0.05 indicating significant influence of all these input parameters. However, the impact of feed is much higher than cutting speed. The impact of axial depth of cut is negligible. R-square values indicate how well the model fits the data. The value of R-square obtained for the predicted tool life is 0.6153, which indicates that 60.53% of the total variation is explained by the model. The R-square values were high except for predicted tool life, which means the model fits the data well. In the case of predicted tool life, the R-square value is comparatively less due to some misclassifications during stage transitions from machining stage to layer change and vice-versa. However, this does not influence the tool life.

Figures 5.8, 5.9, 5.10, and 5.11 illustrate the main effect plots comparing the relative strength of the effects of various process parameters on active power threshold, predicted tool life, material removal rate, and surface roughness, respectively. The main effect plot for active power threshold (Figures 5.8) reveals that lower energy consumption could be achieved only at lower levels of cutting speed, feed rate, and axial depth of cut as this means low material removal rate. With the increase in cutting speed, more power is required by the spindle motor. As the feed rate increases, the axis motor needs to move faster resulting in higher power consumption. The same occurs with the high value of depth of cut, due to higher material removal, the machine spends more power.

The main effect plot for predicted tool life, as shown in Figure 5.9, reveals that the effect of axial depth of cut on the tool life is higher as compared to cutting speed and feed. This is due to the increase in cutting force and tool temperature as the axial depth of cut increases. The main effect plot for material removal rate (Figure 5.10) shows that higher amount of material removal rate can be achieved at higher levels of axial depth of cut, feed, and spindle speed, as expected. The main effect plot for surface roughness (Figure 5.11) shows that increase in cutting speed decreases the surface roughness. There is an increase in surface roughness with the increase in feed rate. Surface roughness is observed to be highest at the lowest level of axial depth of cut as small depth of cut results in friction when machining top layer of workpiece and therefore results in poor surface finish.

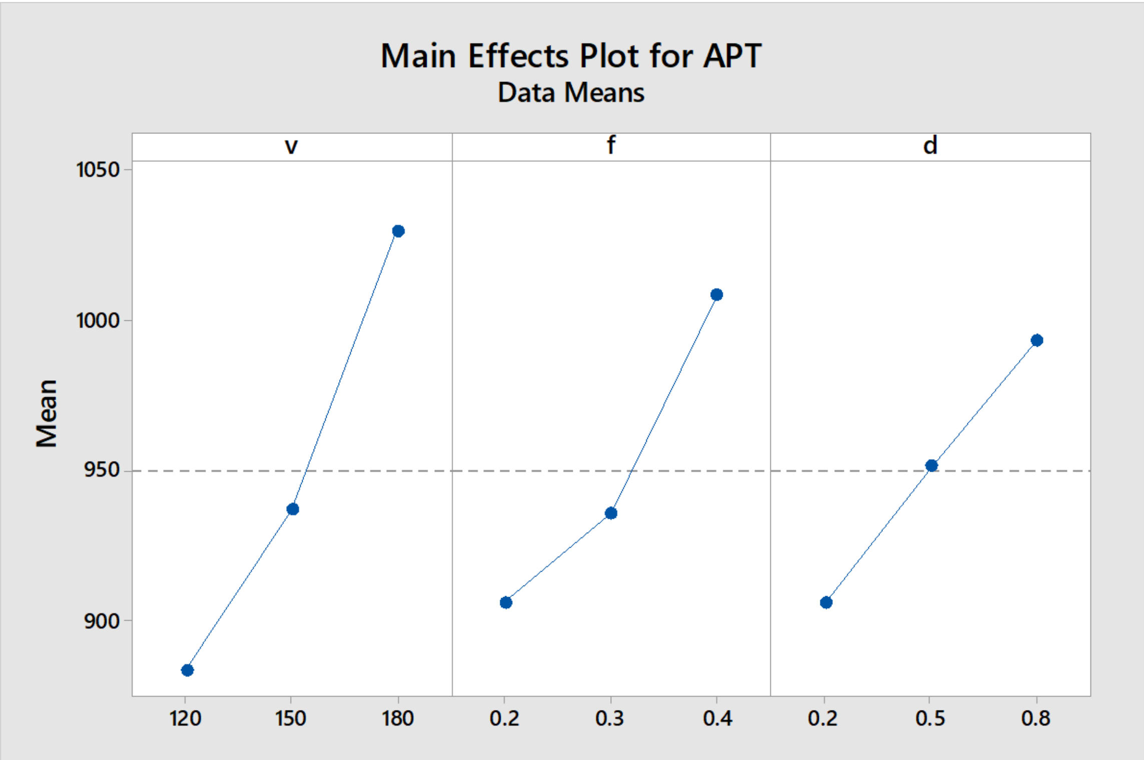


Figure 5.8 Main effect plot for active power threshold

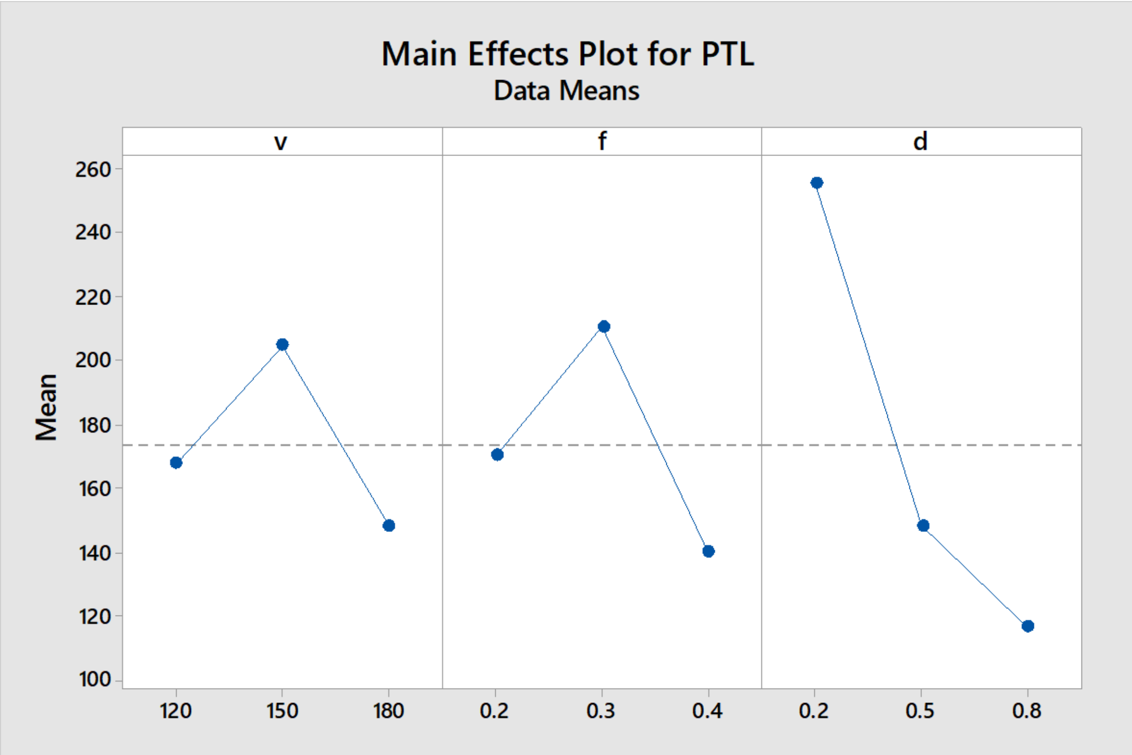


Figure 5.9 Main effect plot for predicted tool life

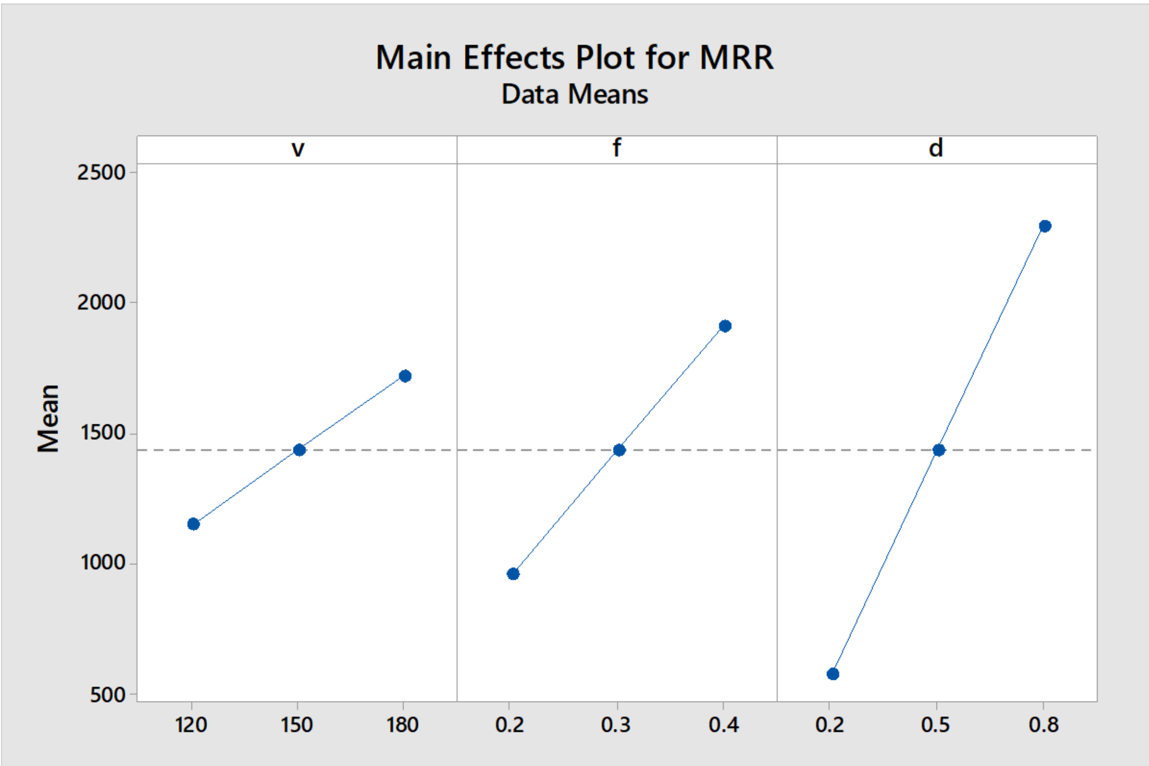


Figure 5.10 Main effect plot for material removal rate

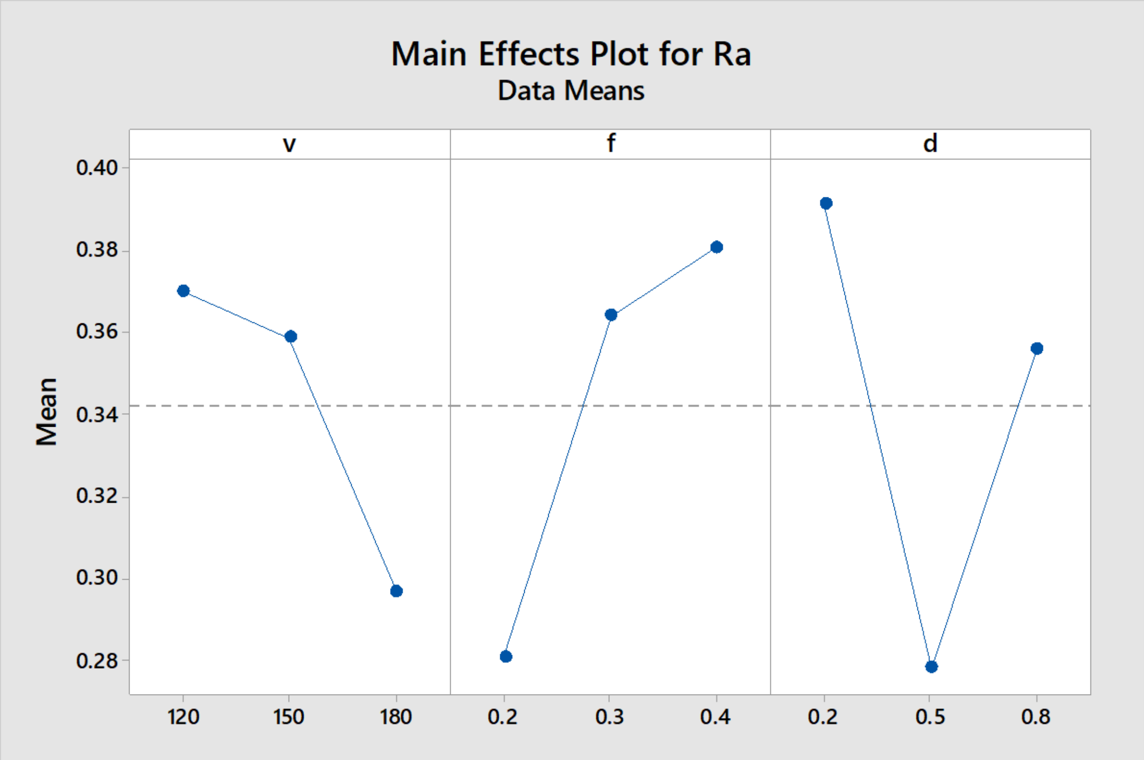


Figure 5.11 Main effect plot for surface roughness

Interaction plot is a powerful graphical tool which plots the mean response of two factors at all possible combinations of their settings. Figures 5.12, 5.13, 5.14, and 5.15 illustrate the interaction plots for active power threshold, predicted tool life, material removal rate, and surface roughness, respectively to demonstrate the relationship between categorical factor and a continuous response. There exist interactions between the process parameters and the response variables. The results also agree with the ANOVA test results of Tables 5.5, 5.6, 5.7 and 5.8.

Figures 5.16, 5.17, 5.18, and 5.19 reveal that the residual plots for active power threshold, predicted tool life, material removal rate, and surface roughness, respectively are not showing any trend and the errors are distributed normally.

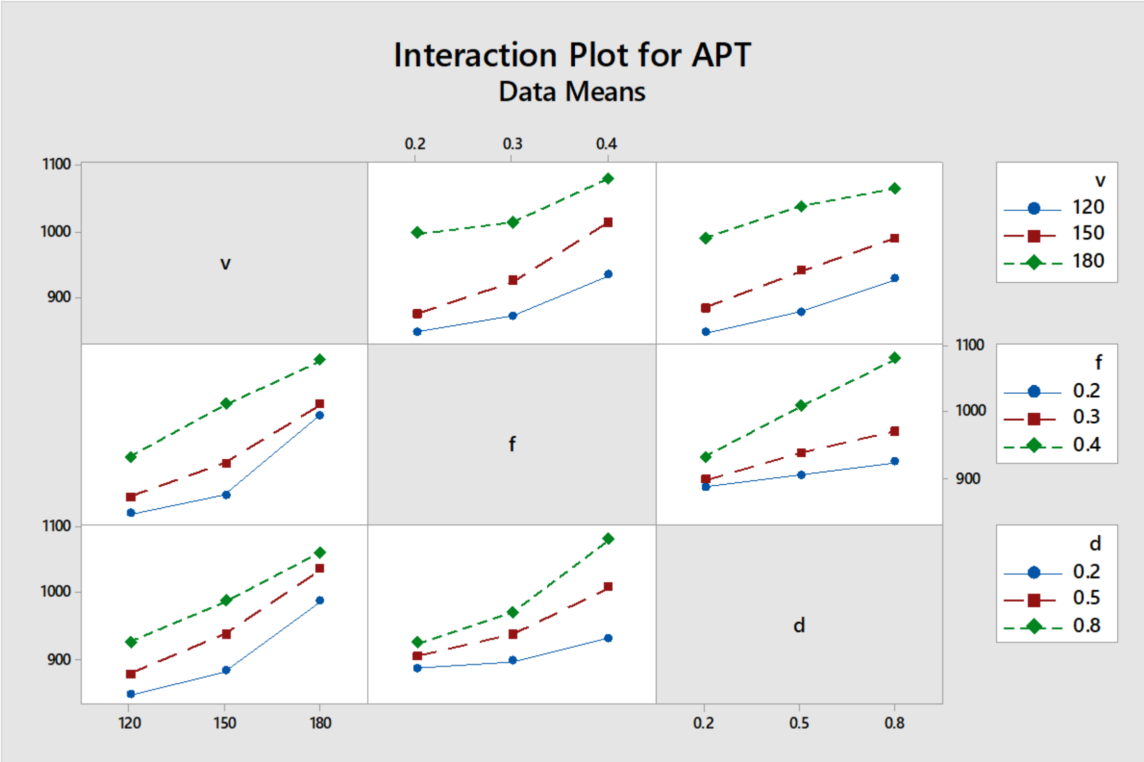


Figure 5.12 Interaction plot for active power threshold

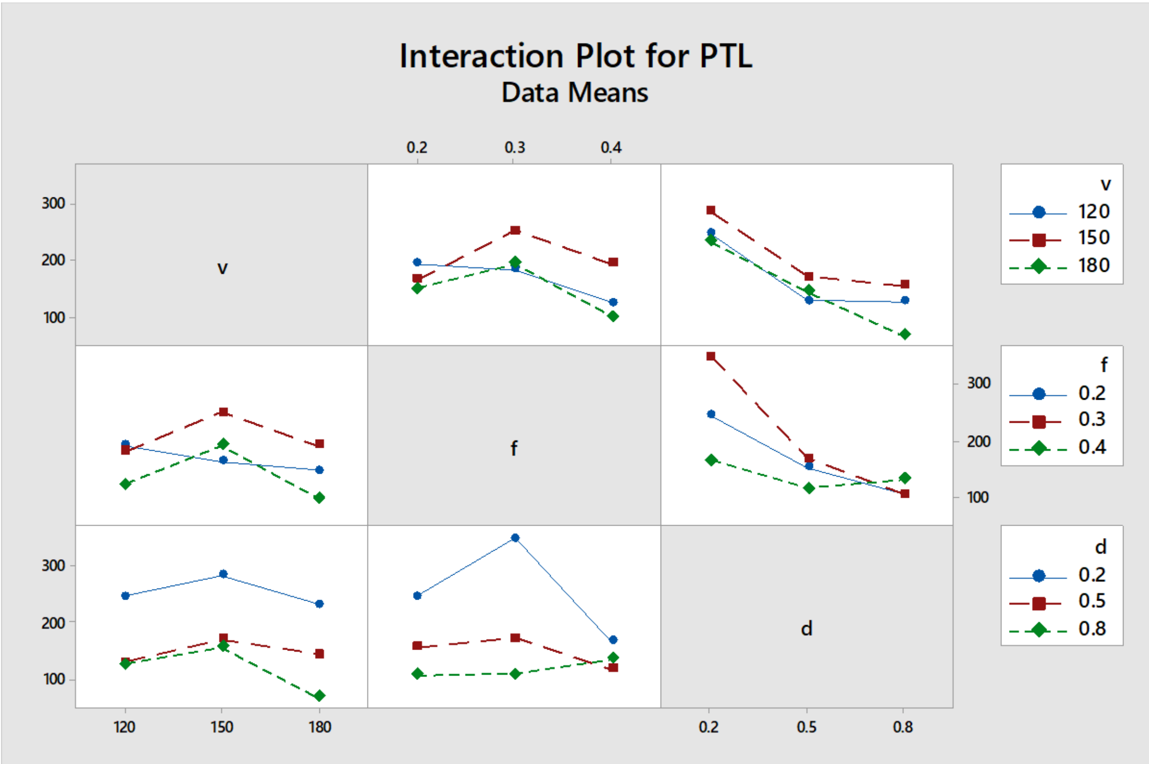


Figure 5.13 Interaction plot for predicted tool life

Figure 5.14 Interaction plot for material removal rate

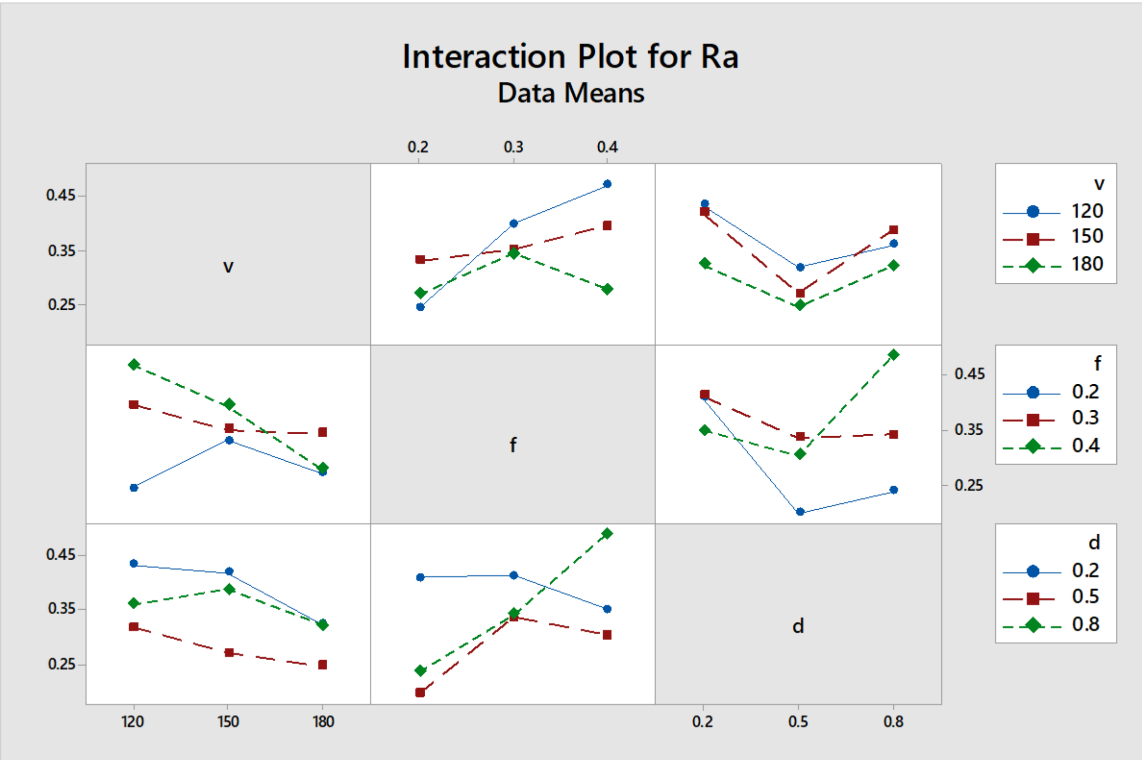


Figure 5.15 Interaction plot for surface roughness

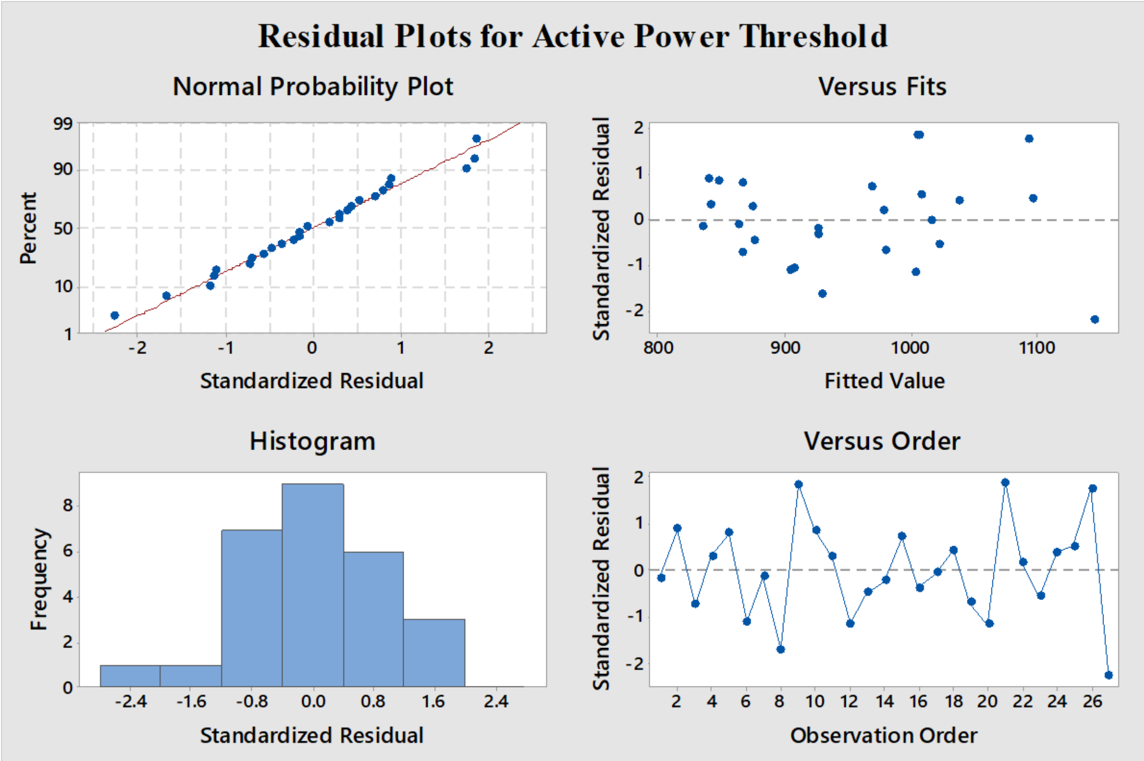


Figure 5.16 Residual plots for active power threshold

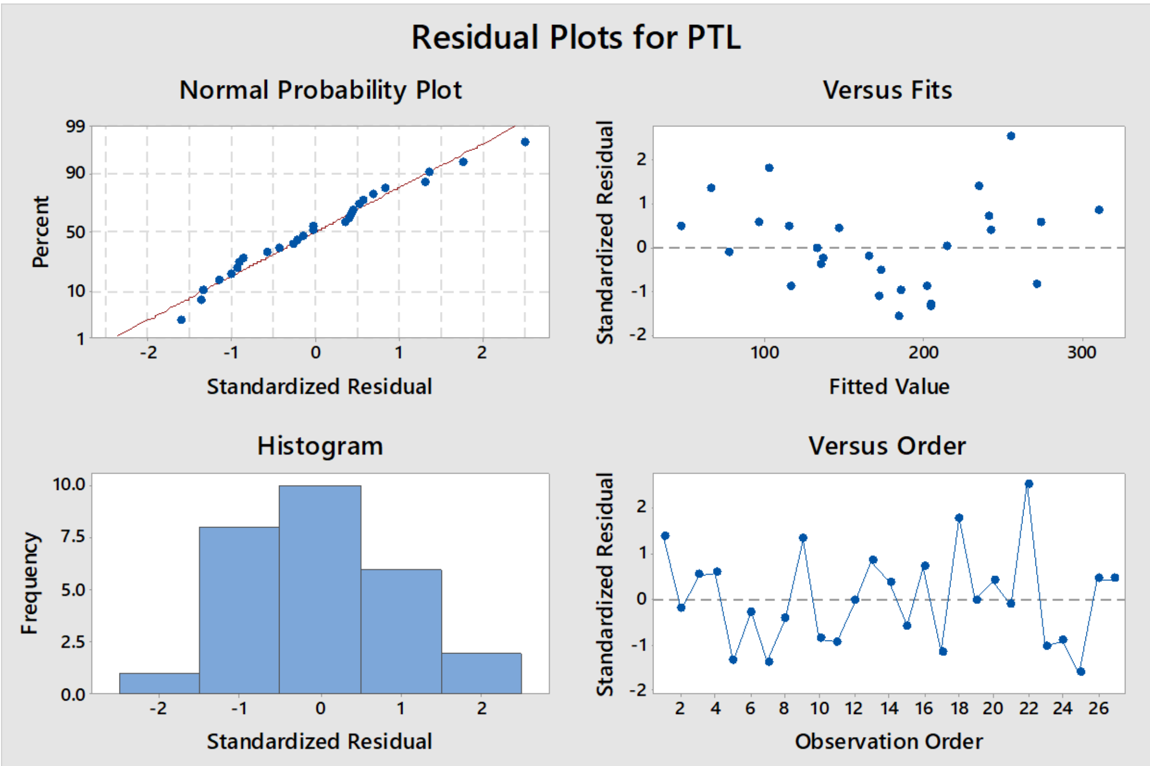


Figure 5.17 Residual plots for predicted tool life

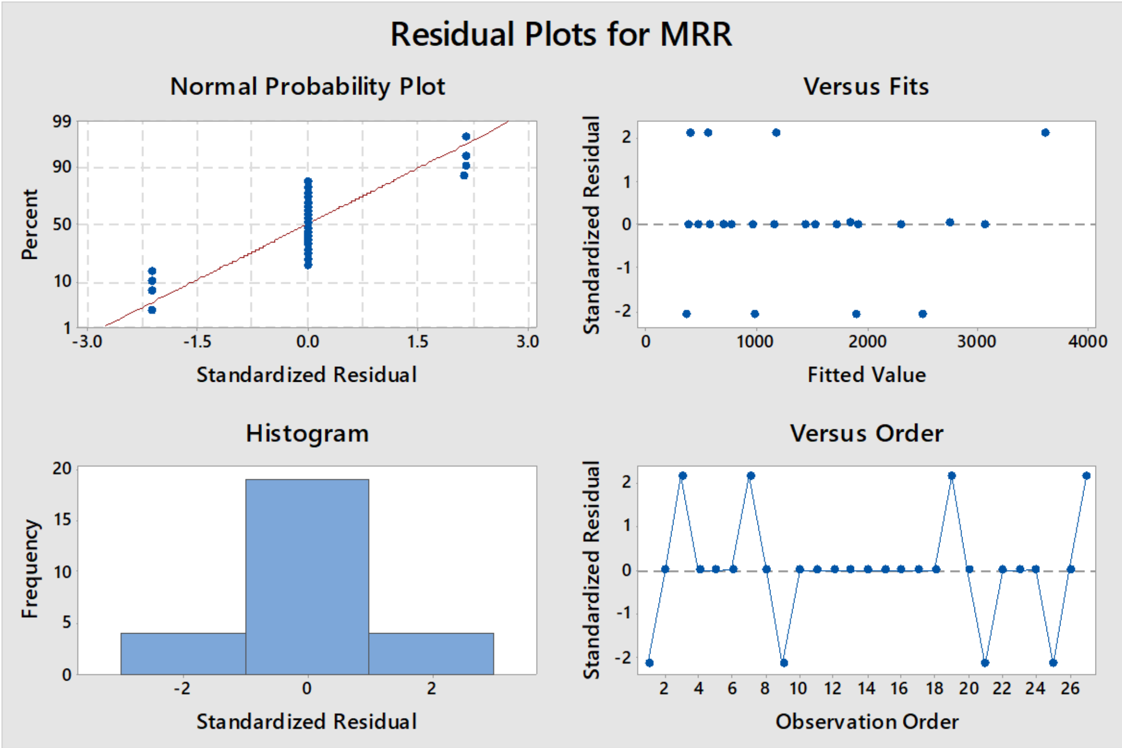


Figure 5.18 Residual plots for material removal rate

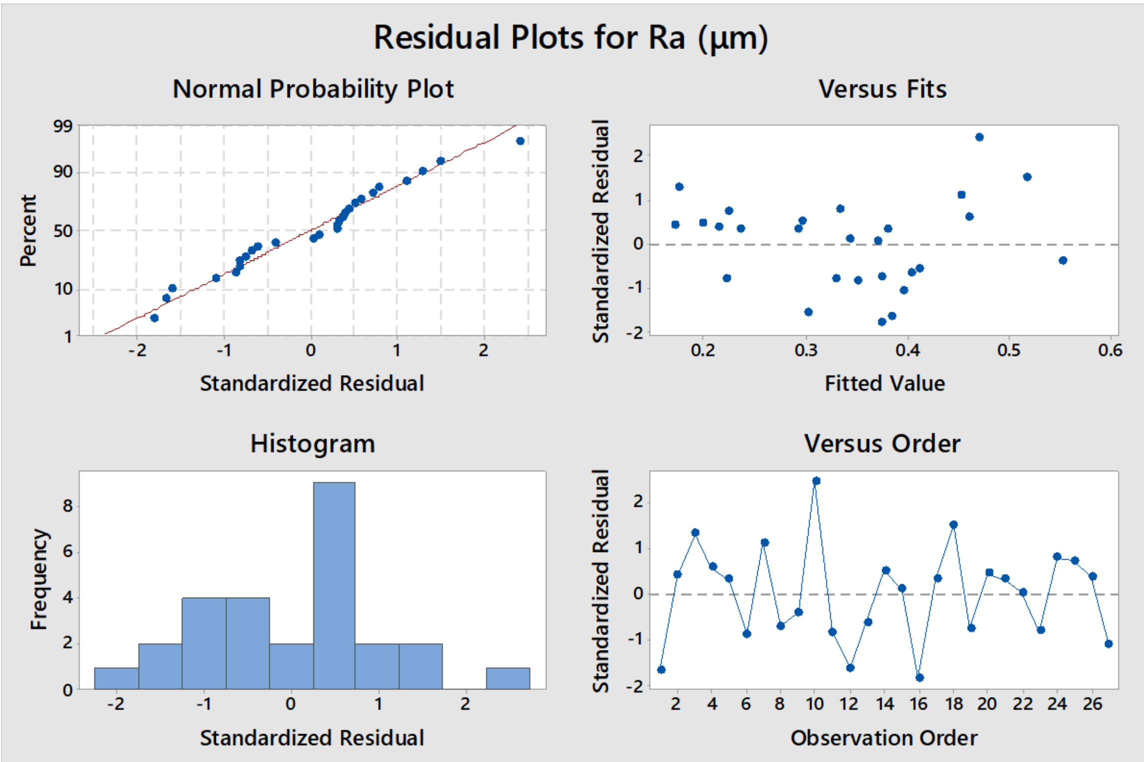


Figure 5.19 Residual plots for surface roughness

Once the regression models were developed and validated using ANOVA then desirability function approach was used to prescribe the cutting parameters to get the optimum APT, PTL, and MRR at the targeted R_a. The desirability function approach, first proposed by Derringer and Suich, is one of the most widely used multiobjective optimization techniques for parameter optimization (Sangwan & Sihag, 2019). The values of individual response variables are transformed into a dimensionless desirability function value ranging from zero to one. The first step is to develop a regression model for each response, and then estimate the desirability functional value for each response according to the response characteristics (minimization, maximization or attain target value). Multi-objective optimization problems are converted into a single objective problem by combining all objectives into one composite desirability function (Zoghipour *et al.*, 2021). Reduced gradient algorithm is used to maximize the composite desirability function value. This algorithm starts with multiple possible solutions and then converges to a final optimal solution. Trial version of Minitab 18 was used to determine the optimal settings for the parameters using the developed regression models for each response (equations 5.1 to 5.4).

Multiobjective optimization is performed to prescribe optimal cutting parameters for three different scenarios. In the first scenario, optimal cutting parameters were prescribed for the maximization of both predicted tool life and material removal rate, simultaneously. In the second scenario, both predicted tool life and material removal rate were maximized, simultaneously at the target surface roughness value. In the third scenario, predicted tool life and material removal rate were maximized, whereas active power threshold was minimized, simultaneously for the target surface roughness value. Prescription of optimum results (optimal cutting parameters setting with optimal solution) under different scenarios are presented in Table 5.9. Figures 5.20, 521, and 5.22 illustrate the optimization plots with interactive variable settings to visualize how responses are affected with changes in parameters or variables.

Table 5.9 Prescription of optimum results under different scenarios

Scenarios	**Optimum cutting parameters**			**Optimum responses**				**Composite desirability**
	Cutting speed (m/min)	f (mm/rev)	d (mm)	MRR (mm^3/min)	PTL (min)	Ra (µm) (Target)	APT (W)	
First scenario	156	0.32	0.65	2110.695	195			0.461
Second scenario for target Ra = 0.27 µm	164	0.32	0.57	1888.963	207	0.27		0.588
Third scenario for target Ra = 0.27 µm	146	0.28	0.57	1498.546	226	0.27	913.9	0.592

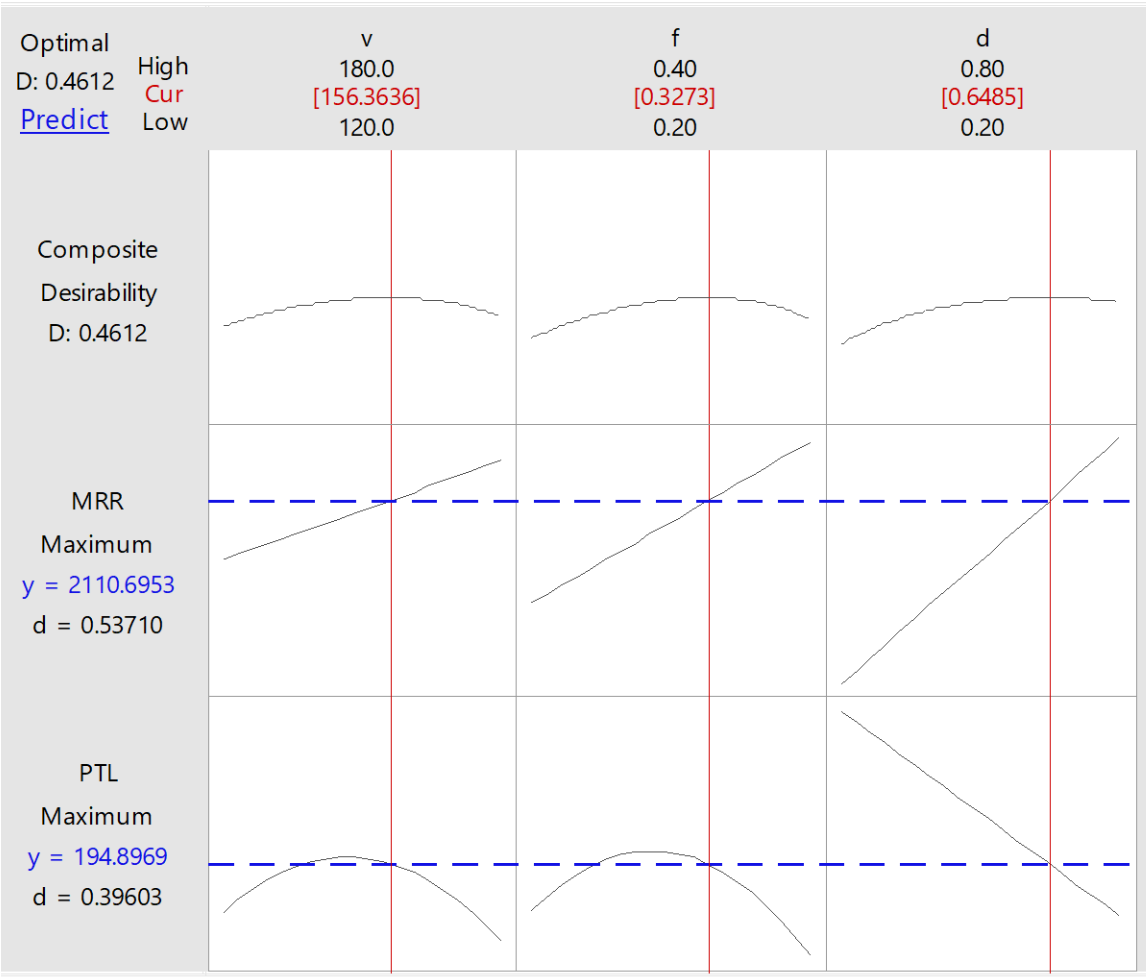


Figure 5.20 Optimization plot for the first scenario (PTL and MRR maximization)

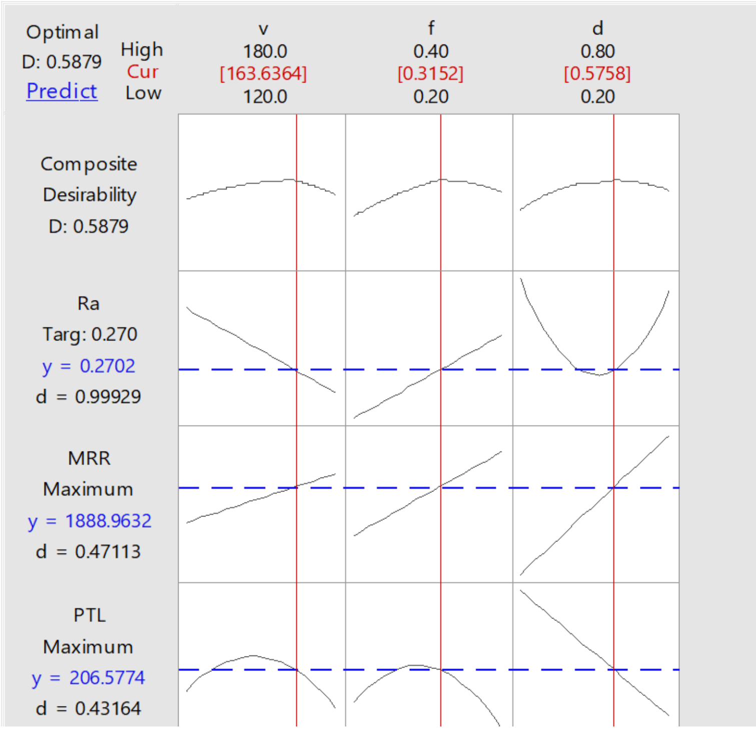


Figure 5.21 Optimization plot for the second scenario (PTL and MRR maximization at target surface roughness value)

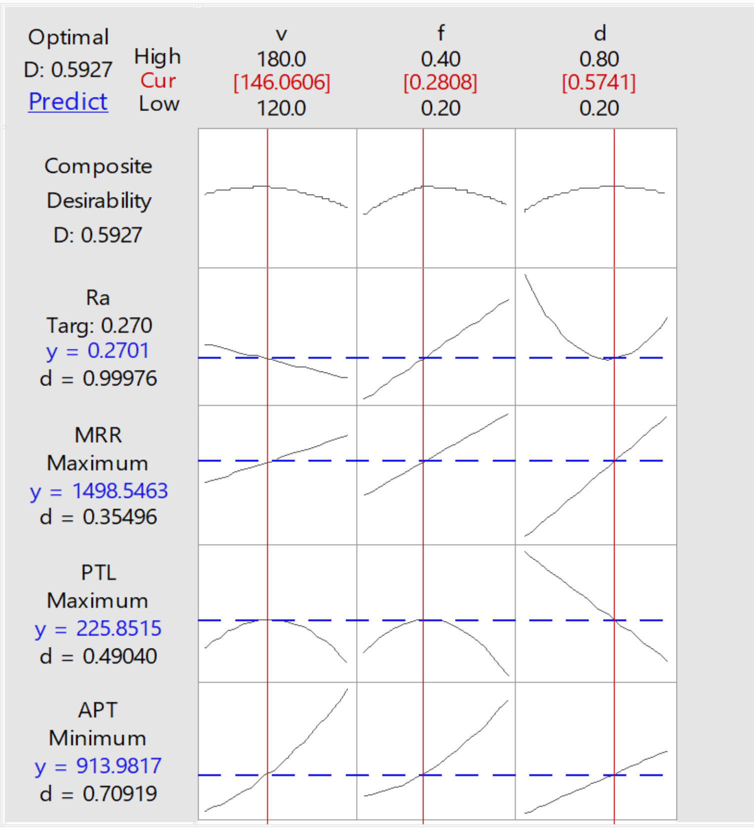


Figure 5.22 Optimization plot for the third scenario (PTL and MRR maximization, and APT minimization at target surface roughness value)

5.7.3 Anomaly Detection (Diagnostic Analytics)

Power data was acquired at the sampling frequency of 5 Hz using NI DAQ system (type 9244 for current, type NI-9227 for voltage), visualized and stored on LabVIEW programming interface. Force data was acquired using Kistler 9272 dynamometer at a sampling frequency of 1000 Hz. Raw data may contain significant deviations within the features which makes the model hard to learn. Therefore, standardization is performed on the data to acquire the values within a specific range using standard scaling technique where the values are centered around the mean with a unit standard deviation. Also, other pre-processing steps of filtering, cleaning, and formatting were done to make the data suitable for machine learning models. The extracted data were split into training and testing sets in the ratio of 70:30, respectively. Different algorithms were trained and tested on the historical data to select the best algorithm using diagnostic performance metrices, namely classification accuracy, F1 score, and area under the receiver operating characteristic curve (AUC).

Classification accuracy defines the model performance as the number of correct predictions divided by the number of all predictions. F1-score metric combines the precision and recall of a classifier into a single metric by taking their harmonic means and is primarily used to compare the performance of two classifiers. AUC indicates how well the model distinguishes between positive and negative classes. The greater the AUC, the better is the model performance. The model is finally deployed to be used for the new data if the user is satisfied with the model evaluation step, otherwise the model is tuned, retrained, and tested for better performances.

Both force and power data under normal and abnormal conditions were manually labelled as 1 and 0, respectively. Normal condition for the present case refers to the data collected for the twenty-seven trials during the useful life of the cutting tool whereas abnormal conditions refer to the data set obtained under various circumstances such as workpiece loosely fixed, catastrophic tool failure, sudden breakdown of machine, *etc.* Data obtained under both normal and abnormal conditions were then combined to be trained and tested using supervised machine learning algorithms of logistic regression, k-nearest neighbor (KNN), decision tree, and random forest. Different algorithms were trained and tested on the historical data to select the best algorithm based on accuracy. Table 5.10 lists the performance of the different algorithms for anomaly prediction using force and power data, respectively.

Table 5.10 Performance of different anomaly detection machine learning algorithms using force and power data

Machine Learning Algorithm	**Force Data**			**Power Data**		
Performance Metrics	Accuracy	F1-score	AUC	Accuracy	F1-score	AUC
Logistic Regression	0.84	0.88	0.85	0.77	0.84	0.7
KNN	0.90	0.92	0.93	0.81	0.85	0.86
Decision Tree	0.84	0.89	0.88	0.82	0.86	0.88
Random Forest	0.89	0.91	0.95	0.83	0.87	0.90

Random forest algorithm using force data is finally selected for predicting anomaly. Wu *et. al.* (2017a) also confirms that random forest is better for predicting tool wear as compared to ANNs and SVR. Figure 5.23 illustrates the area under the receiver operating characteristic (ROC) curve obtained for random forest algorithm using force and power data. AUC is basically a probability curve that compares the true positive rate (TPR) to the false positive rate (FPR) at various thresholds and measures a classifier's ability to distinguish between classes. It ranges in value from zero to one. If model predictions are 100% wrong, then AUC is zero, and if predictions are 100% correct then AUC is 1.0. The AUC obtained for random forest algorithm using force data is 0.95 and power data is 0.90. This implies that the developed model for predicting anomaly is robust.

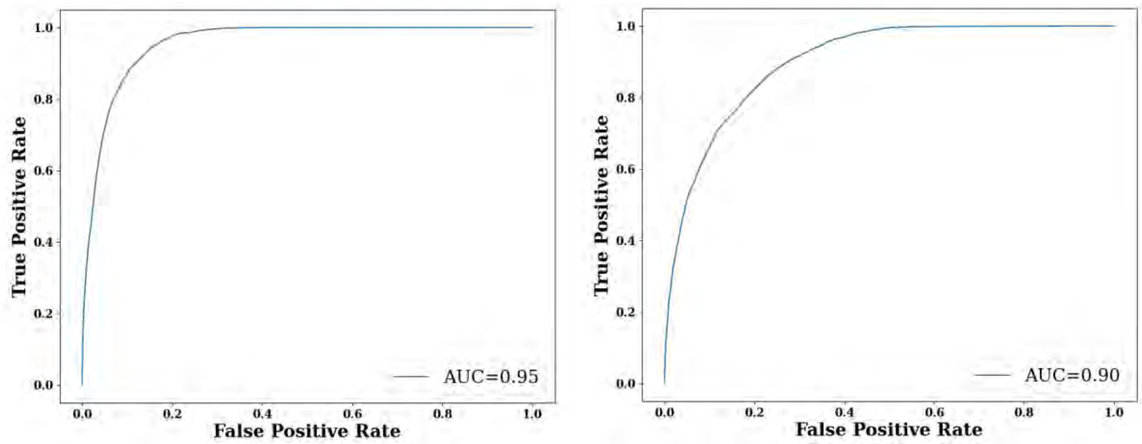


Figure 5.23 Area under the ROC curves obtained for random forest algorithm using (a) force and (b) power data

5.8 A SMART TOOL HEALTH MANAGEMENT SYSTEM

Computations and deployment of machine learning models in the cyber world would result in useful insights which could be displayed on the dashboard to provide active decision support to a user in real-time. Figure 5.24 shows the anomalous behaviour under two different cases. In the first case, anomalous behaviour is seen as a sudden spike in power value due to the sudden failure of the tool. In the second case, there is a steady increase in the power value due to gradual wear of the tool at the end of the useful life. Alarms can be actuated when the stated variables or KPIs cross certain predefined or dynamic threshold values. Anomaly can be detected in real-time, enabling adaptive adjustments for process parameters to prevent dynamic breakdowns/failures and geometric irregularities. Real-time prediction with a reasonable forecast horizon of power or force is a crucial aspect influencing tool wear. This can result in achieving the better possibility to adapt or stop the process even before unwanted events could occur (Finkeldey *et al.*, 2020). The remaining useful life estimation of the cutting tool could assist maintenance engineers to optimize a maintenance schedule and sequence the order. Spare parts can be ordered in advance based on the predicted RUL. The operator has the minimum interventions to override the parameters based on the anomaly detection alarm.

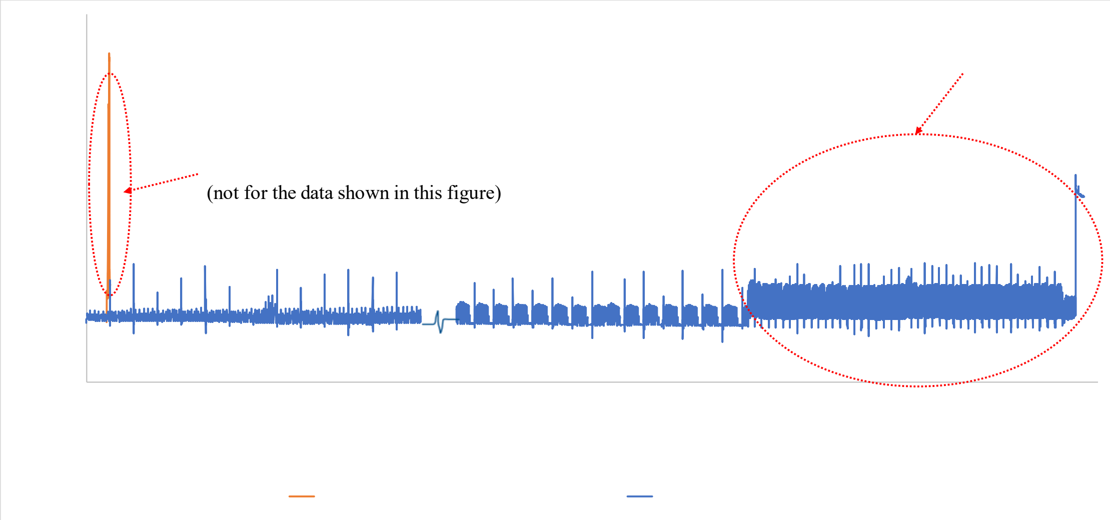


Figure 5.24 Anomalous behaviour for sudden tool breakdown and gradual tool wear

5.9 KNOWLEDGE-BASED SYSTEM

There are several tool rejection criteria such as maximum allowable flank wear, power consumption or force values, or surface roughness of workpiece (Corne *et al.*, 2017; Dadgari *et al.*, 2018). Cutting tool is generally rejected and not used for machining if any of these criteria is met – flank wear greater than 0.3 mm, power consumption or cutting force increases above 120% to 130% of the initial value, surface roughness of the workpiece reaches to a predefined value. Actual tool life is determined using experiments performed in several passes until the cutting tool wears off to the threshold limit. Figure 5.25 plots the variation of energy consumption, surface roughness, and tool wear with respect to the machining time until the flank wear reaches 0.3 mm. The process parameters for this experiment are selected from Table 5.4 for experimental run 26 (v = 180 m/min, f = 0.4 mm/rev, d = 0.5 mm). Variation of tool wear with respect to time is shown in Figure 5.25 (c). The tool life is around 130 minutes when the tool wear reaches 0.3 mm. Similar trends can be observed for power consumption and surface roughness, as shown in figures 5.25 (a) and 5.25 (b), respectively. Figures 5.26 (a) to (f) show the variation of tool (flank wear) and chip colour at various intervals of machining time. The colour of the chips changes from metallic colour in normal condition to sky blue as the cutting tool fails. The predicted value of RUL at run 26 (Table 5.4) is 137 minutes, whereas the experimental tool life for the same conditions was found to be 130 minutes. The percentage error between the predicted and the actual tool life is around 5.38%.

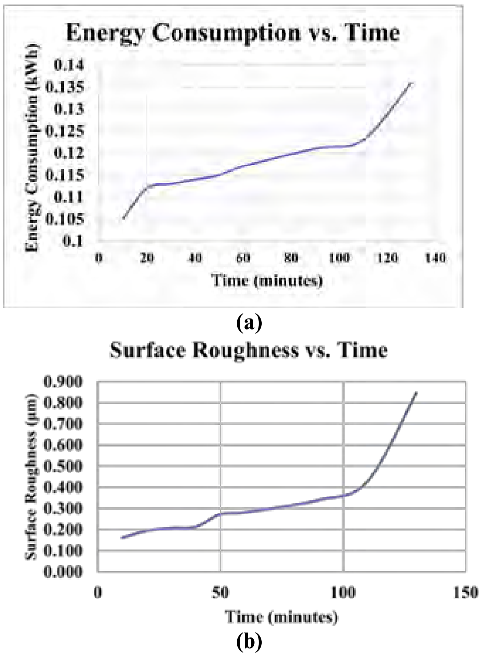


Figure 5.25 Time series plots for (a) energy consumption, (b) surface roughness, and (c) tool wear

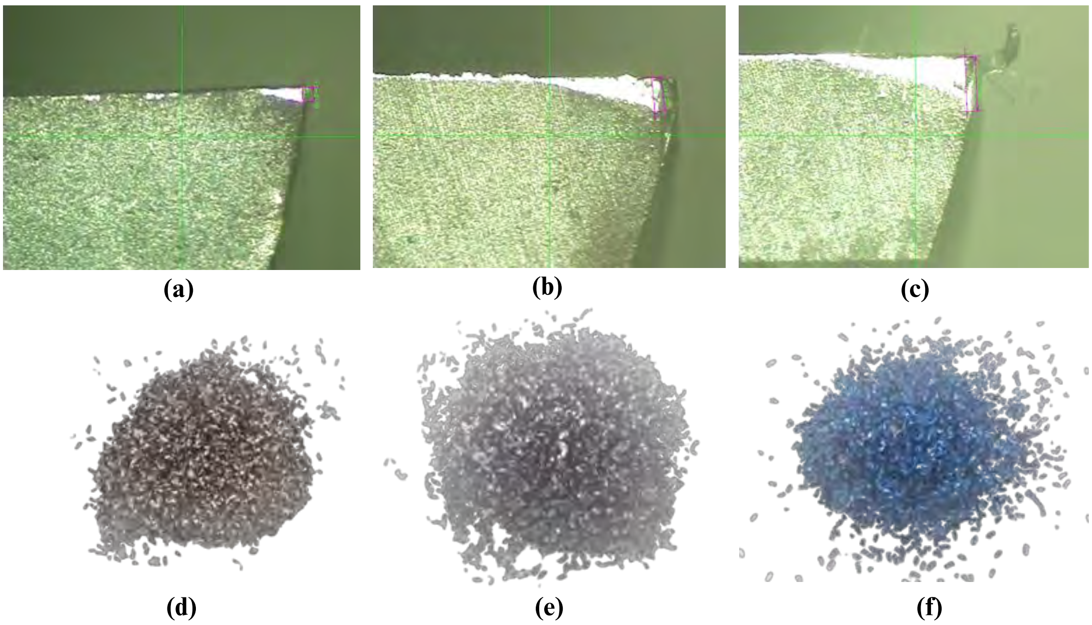


Figure 5.26 Tool wear after (a)10 minutes, (b) 90 minutes, (c) 130 minutes; chips colour after (d) 10 minutes, (e) 90 minutes, and (f) 130 minutes

5.10 SUMMARY

This chapter presents a CPPS framework for smart tool health management for a CNC milling center using prescriptive and diagnostic analytics. Further, the following models have been developed to demonstrate the usefulness of the proposed CPPS framework:

- Development of machine learning algorithm to predict RUL of a cutting tool
- Development of a machine learning algorithms for anomaly detection during milling process
- Development of a prescriptive model to prescribe optimum cutting parameters to optimize RUL in conjunction with MRR and APT at the required surface finish
- Development of a knowledge-based system to update the learning from the machine learning algorithms to update the tool life curve and chip conditions at different phases of a cutting tool life

It was also found that power consumption of 130% of the initial power consumption is a good active power threshold for the cutting tool life. Autoregressive machine learning algorithm was used in conjunction with GMM-HMM algorithm to predict the RUL of the cutting tool using live machine tool power data. The accuracy of the predicted RUL was found to be 94.62% as compared to the actual tool life obtained during validation experiment. Another machine learning algorithm developed for the detection of anomalous behaviour of the tool using random forest model on force and power data was found to be robust for anomaly detection with an AUC score of 0.95 and 0.90 for force and power datasets, respectively.

The prescriptive analytics using response surface modelling of the active power threshold, predicted tool life, material removal rate, and surface finish using Taguchi method and ANOVA prescribes the optimum cutting parameters for the optimum combination of RUL, APT, and MRR at the targeted surface finish of the part. The ANOVA results, interaction plots and optimization plots revealed that higher tool life can be achieved at lower levels of cutting speed, feed rate, and axial depth of cut. However, the effect of axial depth of cut on the tool life is the highest.

Prescriptive and diagnostic analytics for tool health based on CPPS is valuable in monitoring tool degradation, detecting anomalous behaviour, predicting tool life of cutting tool, and prescribing optimum cutting parameters. Useful insights using sensor data analysis could assist a practitioner with real-time alerts to avoid unexpected failure of cutting tool, maintain machining accuracy, and product quality. RUL prediction of the cutting tool can assist the production manager to optimize the maintenance schedule and sequence. Finally, the proposed framework would provide better resource utilization and improve the energy efficiency of machine tools with reduced production cost, lower downtime, reduced maintenance costs, and increased productivity and quality.

This study also leads to the development of a KBS to continuously update various curves (tool life, energy consumption, surface roughness) and chip colours at the different health conditions of a tool for the researchers to compare, validate and benchmark. Future research could consider factors such as maintenance planning (unplanned downtime, scheduling, *etc.*), system vibration, cutting tool deflections, *etc.* In future, more robust, interoperable, and versatile models trained with large volumes of datasets acquired from different types of workpiece materials, cutting tools, cutting parameters, and machine tools can be used. The computation time for model processing can be decreased with better computational capacity of the system so that the latency is reduced. Future research can also be performed on securing the proposed CPPS framework using blockchain technology.

Although the findings of the current study are constrained to a specific CNC machine, considering its capabilities, the process involved, and the physical and chemical properties of the cutting tool and workpiece; but the proposed CPPS framework is generic in nature. It is reproducible and scalable to a variety of machining applications, such as turning, broaching, drilling, *etc.*

Another limitation of the current research is that it monitors the health of the cutting tool only and not the machine tool at the system level. The present work is a step towards meeting the various Industry 4.0 environment requirements outlined by Lee *et al.* (2015) – self-awareness, self-prediction, self-configuration, and efficient maintenance.

CHAPTER 6

DEVELOPMENT OF A CPPS FRAMEWORK FOR A LEARNING FACTORY TO FACILITATE TEACHING, TRAINING AND EXPERIENTIAL LEARNING

This chapter proposes a CPPS framework for a learning factory to facilitate teaching, training, and experiential learning to meet the needs of the Industry 4.0 workforce, industrial engineers, and engineering students in general.

6.1 INTRODUCTION

The fourth industrial revolution, also known as Industry 4.0, is characterized by incorporating the IoT and services into the manufacturing environment, where intelligent machines, storage systems, and production facilities communicate, stimulate actions, and autonomously monitor and control one another (Kagermann *et al.*, 2013). The accelerated digitalization due to technological advancements in the Industry 4.0 environment has widened the gap in the technical competencies between academia and industry. Future manufacturing scenarios necessitate that industrial engineers possess complex and interdisciplinary skills to handle the modelling of intricate processes and integrate multiple systems across domains. Learning factories enable students to acquire additional IT knowledge by working with digital models, utilizing simulation software, manipulating, and analysing data, or designing cyber-physical-world interfaces (Abele *et al.*, 2017). Learning factories provide competitive, safe, and cost-effective environment for the development of transversal competencies in engineering students or newly inducted employees (Devika *et al.*, 2020). It provides a didactic platform where challenges related to future factories based on Industry 4.0 can be experienced and demonstrated based on 'learning by doing' to meet the requirement of Industry 4.0 workforce (Louw & Walker, 2018). Initial studies have shown better performance among students with respect to skill development and knowledge acquisition (Baena *et al.*, 2017). It also provides a learning environment for several applications such as process improvement, layout planning, energy efficiency, lean administration, resource efficiency, sustainability, logistics optimization, management and organization, product emergence, process automation technology, *etc.* (Abele *et al.*, 2018).

Product traceability has become an essential component of any supply chain. The availability of real-time tracking and tracing data among the various business supply chain partners facilitates the making of well-informed, accurate decisions (Dessureault, 2019). This also provides efficient real-time monitoring and dynamic dispatching of inter-enterprise production and transportation enabling manufacturers to manage highly fluctuating, diverse, and customised customer requirements swiftly through an efficient collaboration between different stakeholders (Ding *et al.*, 2018).

Machine vision (MV) systems are camera-based solutions which can be used for quality control and object tracing. Machine learning algorithms have made the MV systems capable of image recognition. Manual inspections, measurements, and fault detections are inefficient leading to higher time, cost, and manpower. MV systems are increasingly being used in manufacturing environments for quality control and tracking parts in a mass production environment (Frustaci *et al.*, 2020). MV system also removes possibilities of human biased decisions in quality control and facilitates the development of more efficient production processes, such as lean and agile manufacturing systems (Wagner *et al.*, 2017).

RFID, unlike barcodes and QR codes where the object must be in the line of sight and only one code can be read at a time, can read multiple tags at a time even when the tags are not in line of sight. RFID technology can be used to accurately read and store data about the material flow in the production line. This in turn helps in real-time capturing of data and object visibility (Yang *et al.*, 2012). The real-time data can be used by the managers for efficient planning of logistics and material consumptions. Now a days, RFID tags are cost effective, robust, high temperature and moisture resistant (Zhekun *et al.*, 2004). RFID technology compared to other similar technologies offer higher accuracy and instantaneous detection without visual contact; and is reprogrammable in nature (Gladysz *et al.*, 2020). RFIDs can be installed in places where humans cannot reach or it is unsafe for the operator. The data can be written, erased, rewritten on RFID which is not possible for barcode or QR code. RFID tags can be reused which is important for resource sustainability.

Utilizing RFID and MV together enables product/part tracing through the value chain as well as real-time defect control. The traceability becomes useful during product recalls as in automotive industry or reverse logistics as in garments and apparel, pharmaceutical, and online retail business. RFID equipped product/part can address industrial challenges related to part identification, monitoring, and tracking (Velandi *et al.*, 2016).

A two-way knowledge transfer between innovation and learning is required for new-age manufacturing. Such knowledge transfer helps in providing the hands-on approach for skill development which in turn helps in developing novel solutions for industrial growth (Chryssolouris *et al.*, 2016). Since RFID, MV, and CPPS systems are currently emerging production paradigms, it becomes necessary to provide a well-defined framework with respect to CPPS for a learning factory to facilitate teaching, training and experiential learning.

This chapter aims to propose a CPPS framework for learning factory to facilitate teaching, training and experiential learning. This is achieved by incorporating the following objectives.

- Integration of an inexpensive RFID technology and a machine vision system in an existing learning factory.
- Development of a machine vision-based defect detection system.
- Development of a RFID based real-time part traceability system.
- Development of a live dashboard to monitor energy demand, track and trace the workpieces in real-time, and provide immediate feedback through visibility to operators and floor managers.

This chapter is organized as follows: Section 5.2 presents the research background and outlines significant existing contribution in the field. Section 5.3 provides an overview of learning factories, including their fundamental concepts, dimensions, key characteristics, as well as their global distribution and major thrust areas. Section 5.4 presents the research methodology and proposes a CPPS framework for learning factory to facilitate teaching, training and experiential learning. Sections 5.5 and 5.6 discuss the physical world, and data acquisition system, respectively. Section 5.7 discusses the cyber world through development of a machine vision-based defect detection system and RFID-based real-time part traceability system. Section 5.8 discusses the smart learning factory management system for real-time monitoring, visualization, traceability & tracking, feedback, and control. Finally, Section 5.9 summarizes the chapter and highlights the major contribution of the chapter.

6.2 BACKGROUND

A cost-effective machine vision application has been reported for a learning factory for research and development in the field of intelligent manufacturing systems. This resulted in the development of competencies and skills, practical training to engineering students through self-learning and working on projects dealing with real-life challenges (Louw & Droomer, 2019). MV system based on CPS has been implemented for monitoring of tool wear in a production system (Lins *et al.*, 2020). Similarly, MV systems have also been applied in a learning factory for quality control solutions at a sorting station (Zancul *et al.*, 2020). An automated and non-contact type MV system-based surface roughness measurement technique has also been reported (Joshi & Patil, 2020). A low-cost CPS based MV system has also been reported to control, monitor, and visualize the quality of spur gears processing in real-time (Ramírez, 2019). MV system implementation in a learning factory increases the awareness among students and practitioners about its possible applications (Zancul *et al.*, 2020).

Although, the adoption of RFID technology is increasing primarily in retail and supply chain management applications but its potential in manufacturing industries remains largely untapped (Zhekun *et al.*, 2004). RFID technology has been used in a learning factory enabling students to understand and upgrade their skills (Crnjac *et al.*, 2019). A low-cost RFID system integrated with learning factory has been used for the demonstrator purpose in the real production environment (Afonso & Walker, 2018). RFID technology has been applied for developing automatic identification systems capable of storing the complete component history to prevent expensive downtime through repairing the processing defects and enabling the product recalls (Velandia *et al.*, 2016). However, the main limitation of RFID application in industry is decreased processing speed on the shop floor (Gjeldum *et al.*, 2018).

Traceability 4.0 is gaining popularity in conjunction with Industry 4.0, with emphasis on the 4Ms (man, machine, material, and method) (Zosel, 2020). Traceability is a significant supply chain feature and has been a pain point for manufacturers during product recalls. RFID technologies have revolutionised traceability facilitating the product recall issue (Dai *et al.*, 2021). Traceability has been applied in lithium-ion battery production for intelligent tracking and tracing production and product characteristics, such as energy consumption, material*, etc.* enabling automated identification of processes, linking of all acquired product-specific data, and facilitating data driven applications (Wessel, 2020).

The application of traceability in a learning factory to monitor product origin and provide real-time visibility of its movement in the value chain has not found researcher's attention. The present work aims to enable traceability and defect detection system within an existing learning factory.

6.3 LEARNING FACTORY

The concept of a learning factory provides a didactic platform where real challenges associated with factories can be experienced and demonstrated in a cost-effective and safe manner, developing multidisciplinary skills and practically oriented approaches based on 'learning by doing'. The term "learning factory" was coined and patented in 1994, when the National Science Foundation (NSF) of the United States awarded a consortium led by Penn State University a grant to develop a "learning factory" (Abele *et al.*, 2015). It is composed of two words "learning" and "factory" to incorporate both learning and teaching elements and a production environment (Wagner *et al.*, 2012). The term "learning", as opposed to "teaching" emphasizes experiential learning, which, according to research, improves retention and application more than traditional methods such as lectures (Cachay *et al.*, 2012). The initial version of learning factories emphasized the practical application of knowledge acquired during engineering education to address industry challenges and design or redesign products to meet specific requirements. A learning factory encompasses, namely purpose, process, setting, product, didactics, and operating models (Abele *et al.*, 2015). Figure 6.1 shows the dimensions and key features of learning factories. The purpose of learning factory is to provide teaching, training, and/or research. The process involved can be authentic, multistage, technical and/or organizational innovation.

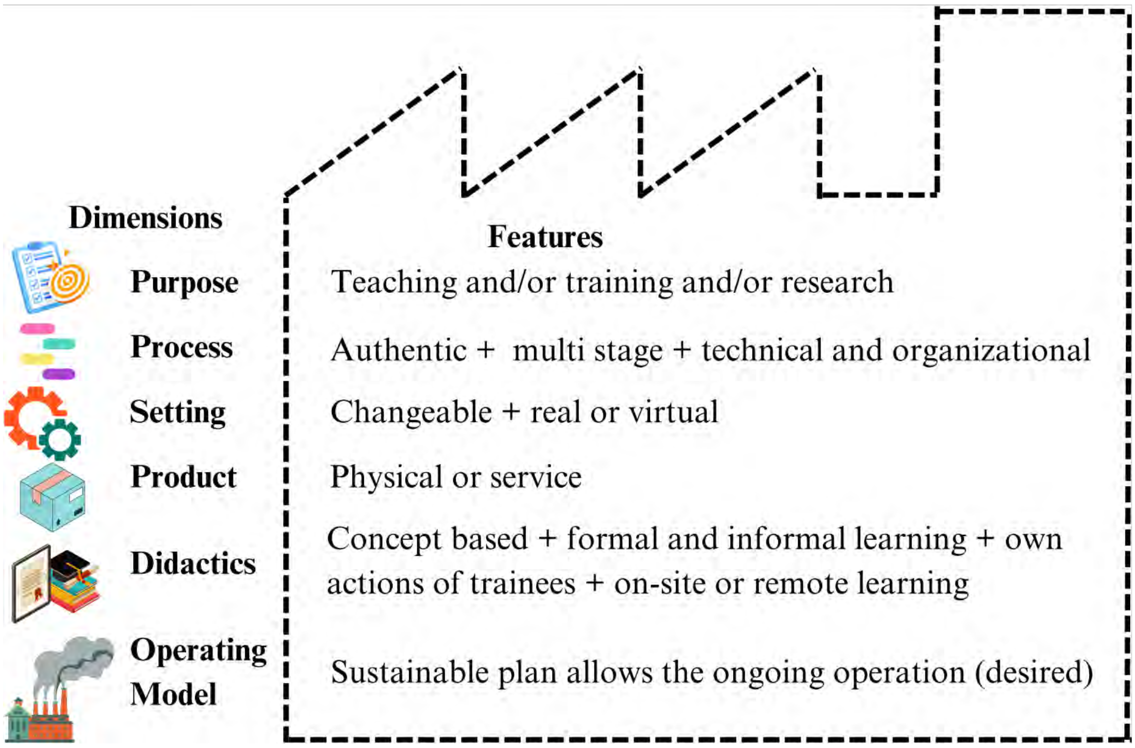


Figure 6.1 Dimensions and key features of learning factories, adapted from Abele *et al.* (2015)

The setting can be changeable, real, and/or virtual. The product can be physical objects or services. The didactics can be concept based, formal and informal learning, own actions of trainees, on-site and/or remote learning which allows the ongoing operation. In recent years, there has been a rise in the development of learning factories with the aim of improving the learning experiences of trainees in various fields of knowledge (Abele *et al.*, 2015). According to the International Association of Learning Factories (IALF), there are currently twenty-seven learning factories around the world that provide research and training. Table 6.1 lists the geographical distribution of learning factories across the globe with their major thrust areas.

Table 6.1 Distribution of various learning factories with major thrust area across the globe, adapted from IALF (2023)

Country	Affiliation	Major thrust area
Austria	Vienna University of Technology	Smart data analytics, collaborative human robotic systems, cloud-based automation
Austria	Graz University of Technology	Agile manufacturing, lean management, energy efficiency, agility, digitalization
Greece	University of Patras	Manufacturing processes modelling and energy efficiency, robots, automation
Germany	RWTH Aachen University	Industry 4.0, condition monitoring, sensor technology, automation
Germany	University of Potsdam	CPPS, IoT, IIoT, digital twin, cyber security, human machine interaction, smart factory, AR/VR
Germany	Technical University, Braunschweig	Energy and resource efficiency, Industry 4.0, urban factories
Germany	Reutlingen University	Human-robot-collaboration, intralogistics systems, digital twin
Germany	Ruhr University Bochum	Lean management, human-robot-collaboration, digital twin, digital shadow, AR/VR applications in lean/six sigma
Germany	Karlsruhe Institute of Technology	Site selection, lean and Industry 4.0, quality control
Germany	Technical University of Munich	Animation for process stability during milling, solution to vibration problems
Sweden	KTH Royal Institute of Technology	flexible/adaptive manufacturing
South Africa	Stellenbosch University	Lean operations, ergonomics, shop-floor-management
Italy	Free University of Bolzano	Automation and robotics, human machine collaboration, lean and flexible assembly, worker assistance systems
Hungary	Hungarian Academy of Sciences	Collaborative and advance robotic assembly
Luxembourg	University of Luxembourg	Lean Manufacturing, process optimization, augmented reality and digital manuals, quality management
Neatherlands	University of Twente	Smart manufacturing solutions based on CPPS, sustainable manufacturing, human factors in manufacturing systems
Crotia	University of Split	Lean management tools, plan layout, digital factory, assembly in Industry 4.0, additive manufacturing
Finland	Aalto University	Flexible production systems, artificial intelligence, digital twins, simulation models safety and security
Malaysia	University Malaysia Pahang	CPPS, blockchain and artificial intelligence technology, smart logistics and supply chain system

Table 6.1 Distribution of various learning factories with major thrust areas across the globe, adapted from IALF (2023) (contd…)

Country	**Affiliation**	**Major thrust area**
Singapore	Agency for Science, Technology and Research	Contextual and dynamic planning, prescriptive and predictive models, quality monitoring
China	Tongji University	Cloud/edge computing, sensor, and data acquisition
Canada	University of Alberta	Sustainable production, automation, and AI technologies
Canada	McMaster University	3D printing, CNC machine tools, robotics assembly
USA	Purdue University	Quality control/assurance, workplace Safety, AR/VR
Brazil	University of São Paulo	Production planning and control; ergonomics
India	Birla Institute of Technology & Science, Pilani	CPPS, digital twin, AR/VR, quality control

Most of the learning factories are in Germany, followed by other developed nations such as Austria and Canada. India, China, Brazil, and South Africa also have learning factories providing research and training. However, there is a need to set up additional learning factories across universities, depending on the size and population of these countries. The major thrust area for these learning factories is primarily on Industry 4.0 technologies (*e.g.*, CPPS, digital twin, cloud manufacturing, AR/VR applications, data analytics, HMI, M2M, interactions *etc.*), sustainable manufacturing, agile manufacturing, lean management, *etc.*

Figure 6.2 shows the existing learning factory infrastructure at Birla Institute of Technology & Science, Pilani, Pilani campus, Rajasthan, India. It currently consists of six modular production systems, namely distribution, measuring, storage, pick & place, separating, and sorting station, in addition to sensors, AR/VR devices, and integrating 3D printers.

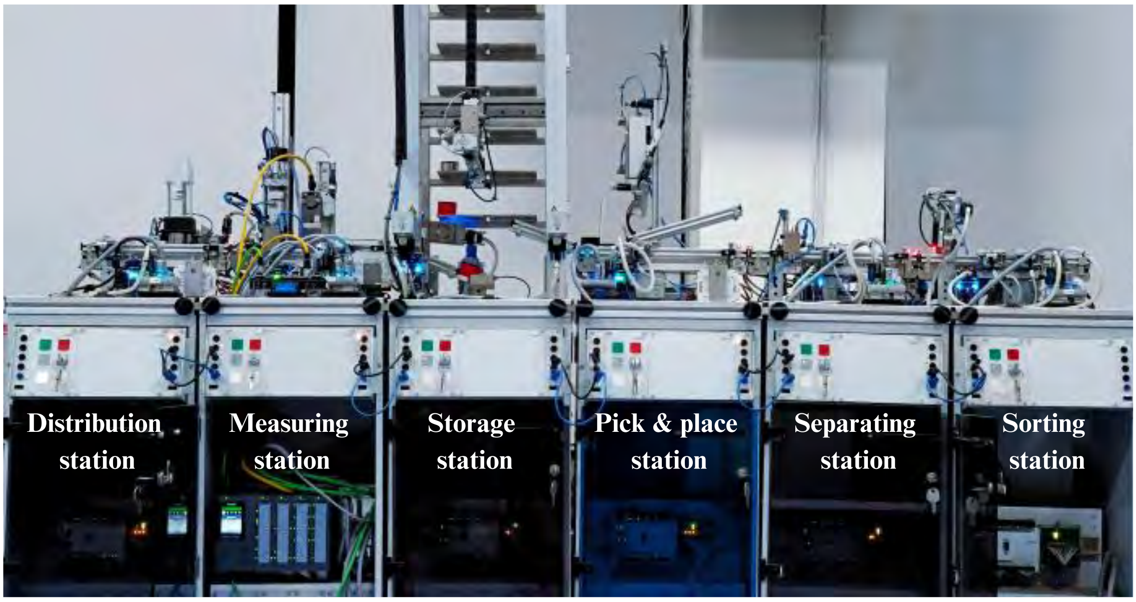


Figure 6.2 Existing learning factory infrastructure at Birla Institute of Technology & Science, Pilani, Pilani campus, Rajasthan, India

6.4 RESEARCH METHODOLOGY

Figure 6.3 depicts the four-step research methodology adopted for the development of a smart learning factory management system.

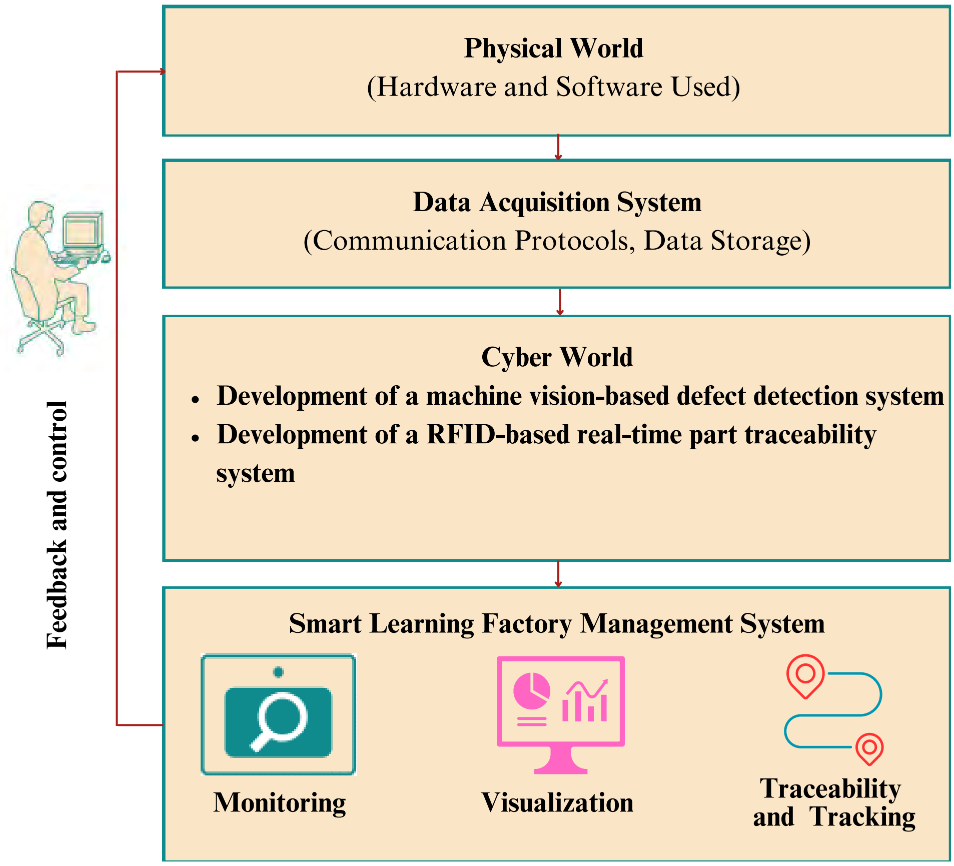


Figure 6.3 Development of a CPPS framework for smart learning factory

The first step consists of setting the physical world through the integration of hardware and software. The second step consists of acquiring online data from the physical world. The third step consists of developing smart functionalities in the cyber world through the development of machine vision-based system to identify part defects and RFID-based real-time part traceability system. The fourth step consists of deployment of smart features of online monitoring, visualization, traceability & tracking, feedback and control for a smart learning factory management system.

6.5 PHYSICAL WORLD (HARDWARE AND SOFTWARE USED)

The physical world consists of a learning factory where various modular production systems, such as distribution, storage, pick-and-place, separating, and sorting stations are interconnected to represent a prototypical assembly line. These modular production systems are controlled using programmable logic controllers (PLCs) and interconnected through a moving conveyor line. The learning factory is integrated with various hardware and software, as listed in Table 6.2, along with their technical specifications/source and applications.

The products for the present case are prototype cylindrical workpieces of different colours, namely silver, black and red. RFID modules have been set up at places where monitoring is required. The RFID modules are placed at the exits of the stations and RFID tags are attached to the products. The workpieces are attached with RFID tags which can be detected when the workpiece is around 10 cm from the scanner. The tags operate on a radio frequency of 13.56 MHz and are passive in nature. The raspberry pi camera uses an eight-megapixel sensor which supports 720p at 30fps. The camera is attached to the pi using a 15 cm ribbon cable to the CSI port.

Table 6.2 List of hardware and software resources with their technical specifications and applications

Resources	CPPS components	Technical Specifications/source	Applications
Hardware	Modular Production System	Combinations of FESTO MPS in sequence: Pick & Place, Separation, and Sorting Stations	Prototypical representation of assembly line
	Programmable logic controllers (PLCs)	12 digital inputs, 8 digital outputs, USB interface for data transfer, I-Port and Modbus TCP protocol	Controller
	Raspberry Pi 4 Model-B	RAM: 8GB LPDDR4 SDRAM, Processor: Broadcom BCM2711, quad-core Cortex-A72 (ARM v8) 64-bit SoC @ 1.5GHz	Micro-processor
	Raspberry Pi Camera V2	Resolution: 8 Megapixel, Image Sensor: Sony IMX219, Sensor Resolution: 2592 x 1944 pixels, Video Modes: 1080p30, 720p60 & 640x480p60/90, Focal Length: 3.60 mm +/- 0.01, F Stop: 2.9	Live monitoring
	Arduino Uno	Microcontroller Chip: ATmega328P, Clock Speed: 16 MHz, Flash Memory: 32 KB, SRAM: 2 KB	Micro-processor
	RFID Reader/Writer	Operating Frequency (MHz): 13.56, SPI data rate (Mbit/s): 10, Operating distance (mm): 50	Tracing and tracking
	Smart energy meter (Beckhoff system module)	Supply voltage: 24 V DC, External feed current: 6 A	Energy monitoring
Software	Python 3.8	Open source	Developing logic/algorithm
	TensorFlow	Open source	Developing AI applications
	Node-RED	Open source	Developing dashboards

6.6 DATA ACQUISITION SYSTEM

6.6.1 Communication Protocols

Data transmission among CPPS components takes place using various wired/wireless communication protocols, such as Modbus TCP/IP and MQTT protocol. The RFID module is programmed using Arduino IDE that communicates with the Raspberry Pi using MQTT protocol. The real-time tracking and tracing data are sent to live dashboard wirelessly using MQTT protocol. The Beckhoff system module is used to acquire energy data based on Modbus TCP/IP protocol. Machine-to-machine communication among modular production systems and control actions such as actuations takes place using Modbus TCP/IP protocol.

6.6.2 Data Storage

The energy data is stored locally where an onboard SQL database on the PC supports the efficient storage and retrieval of the data. Other data related to tracking and tracing such as unique identity number of the workpiece, date, time, station information, defect status are stored locally on the hardware storage of the raspberry pi.

6.7 CYBER WORLD

6.7.1. Development of a Machine Vision based Defect Detection System

Figure 6.4 illustrates the process flow diagram for the development of a machine vision-based defect detection system deployed in the learning factory. The defect detection system was created using Quantized SSD Mobilenet in TensorFlow Lite, an open-source machine learning platform known for its versatility and extensive range of tools, including libraries, community forums, and resources. The developed model was trained with images of defective and non-defective workpieces. A dataset consisting of 1200 images was divided into two subsets: a testing set, which comprised 20% of the images, and a training set, which comprised the remaining 80% of the images. The model was trained for approximately sixteen hours to achieve a loss function value below two. Figure 6.5 shows the loss function with respect to the total number of iterations. A total of 21674 iterations were carried out for achieving loss consistently below two. The prediction results showed that the developed machine vision-based defect detection system can detect geometric defects (cracks), color defects (presence of other colours) as well as the surface quality of the workpieces (presence of other materials on the surface) of the workpieces with high accuracy (around 98%). The developed model was then deployed in the real environment where an accuracy rate of over 85% was set as a benchmark for ensuring error-free outcomes. Only results with an accuracy rate of 85% or higher are included in the database. Frames with accuracy below the specified threshold were used to update and enhance the accuracy of the trained model.

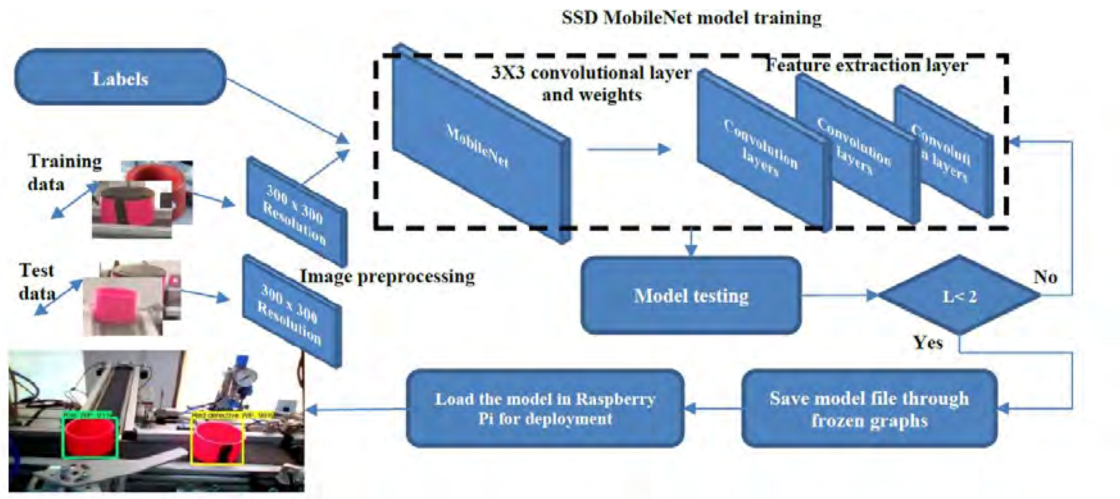


Figure 6.4 Process flow diagram for a machine vision-based defect detection system

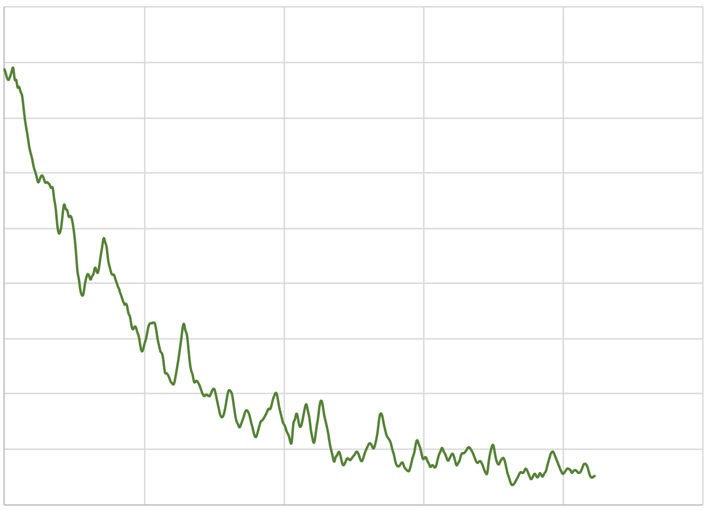


Figure 6.5 Loss function with respect to the total number of iterations

6.7.2. Development of a RFID-based Real-Time Part Traceability System

Figure 6.6 shows the process flow diagram for a RFID-based real-time part traceability system in a learning factory. A python program was developed and installed on the Raspberry pi processor for providing the logic for production initiation and object detection-based quality control. The process starts with the customer placing an order for the product. Availability of materials required for the product is checked. If all the materials are not available, then the operator is notified, the database is updated with the required information, and the process stops. In case the materials are available, production is initiated. The product is tracked by the RFID as it exits each station and the database is updated. When a product exits a station, it is assumed that the activities for that station have been carried out without any problem. Any anomaly in the workpiece is detected using the defect detection module that has been developed based on machine vision. If it passes the quality check, then the customer is notified about it and the database is updated. If it fails the quality check, then the operator is informed about it and the database is updated again. The program is terminated until the customer initiates it again by placing a new order.

6.8 A SMART LEARNING FACTORY MANAGEMENT SYSTEM

The smart learning factory management system enables various smart functionalities, such as live monitoring, visualization, traceability and tracking, and feedback and control. Figure 6.7 (a) shows the learning factory with MPS stations. Figure 6.7 (b) shows the dashboard for live energy monitoring where Beckhoff energy meter running on TwinCAT software is used to acquire energy data. The control action takes place in both manual and automated modes. Figure 6.7 (c) shows the graphic user interface for manual control actions. Figures 6.8 and 6.9 show the plots for energy consumptions with respect to time for different stations. Table 6.3 shows power consumption in idle as well as working modes of each MPS station. It is observed that whenever the system is idle then power consumed remains to fluctuate at approximately 10 watts. When all components of the system (such as slider, pneumatic lid, pick and place arm) are active or in working condition then peaks in power consumption can be seen at each station and a cyclic pattern is observed. The database variables are used for developing a dashboard for ease of understanding and traceability of products using Node-RED, an open-source software. Figure 6.10 shows the developed dashboard for visual tracking of the entire assembly process in the learning factory. It displays real-time data for each product, obtained from the developed RFID and MV systems. It keeps track of the timestamp of each part's movements from one station to another and data logs when the part crosses the sorting station. The dashboard also features a search function that enables users to trace products by their part ID or defective status. This allows users to search the database for specific parts and filter results based on the defect status.

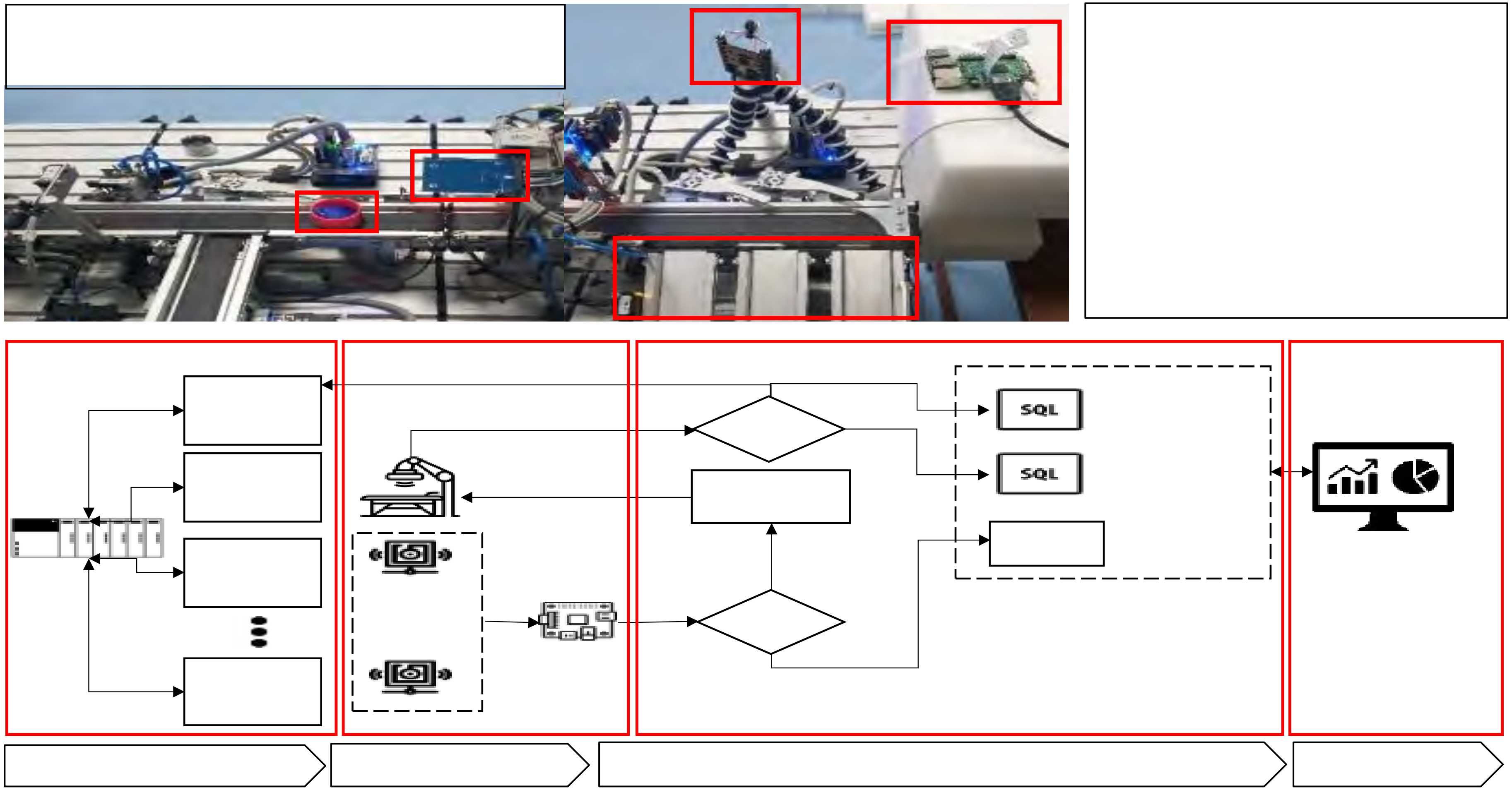
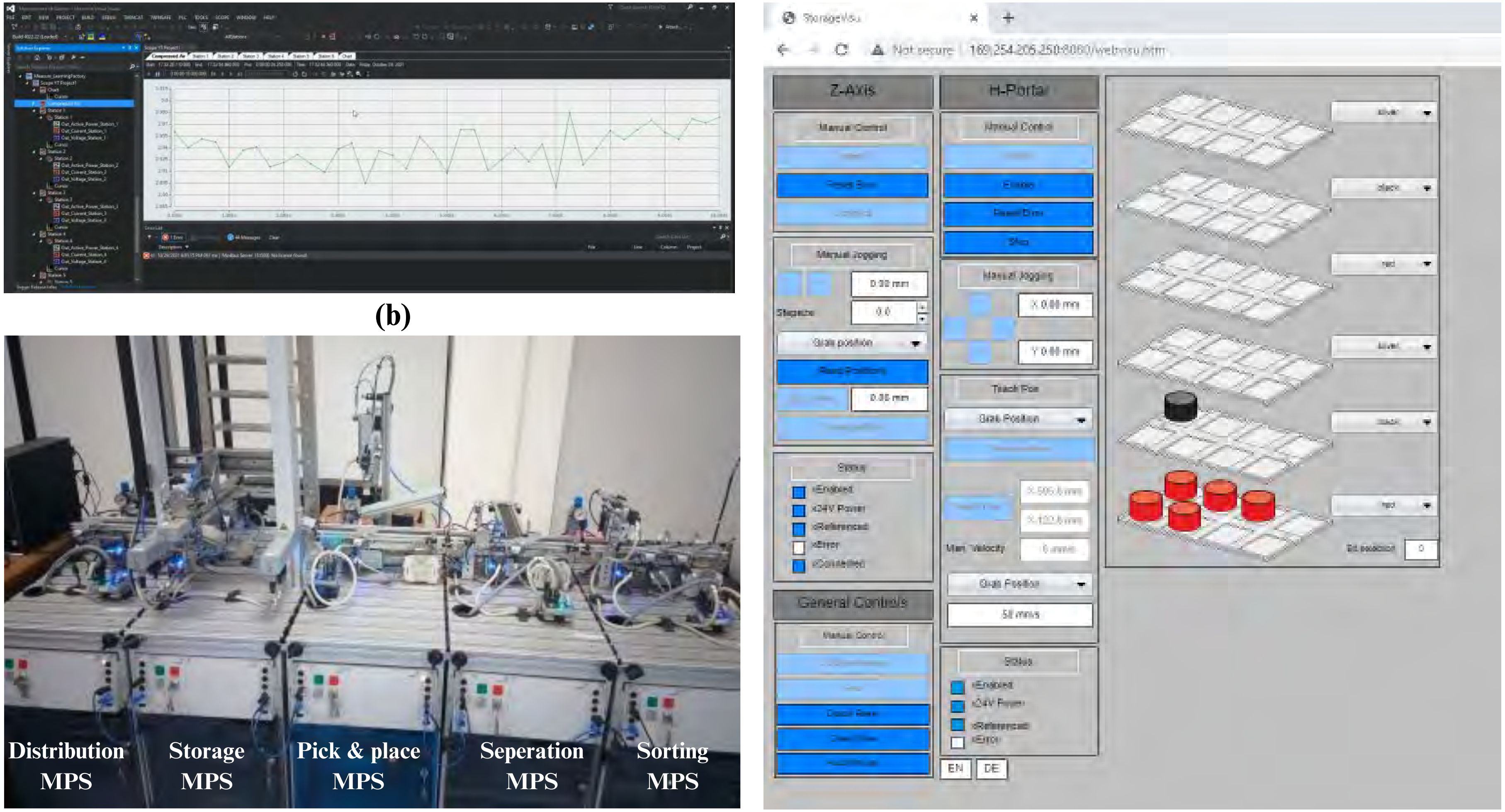


Figure 6.6 Process flow diagram for RFID-based real-time part traceability system in a learning factory



(b)

(a)

(c)

Figure 6.7 Learning factory with (a) various MPS stations, (b) dashboard for live energy monitoring, (c) graphic user interface for manual control action

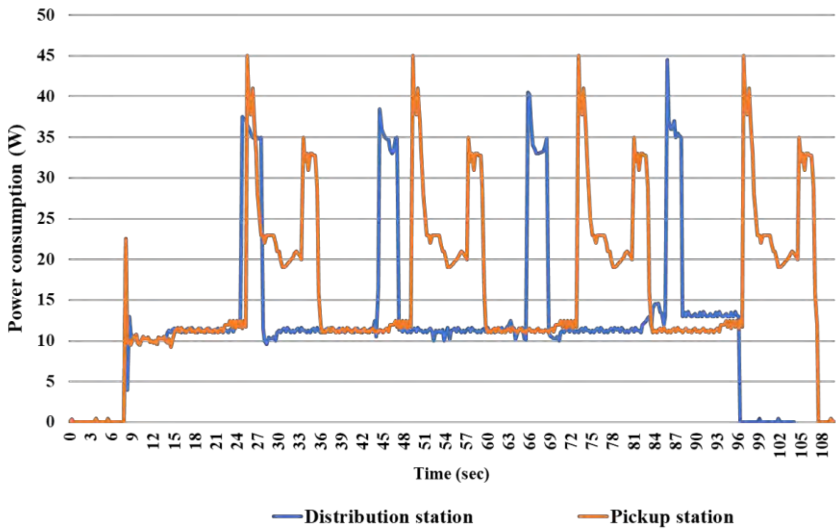


Figure 6.8 Energy consumption with respect to time for distribution and pickup station

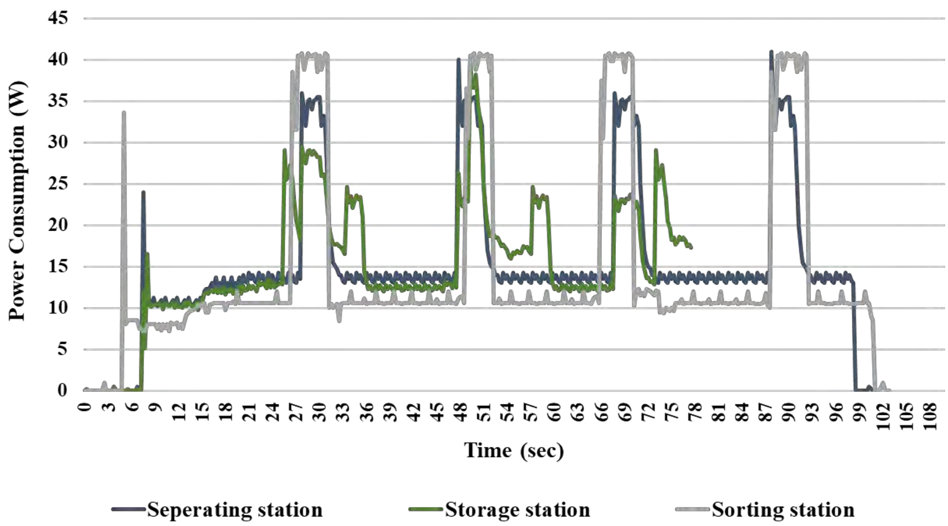
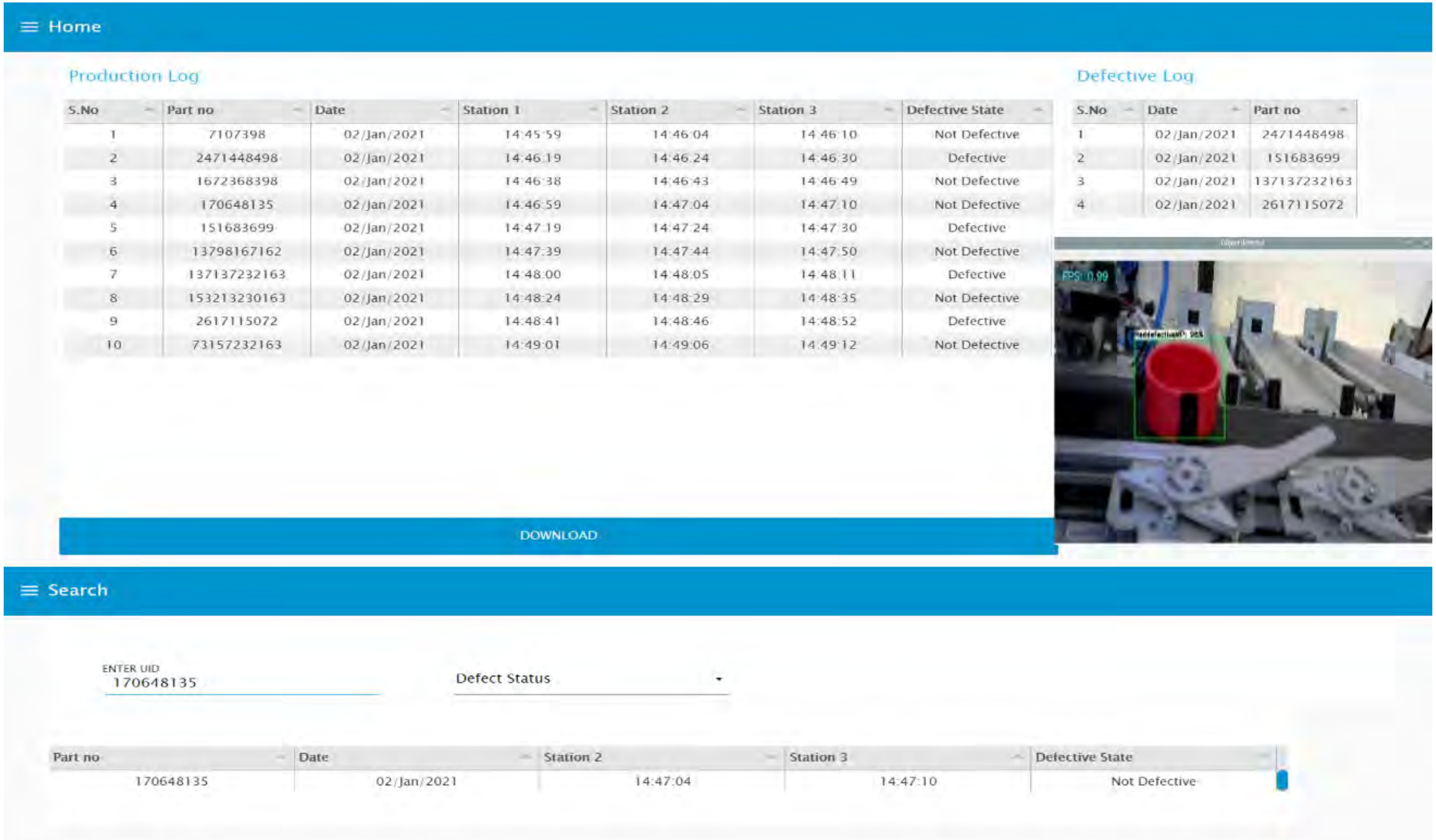


Figure 6.9 Energy consumption with respect to time for separating, storage and sorting stations

Table 6.3 Energy consumption (in idle as well as the working mode) of each MPS station with a cycle time of 20 seconds

Sl. no.	Station	Energy utilization per cycle (W)
1	Distribution	285.3
2	Storage	703
3	Pick and Place	388.6+320
4	Separating	366.1
5	Sorting	320



S.No	Part no	Date	Station 1	Station 2	Station 3	Defective State
1	7107398	02/Jan/2021	14:45:59	14:46:04	14:46:10	Not Defective
2	2471448498	02/Jan/2021	14:46:19	14:46:24	14:46:30	Defective
3	1672368398	02/Jan/2021	14:46:38	14:46:43	14:46:49	Not Defective
4	170648135	02/Jan/2021	14:46:59	14:47:04	14:47:10	Not Defective
5	151683699	02/Jan/2021	14:47:19	14:47:24	14:47:30	Defective
6	13798167162	02/Jan/2021	14:47:39	14:47:44	14:47:50	Not Defective
7	137137232163	02/Jan/2021	14:48:00	14:48:05	14:48:11	Defective
8	153213230163	02/Jan/2021	14:48:24	14:48:29	14:48:35	Not Defective
9	2617115072	02/Jan/2021	14:48:41	14:48:46	14:48:52	Defective
10	73157232163	02/Jan/2021	14:49:01	14:49:06	14:49:12	Not Defective

S.No	Date	Part no
1	02/Jan/2021	2471448498
2	02/Jan/2021	151683699
3	02/Jan/2021	137137232163
4	02/Jan/2021	2617115072

Part no	Date	Station 2	Station 3	Defective State
170648135	02/Jan/2021	14:47:04	14:47:10	Not Defective

Figure 6.10 A dashboard for visual tracking of the entire assembly process in the learning factory

6.9 SUMMARY

This chapter proposes a CPPS framework for a learning factory to facilitate teaching, training and experiential learning. The proposed framework integrates low-cost RFID technology and machine vision system in a learning factory environment. It consists of four main components of CPPS, namely physical world, data acquisition, cyber world, and visualization for enabling various smart functionalities of live monitoring, visualization, traceability & tracking, and feedback and control. The inexpensive system provides immediate visible feedback to the operators and floor managers, and enables part traceability. Further, the following models have been developed to demonstrate the usefulness of the proposed CPPS framework:

- Development of a machine vision-based defect detection system.
- Development of a RFID based real-time part traceability system.
- Development of a live dashboard to monitor energy demand, track & trace the workpieces in real-time and provide feedback to operators and floor managers.

The conclusions drawn and the practical significance are as follows:

- RFID system allowed intelligent tracking and tracing of workpieces in real-time at all the stations, enabling the visibility of the product's entire movement in the value chain. The significance lies in the ability to identify irregularities or detect anomalies in the process chain by observing cycle time patterns over time.
- Machine vision system enables the detection of workpiece defects. The proposed system can be used to monitor and control the product quality in real-time without human intervention.

- The research also shows how a learning factory provides an ideal platform for developing, implementing, and testing new concepts and technologies. Industry 4.0 workforce, industrial engineers, and engineering students can develop multidisciplinary competencies based on “learning by doing”, which is extremely beneficial for training multidisciplinary and complex concepts and technologies of Industry 4.0. Therefore, the proposed framework would be useful in bridging the gap between academic and industrial technical competencies.
- Integration of smart energy meter with the learning factory enabled online monitoring of energy demand for each MPS station. It could facilitate smart energy management if an abnormal energy pattern is detected.

Lastly, the proposed framework can be transferred to shop floor facility assisting the manufacturers to trace the parts at any point of time in a value chain including aftersales where traceability has been a pain point for manufacturers during product recalls.

CHAPTER 7

CONCLUSIONS

CPPS is an essential prerequisite to facilitate real-time monitoring, data acquisition, visualization, control, and analytics of a manufacturing system. Its implementation enhances the management capabilities and performance of traditional manufacturing systems to meet several engineering requirements. Some of these significant engineering requirements are self-awareness, self-prediction, self-configuration, efficient maintenance, robustness, autonomy, adaptability, reconfigurability, *etc.* at the unit level; flexibility, leanness, agility, reconfigurability, context awareness & energy efficient scheduling, decentralized production control, *etc.* at the system level; and product lifecycle management, flexibility, leanness, agility, reconfigurable supply chains, *etc.* at the system of systems level.

These engineering requirements provides several technological benefits, such as higher level of intelligence, autonomy, connectivity, better product quality, smart energy management, enhanced system reliability, reduced production downtime, improved production planning, enhanced inventory management, proactive decision making, *etc.* Implementation of CPPS has resulted in energy & resource savings, increased transparency regarding environmental performance from the environmental perspective; reduced business risks, reduced maintenance costs, increased productivity, decreased production loss, enhanced occupational safety of workers, improved customer services, enhanced abilities for humans to interact and control the physical world, improved symbiotic human-robot collaboration.

This thesis proposed a generic CPPS framework for smart manufacturing analytics and management. Further, the generic CPPS framework was used to develop and implement smart functionalities in Industry 4.0 non-compliant physical systems, namely a 3D printer, a CNC machine center, and a learning factory for real-time monitoring, visualization, control, and analytics.

A systematic literature review of 164 articles relevant to the topic of cyber physical production system is presented in **chapter 2.** The literature review discovered interrelationships among various CPPS concepts. It added to the body of knowledge of the CPPS in terms of latest developments, characteristics (data types, autonomy, analytics, modelling techniques), enabling technologies, application areas, and challenges. The chapter also provides an impact-efforts matrix, outlines future research directions, and proposes a concept map.

In c**hapter 3**, a generic CPPS framework was proposed for smart manufacturing analytics and management using the components, elements and sub-elements identified through the literature review.

In **chapter 4**, a CPPS framework for smart 3D printing analytics and management was proposed, where a conventional 3D printer was transformed into a smart 3D printer by integrating cost-effective solutions (low-cost sensors, devices, actuators, and open-source software) to enable smart management capabilities of online monitoring, data acquisition, visualization, control, and analytics.

In **chapter 5**, a CPPS framework for smart tool health analytics and management was proposed. A CNC milling center was integrated with smart sensors and devices to enable smart management capabilities of online monitoring, data acquisition, visualization, control, and analytics.

Finally, in **chapter 6,** a CPPS framework for a learning factory was proposed, where an existing learning factory infrastructure was integrated with an inexpensive RFID and

MV systems for facilitating smart functionalities of live monitoring, visualization, traceability & tracking, and feedback & control.

MAJOR RESEARCH CONTRIBUTIONS

The present study contributes both theoretically and practically to the existing body of knowledge on CPPS by proposing a concept map, frameworks, and providing useful insights and knowledge updates, and implementing pragmatic solutions based on the proposed CPPS framework for solving real-world manufacturing problems. The major research contribution of the present study are as follows:

- The scientometric analysis of literature provides an overview of the latest trends by analyzing various perspectives, namely research methodology classification, timeline distribution, geographical distribution, source analysis, SDGs analysis, keyword co-occurrence analysis, co-authorship among countries, and author and co-citation analysis.
- Content analysis of literature provides useful insights to enhance the understanding of the multidisciplinary concepts of CPPS from a broader perspective by classifying/grouping various concepts of CPPS such as, hierarchical levels, data types, types of autonomies, types of analytics, modelling techniques, enabling technologies; and analyzing applications areas, barriers/challenges, engineering needs/ requirements, and significance of its deployment.
- Development of a concept map for CPPS that is well-suited for a researcher or practitioner working in the manufacturing domain.
- Development of a generic CPPS framework for smart manufacturing analytics and management considering possible elements and sub-elements.

- A CPPS framework for smart 3D printing analytics and management was proposed based on data-driven analytics techniques and cloud, fog, and edge computing technologies.
- Descriptive, prognostics, prescriptive, and diagnostics analytics provided insights and predicted energy distribution during various 3D printing stages, live estimation of environmental impacts for a 3D printed product, computed the remaining useful life of the nozzle, and prescribed the optimal printing parameters depending on the managerial requirements.
- Insights were generated through various data analytics techniques for monitoring tool degradation, detecting anomalous behaviour, predicting tool life of cutting tool, and prescribing optimum cutting parameters depending on the managerial requirements.
- A knowledge-based system was also developed to update tool life, energy consumption, surface roughness, and chip colours at the different health conditions of a cutting tool which can be used to compare, validate and benchmark.
- In the case of learning factory, implementing CPPS facilitated various smart functionalities, such as live monitoring, visualization, traceability & tracking, and feedback & control. The developed dashboard provided visible feedback to operators and floor managers, and enabled part traceability at any point of time in a value chain.

PRACTICAL SIGNIFICANCE

The practical significance of the present study are as follows:

- The value addition to the body of knowledge of CPPS through systematic literature review would serve as a reference in providing researchers and practitioners with valuable insights, knowledge updates, and decision support in selecting CPPS elements and sub-elements according to their impacts and required efforts. It will assist in understanding the maturity status, guiding future developments by addressing the important needs, and advancing the knowledge, management capabilities, and potentials of traditional manufacturing in an Industry 4.0 environment.

- Characterization and estimation of energy consumption during various stages of 3D printing would be significant in comprehensive understanding of the energy consumption in each stage of the 3D printing process and providing decision support to practitioners in improving the areas of energy consumption and time inefficiencies.
- Live estimation of environmental impact for the 3D printed products offers stakeholders (operator, manager, manufacturer) in understanding the results of life cycle assessment and take prompt actions. It also enables environmentally conscious consumers to make well-informed purchasing decisions through enhanced transparency and visibility.
- Nozzle health monitoring of a 3D printer, cutting tool health monitoring of a CNC machine and their remaining useful life predictions are significant in improving the system uptime, reliability, energy efficiency, and product quality. It assists the production manager to optimize the maintenance schedule and sequence. It also prevents abnormal power usage and facilitates proactive planning of maintenance schedule and sequence of orders.
- Prescriptive analytics enabled real-time recommendation of optimal process parameters in 3D printing and milling operations. This supports practitioners in overriding the parameters, depending on the managerial requirements.
- In the case of 3D printing, diagnostics analytics enabled detection of anomalies due to mechanical or structural failure during the process for achieving error-free 3D printing. This results in less material waste, reduced human intervention & costs, and improved product quality.

- In the case of CNC machining process, diagnostics analytics enabled detection of anomalous behaviour during milling process, thereby assisting a practitioner with real-time alerts to avoid unexpected failure of cutting tools, maintain machining accuracy, and product quality.
- Learning factory provided a didactic platform by supporting teaching, training, and experiential learning, where the technical skills of the Industry 4.0 workforce, industrial engineers, and engineering students can be upgraded and innovative developments in the domain of Industry 4.0 can take place.
- The proposed Industry 4.0 solutions developed with inexpensive hardware and open-source software can be helpful to micro, small, and medium enterprises (MSMEs) in realizing the Industry 4.0 benefits of increased productivity, reliability and product quality at a reasonable price.

Finally, the present work will be a step towards meeting the various Industry 4.0 environment requirements of self-awareness, self-prediction, self-configuration, and efficient maintenance as outlined by Lee *et al.* (2015) to reduce production downtime, improve production planning, and enhance inventory management.

LIMITATIONS AND OUTLOOK

Despite several advantages, there are certain limitations of the present study. A more detailed and comprehensive review can be conducted with additional databases such as ProQuest, EBSCO, JSTOR *etc.*, and various similar search terms related to CPPS such as Industry 4.0, digital twin, cyber physical system, cloud manufacturing, IIoT, *etc.*

In the case of 3D printing, the proposed diagnostic system is limited to detecting anomalies due to structural and mechanical failure, and it does not include anomalies caused by nozzle clogging and wear. In future, work can be done to improve the accuracy of the proposed algorithms and to develop machine learning algorithms for automatically classifying the various types of 3D printing defects in real-time. The results obtained for smart 3D printing analytics and management are limited to the parameters of infill, layer height, extruder and bed temperatures without considering other printing parameters such as fan speed, printing speed, wall thickness, and build orientation. The current framework can be extended to other application scenarios where several smart 3D printers are interconnected on a shop floor or in a smart factory and require massive data processing for automated job scheduling, energy and resource management, user warnings and automated actions in case of failures, automated removal of printed parts and storage in a warehouse using cobots. The future scope also includes use of 5G communication technology for ultra-high speed data transfer, and lowest latency across all the three computing platforms (cloud, fog, and edge). The application of blockchain technology for data sharing can provide enhanced security for access control as well as data storage on all three computing platforms (cloud, fog, and edge).

In the case of CNC machine, the limitation of the current research is that it monitors the health of only the cutting tool and not the machine tool at the system level. Similar frameworks for monitoring the health of other components can turn a conventional machine tool into a smart machine tool, which can be highly useful for the overall maintenance planning of the system. In future, the machine learning models can be more robust, interoperable, and versatile if trained with large volumes of data sets acquired from different types of workpiece materials, cutting tools, cutting parameters, and machine tools.

In the case of proposed RFID and MV systems for learning factory, it was observed that the RFID tags fail to be detected at higher speeds. MV system also needs to be trained with different environments to improve the accuracy as the training environment plays a significant role in defect detection. The present latency of one second can be improved further. The proposed framework for traceability can be transferred to shop floor facility assisting the manufacturers to trace the parts in value chain at any point of time including aftersales where traceability has been a pain point for manufacturers during product recalls. Finally, the thesis outcome can be used to enhance the technical and management skills of workforce, industrial engineers, and engineering students, enabling them to handle the complexities and future challenges of Industry 4.0 with increased confidence.

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Working Papers

10. Development of a human centric cyber physical production system framework for enhanced social sustainability
11. A systematic literature review on cyber physical production system for smart manufacturing analytics and management.
12. Development of a cyber physical production system framework for context aware scheduling in manufacturing systems.

About the candidate (Rishi Kumar)

Rishi Kumar is a PhD candidate in the Department of Mechanical Engineering at Birla Institute of Technology and Science Pilani, Pilani Campus, India. He has published more than 15 research papers in international journals and conferences. He has gained research experience as a visiting researcher at TU Braunschweig, Germany. He is a lifetime member of Indian Society for Technical Education (ISTE), affiliate member of IITI DRISHTI CPS foundation, and student member of American Society of Mechanical Engineers (ASME).

About the supervisor (Prof. Kuldip Singh Sangwan)

Prof. (Dr.) Kuldip Singh Sangwan is a Senior Professor of Mechanical Engineering at Birla Institute of Technology and Science, Pilani (BITS Pilani), Pilani campus. He is the recipient of the prestigious Shri B. K. Birla and Shrimati Sarala Birla Chair Professorship. He has guided one post-doc; eleven PhDs and eleven PhDs are in progress. Prof. Sangwan has published more than 170 papers in international journals of repute. He has an active collaboration with TU Braunschweig, Germany since last 13 years. Prof. Sangwan is a fellow of the Institution of Engineers (India). He has collaborative projects worth more than 7.6 crore INR with international agencies, industry, and Indian Government agencies. Professor Sangwan found a place in the 'top 2% world scientists' list curated by Stanford University researchers.

About the Co-supervisor (Prof. Christoph Herrmann)

Prof. (Dr.-Ing.) Christoph Herrmann is university professor for Sustainable Manufacturing & Life Cycle Engineering and co-director of IWF, Institute of Machine Tools and Production Technology, Technische Universität Braunschweig as well as director of the Fraunhofer Institute for Surface Engineering and Thin Films IST since November 2018. From 2005 to 2008 he was also scientific director of KERP Center of Excellence Environment & Electronics, Vienna. Also, he was scientific director and member of the NFF (Niedersächsisches Forschungszentrum Fahrzeugtechnik/Automotive Research Center Lower Saxony), Germany. He has published more than 300 papers and book publications as author, co-author, and editor. Prof. Herrmann is member of the German Academic Association for Production Technology (WGP), visiting SIMTech fellow at the Singapore Institute of Manufacturing Technology, and fellow of the International Academy for Production Engineering (CIRP).

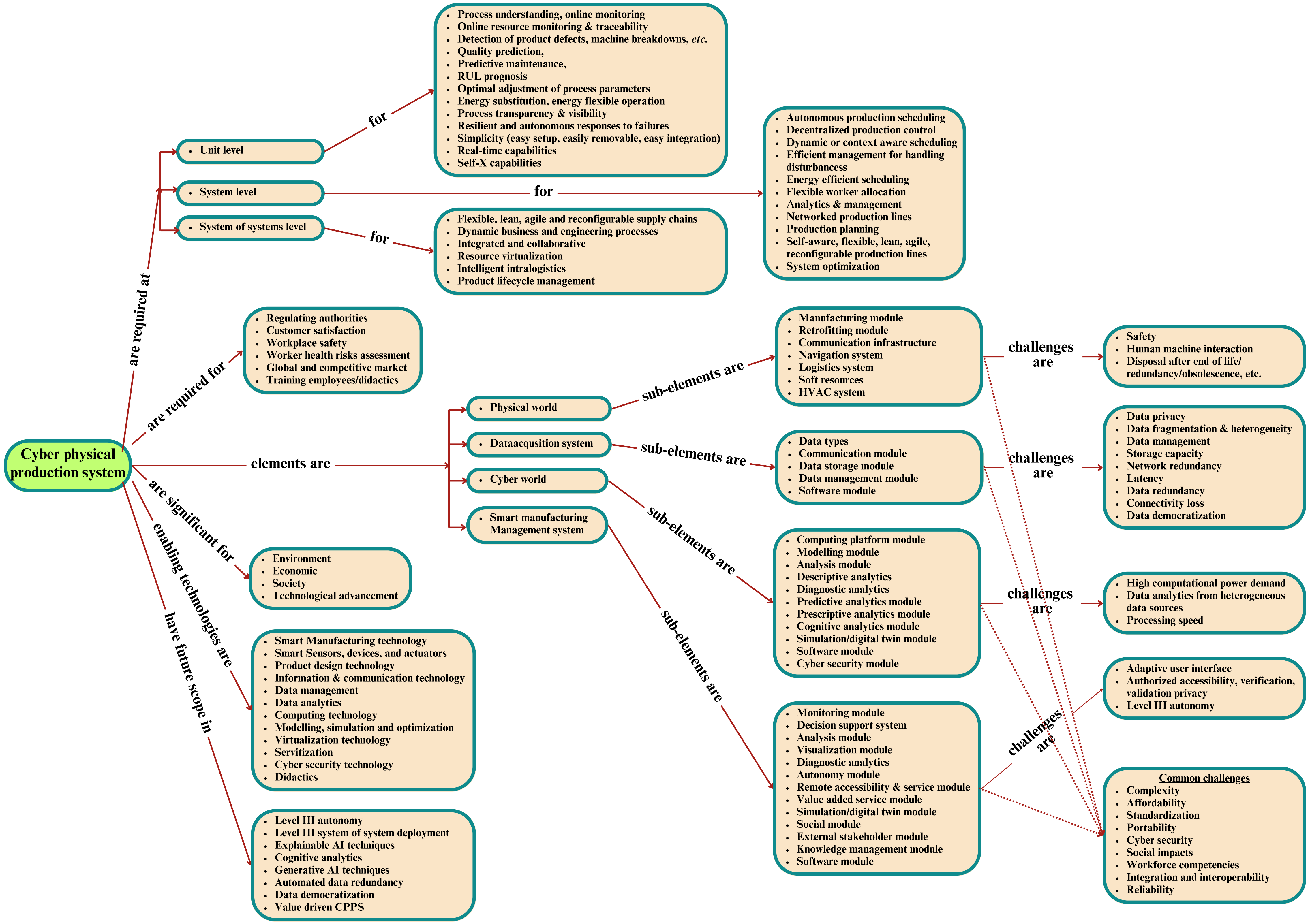

Figure 2.21 Proposed concept map for a CPPS from a holistic perspective

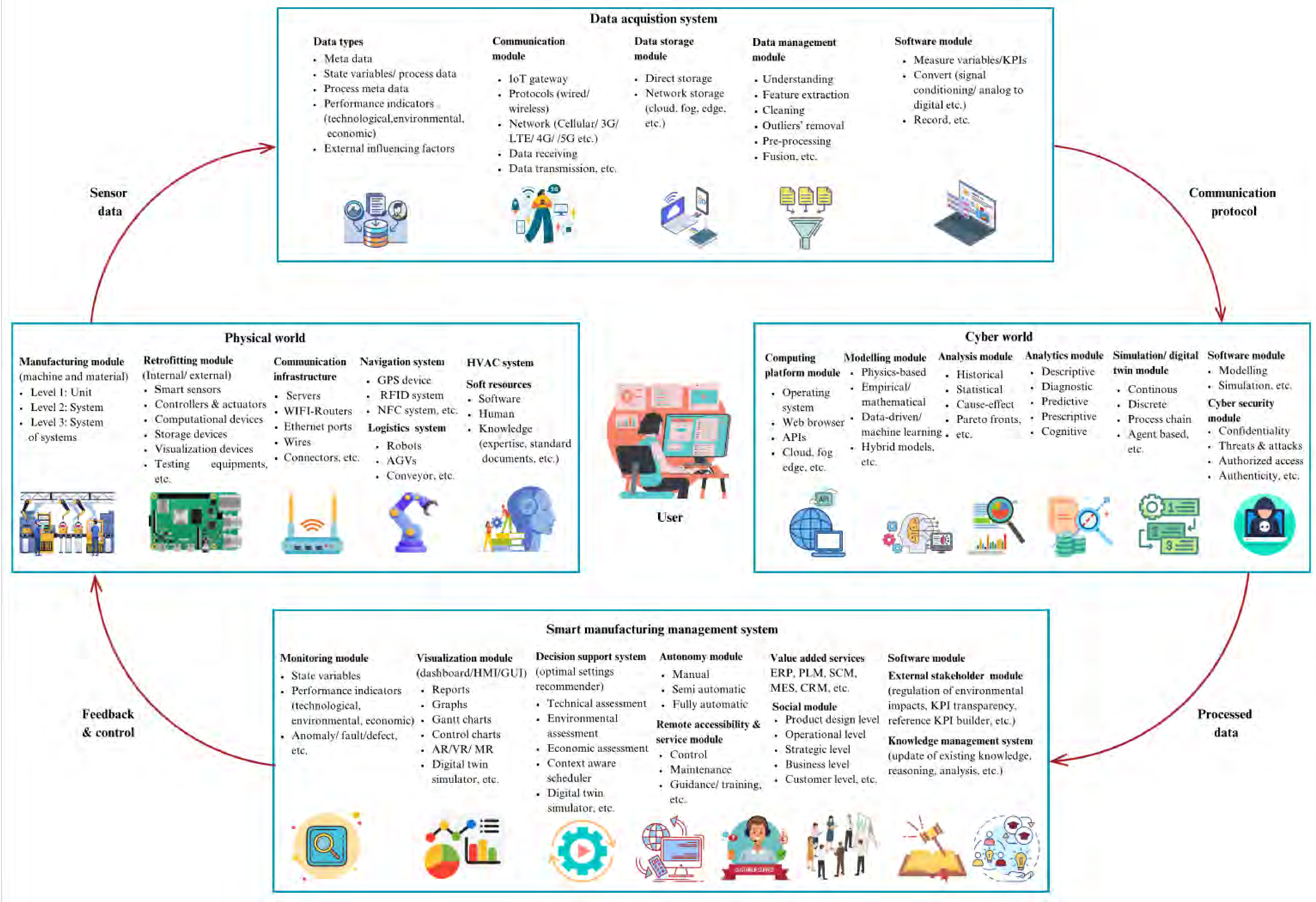

Figure 3.1 A generic CPPS framework for smart manufacturing analytics and management