CAPITAL UNIVERSITY OF SCIENCE AND TECHNOLOGY, ISLAMABAD

A Safe and Intelligent Collaborative Robotic Cyber-Physical Production System

by

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A Safe and Intelligent Collaborative Robotic Cyber-Physical Production System

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My Parents, my wife and my children, without whom none of my success would be possible

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CERTIFICATE OF APPROVAL

This is to certify that the research work presented in the thesis, entitled "**A Safe and Intelligent Collaborative Robotic Cyber-Physical Production System**" was conducted under the supervision of **Dr. Waqas Akbar Lughmani**. No part of this thesis has been submitted anywhere else for any other degree. This thesis is submitted to the **Department of Mechanical Engineering, Capital University of Science and Technology** in partial fulfillment of the requirements for the degree of Doctor in Philosophy in the field of **Mechanical Engineering**. The open defence of the thesis was conducted on **May 19, 2023**.

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List of Publications

It is certified that following publication(s) have been made out of the research work that has been carried out for this thesis:-

1. **Islam, Syed Osama Bin**, **Waqas Akbar Lughmani**, **Waqar Shahid Qureshi**, **Azfar Khalid**, **Miguel Angel Mariscal**, and **Susana Garcia-Herrero**. ”Exploiting visual cues for safe and flexible cyber-physical production systems.” *Advances in Mechanical Engineering* 11, no. 12 (2019), doi : 1687814019897228.

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4. **Islam, Syed Osama Bin**, **Waqas Akbar Lughmani**, **Waqar Shahid Qureshi**, **Azfar Khalid**.”A Connective Framework to Minimize the Anxiety of Collaborative Cyber-Physical System.” *International Journal of Computer Integrated Manufacturing*,(2022), doi: 10.1080/0951192X.2022.2163294.

5. **Islam, Syed Osama Bin**, **Liaquat Ali Khan**, **Azfar Khalid**, and **Waqas Akbar Lughmani**. ”A Smart Microfactory Design: An Integrated Approach.” *In Functional Reverse Engineering of Machine Tools*, pp. 215-253. CRC Press, 2019.

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Abstract

Human-Robot collaboration (HRC) is an integral component of Cyber-Physical Production systems (CPPS) where humans and robots share workspaces, increasing the possibility of accidents. The complex nature of these systems increases uncertainty, anomaly, and threats leading to physical and psychological safety issues. In this work, first of all, a novel concept, "Anxiety of CPS," is defined and categorized for expected and unprecedented situations that a CPS could encounter using the Ishikawa method. Then, a connective decision-making framework is proposed for a flexible CPS, which can quickly respond to dynamic changes and be resilient to emergent hazards. A four-layered connective framework is presented that can promptly respond to changing physical and psychological safety situations. The first layer performs the desired operation of the CPS and gets itself aware of anomalies. Visual cues are used to gather the CPS's current state (such as human pose and object identification). The second layer assesses, categorizes, and quantifies the developed situations' severity as an anxiety factor. The third layer mitigates the arising anxiety through the optimal allocation of resources. A mathematical model is developed using Mixed-integer programming (MIP) to allocate optimal resources that will tackle high-impact situations generating 'anxiety.' The fourth layer makes decisions based on historical knowledge, the current state of anxiety, and the suggested optimization using logic.

The proposed method was tested on realistic industrial scenarios incorporating a Collaborative Robotic Cyber-Physical Production System (CRCPPS). The case study shows that the technique is less time-intensive as the maximum time to decide on a situation was found to be 0.03s. A survey highlighted that the method leads to enhanced fluency, comfort, safety, and legibility during collaboration. The proposed system was 16.85 % more accurate than the standard one. The significance test of the results highlighted that the p-values were less than the threshold $p < 0.05$. The results demonstrated that the method improves the decision-making of a CPS facing a complex scenario, ensures physical and psychological safety, and effectively enhances the productivity of the human-machine team. Therefore, the

proposed method is a real manifestation of the emerging concept of Industry 5.0, which recommends the worker's well-being along with the system's efficiency and productivity. The proposed framework can be applied to any industrial scenario where HRC is involved, like manufacturing, assembling, packaging, etc.

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Abbreviations

ACPS	Anthropocentric Cyber-Physical System
ACPPS	Anthropocentric Cyber-Physical Production System
AI	Artificial Intelligence
ANS	Autonomic Nervous System
API	Application Programming Interface
B&B	Branch and Bound
B&C	Branch and Cut
CC	Computer Component
Cobot	Collaborative Robot
CPS	Cyber-Physical System
CPPS	Cyber-Physical Production System
CRCPS	Collaborative Robotic Cyber-Physical System
CRCPPS	Collaborative Robotic Cyber-Physical Production System
CRF	Classifier with a Conditional Random Field
CS	Computing Science
DOF	Degrees of Freedom
ECG	Electronic Cardiograph
FMS	Flexible Manufacturing System
GUI	Graphical User Interface
HC	Human Component
HCI	Human-Computer Interaction
HMI	Human-Machine Interaction
HMM	Hidden Markov Model

HRC	Human Robot Collaboration
HRI	Human Robot Interaction
IDEF	Integrated Definition for Process Description Capture Method
IPADs	Intelligent Power Assist Devices
IMU	Inertial Measurement Unit
IoT	Internet of Things
IT	Information Technology
ITC	Information and Communication Technology
LP	Linear Programming
M2M	Machine to Machine
MADT	Mean Automated Decision-Time
MI	Mixed Integer
MIP	Mixed Integer Programming
MST	Manufacturing science and technology
OT	Operations Technology
PC	Physical component
RBB	Robot-based Basketball
RDF	Random Decision Forest
RFID	Radio Frequency Identification
RGBD	Red Green Blue-Depth
SAR	Spatial Augmented Reality
SCR	Skin Conductance Response
SEM	Standard Error Mean
SHRC	Safe Human-robot Collaboration
TSensors	Trillion Sensors
URv5	Universal Robot version 5
WMSD	Work-related Musculoskeletal Disorders
WSN	Wireless Sensor Networks
YOLO	You Only Look Once

Symbols

A	Anxiety Index
a	Anxiety factor
G	General anxiety factor
I	Ishikawa's index
K	Agoraphobia factor
kg	kilogram
M	Mean
N	Social norm factor
n	number
O	Obsession factor
P	Panic factor
p	Preference variable
Q	Resource suitability variable
R	Set of resources
S	Set of situations
SD	Standard Deviation
s	seconds
T	Post-traumatic factor
t	Task variable
X	Decision variable
$\sum$	Summation
$\in$	belongs to

Chapter 1

Introduction

1.1 Background

The enabler for the fourth industrial revolution (Industry 4.0) is Cyber-Physical Systems (CPS). They are intelligent system that contains both physical and computational elements. The concept involves decision-making through real-time data evaluation collected from interconnected sensors. The elements of CPS include layers of sensors, network, analysis, and execution [1]. Monostori [2] proposed overall automation of these layers for production systems interconnecting necessary physical elements such as machines, robots, sensors, and conveyors through computer science and termed it a Cyber-Physical Production System (CPPS). The proposed mode of communication within the CPS is the Internet of things (IoT) due to its capability of assigning a unique identity to each element [3]. Flexible systems with high productivity are the demand of the modern industry. The latest CPPS offers time-saving and mass customization and does not require reconfiguration in the existing system. The decision-making is dependent on logic; however, these systems lack the flexibility to handle deviations from the predefined. Extension of the concept was necessitated from fixed to autonomous production systems using artificial intelligence (AI) and IoT leads to a new domain of smart factories [4].

Though technologies have evolved still, there is no substitute for human intelligence. Pirvu et al. [5] explain that human involvement is now necessary to cover the intelligence gap and supervision. The author presented an anthropocentric cyber-physical system (ACPS), which confirmed humans' essential requirement in any CPS. Modern CPSs are now expected to handle social interaction issues between humans, machines, and robots. A representation of a CPS elements' connectivity and the exchange of information is shown in Fig. 1.1.

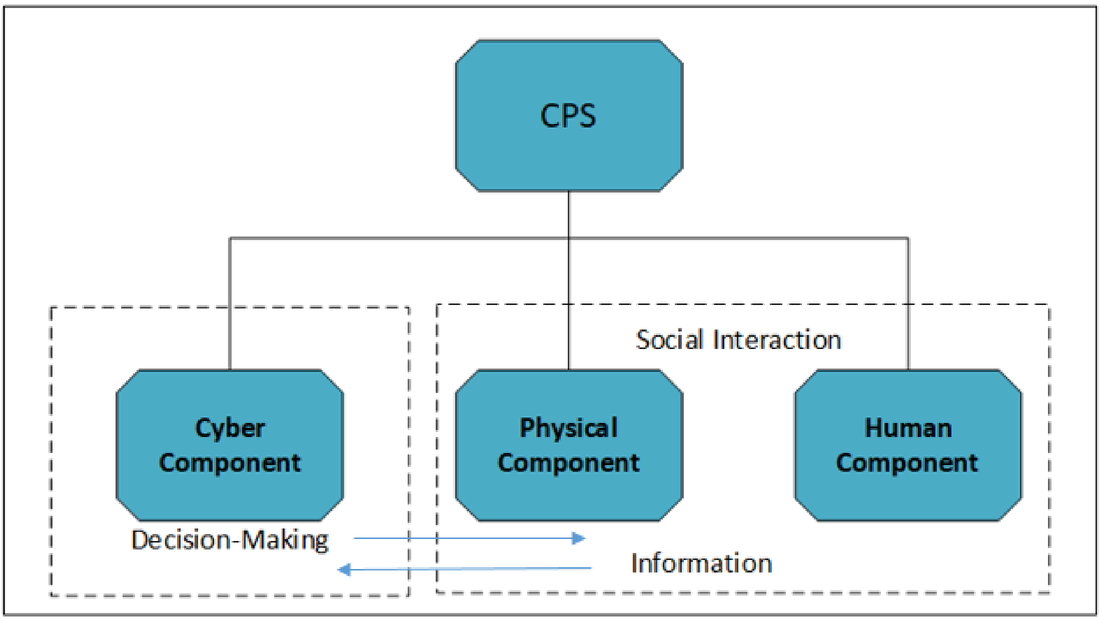


FIGURE 1.1: Components of CPS.

1.2 Social Safety of Collaborative Cyber-Physical Production System

The latest CPPS involves many collaborations between machines and humans to fulfill the process. As humans and machines interact more, the modern CPPSs are designed in social spaces which face various safety issues. Physical safety aspects are in consideration due to this human-machine interaction [6]. On the other hand, continuous interaction with the machines, monotonous operations, closeness, and fatigue possess psychological discomfort to the operator [7]. Any deviations from the task would also pose a psychological threat to the system. The challenge is to provide real-time evaluation of hazards and ensure safety. Designing such systems requires information on social interaction. The information exchange among the social elements can be through various interacting modes, which may be visual, vocal, or physical gestures. In this context, the dynamic status of humans and CPS components will be inferred by measuring their activity (i.e., recognizing and understanding their status while they participate in situations), these activities will then be analyzed, and decisions will be made for necessary tasks to be performed in the physical domain. The cognitive state/intention of the human operator is very important, in addition to the state of other physical components. Islam et al. [8] proposed an assessment of social metrics for smart factories through the integration of AI and IoT.

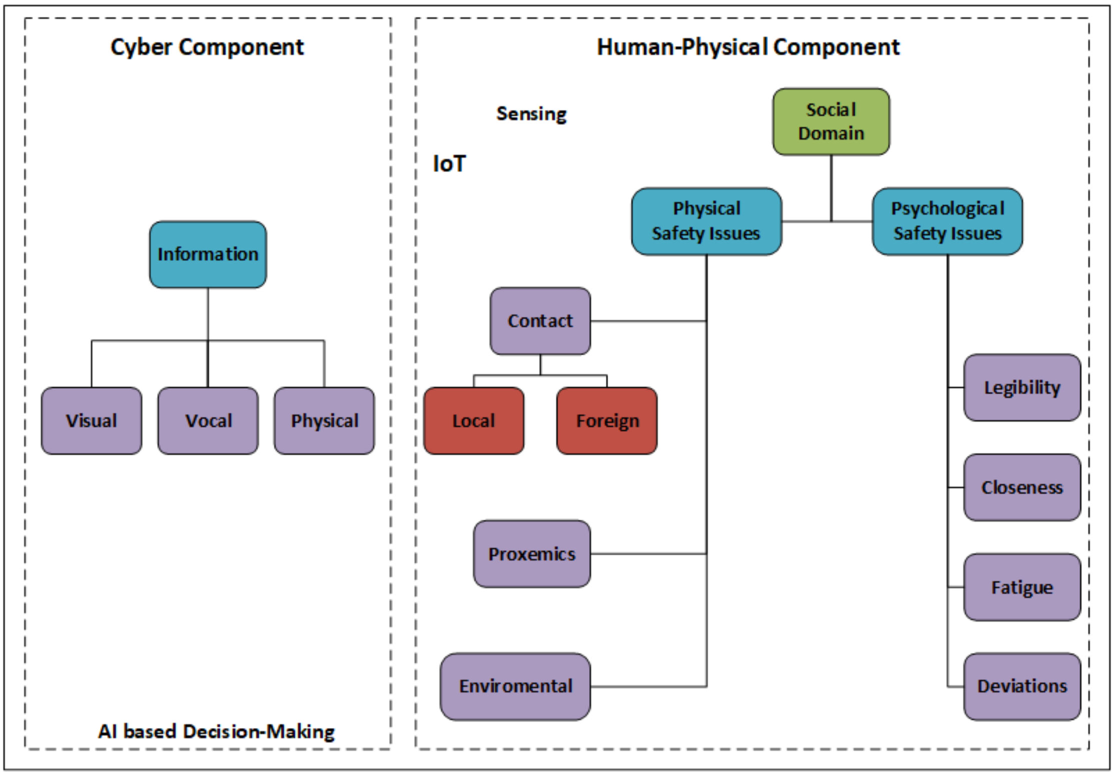


FIGURE 1.2: Decision-Making for Safety Issues in CPS.

As machines and humans collaborate in the latest CPPS, the role of robots in modern production systems has also transformed from automation to collaboration. A shared space is used by humans and robots, and they are expected to attain a common objective while conforming to the rules of social interaction. Here the requirement is felt for collaborative robots (cobots). The robots that may perform joint actions and obey rules of social interaction (like proxemics) still act efficiently and legibly [9]. Cobots are now an essential component of modern CPPS [10]. The concept of collaboration has taken its roots in the social characteristics of animals and humans [11]. The robot's features for collaboration depend on the typical application in which it is used.

An example could be a robot distributing postal letters in offices that would need specific social skills to understand the requirements of its customers through regular encounters. Some may require mail-in alphabetical order, or some may require mail in terms of priority index. On the other hand, a robot that is employed to assist disabled or aged persons must have an extensive list of social characteristics to make them comfortable.

Khan et al. [12] presented a similar example of social interaction between robots and humans in the food industry and highlighted the requirement of special abilities and intelligence in these robots to act in the rising scenario. Moreover, the need for legibility also comprises the requirement that demand cobot should infer the actions performed by the human operator and vice versa [13].

As the requirement for safety in any CPS is essential, similarly, it is for a collaborative robotic CPS (CRCPS). Different physical safety protocols for HRC-based CPS were presented by authors[14–17], whose activation is dependent on the proximity between the cobot and the human operator. Sharma et al. [18] applied an object classification technique to identify objects and the human body for the safe operation of a robot. Khalid et al. [10] presented a survey on the capabilities of the latest cobots for physical safety. The broad sensing techniques recognized to evaluate safe operations were proximity and visual signatures.

A distinctive concept of psychological safety for a human operator was presented by [7]. A CPS was proposed that encompassed the operator's physical and psychological safety. The separation between the cobot and the human was measured for hazard assessment. The safeties were ensured by controlling the speed of the cobot.

Another paper described that legibility ensures psychological safety; a human operator feels more comfortable assessing the robot's goal through its intended motion [19]. The notion of the legibility mentioned is restricted to the robot's motion only. All stakeholders of the CPPS must have the legibility of complete processes and systems designed accordingly. Therefore, the broad categories of safety for any CRCPPS in the social domain are physical and psychological safety.

As the industry transforms from automation to intelligence, a need is felt to extend the concept of psychological safety from humans to the CPSs. Psychological safety is equally essential for an intelligent CPS as physical safety is perceived [20]. The CPPS comprises processes from the supply chain to manufacturing, assembly, packaging, and delivery. Any change in the expected outcome would compromise the system's efficiency, creating a psychological issue. Although interactions among human operators, physical and computational layers of CPS can be quite demanding in terms of cognitive resources, the psychological aspects of safety are not extensively taken into account by existing systems. Yet there is no connective framework that assesses and counters both physical and psychological issues of a CPPS in a social domain. Flexible CPPS in this regard is required to counter the uncertainties by defining contingencies. The above indicates the importance of efficient and reliable integration of each component of CPPS for the next generation, and a framework is required for a new system as follows:

a. A framework that can quantify both the physical and psychological safety of the CPPS.

b. A framework that can assess the CPPS's current state and accordingly provide a thinking base to make it flexible and safe.

c. A framework that can decide, optimize and control based on the situational assessment.

1.3 Problem Statement

The above-mentioned gap found in the literature dictates the following problem statement:

A decision tool is required to provide a thinking base to the CPPS involving Human-Robot Collaboration, which can cater to multiple real-time situations in the overall scenario, addressing both physical and psychological safety issues.

1.4 Objectives

The problem statement leads to the following objectives:

a. To review the safety issues faced by CRCPS in the social domain.

b. To review the existing techniques that address the safety issues of CRCPS in the social domain.

c. To quantify the social safety issues of a CPPS, both physical and psychological, by defining relevant parameters.

d. To establish an AI-based method that can provide a thinking base for the CPPS to cater to multiple situations generating social safety issues making the CPPS flexible and safe.

e. To validate the proposed approach through an industrial problem case study.

1.5 Research Aim

The study aims to devise a framework that can assess and cater to social safety issues of a collaborative robotic CPPS using AI and IoT.

1.6 Research Design

The research is inspired by human behavior when they are exposed to physical or psychological threats. Anxiety is generated in humans to provide safety against these threats, the basis on which they analyze situations and take necessary actions. In this work, the research is further extended to CPSs, and a novel concept of anxiety is proposed for the CPS. Therefore, a decision-making framework for combined safety in the conceptual domain is developed after carrying out the literature review pertinent to existing physical and psychological safety frameworks for CRCPPS. The idea for defining and quantifying anxiety generated by different situations for a CPS is conceived. Then the methodology for the awareness and assessment of the situations and the functioning of the CPPS is conceptualized. Finally, the approach is validated through experimental case studies. A schematic of the overall research methodology is given in Fig. 1.3.

1.7 Thesis Overview

The thesis is arranged as follows. Chapter 1 presents the aims and objectives of this research. The chapter includes background, problem statement, aim, objectives, and the research design. This chapter proposes a framework for decision-making in the collaborative robotic CPPS.

Chapter 2 reviews the latest concepts in the realm of Industry 4.0 especially emphasizing the concepts of human-robot interaction and human-robot collaboration. The chapter also discussed human-robot interaction in the social domain.

Chapter 3 highlighted the safety issues of collaborative robotic CPS. The chapter explains the safety issues of CRCPS are mainly comprised of two aspects. The first part presents various countermeasures to address the physical safety issues in CRCPS. The second part presents the literature on psychological safety measures for collaborative robotic systems. Further, the chapter overviews sensing and interfacing techniques to assess the issues. The chapter also provides literature on combined safety systems that offer both physical and psychological safety.

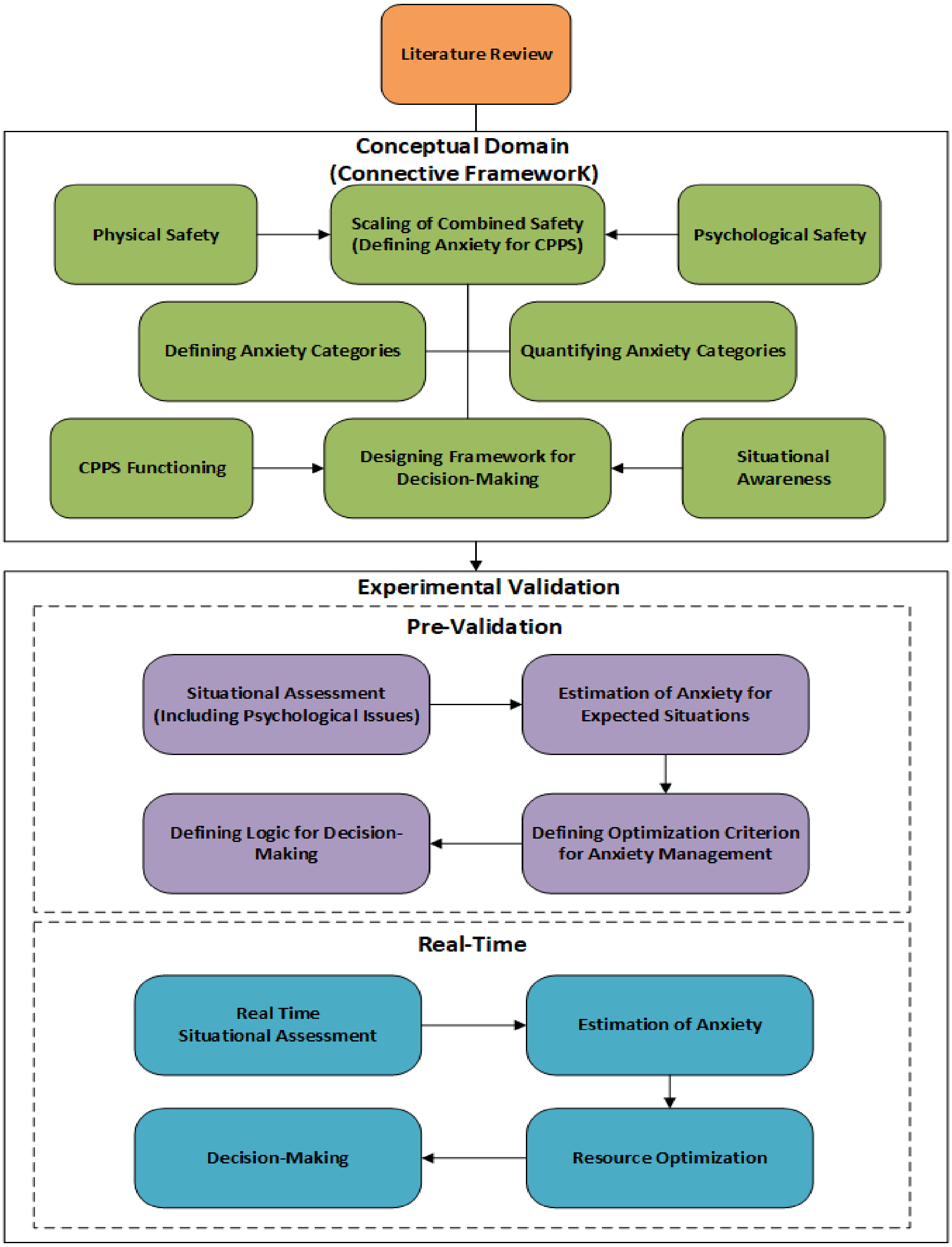


FIGURE 1.3: Research Design.

Chapter 4 presents the concept of anxiety and its types in human beings. The chapter then provides the novel idea of anxiety of CPS proposed for prioritizing the combined safety situations, i.e., physical and psychological safety both. The chapter first defines a biomimetic concept of anxiety in CPS derived from the medical terms and then quantifies them through a proposed model.

Chapter 5 explains the proposed method for a decision-making system that mitigates the anxiety generated by situations confronted by a CPPS. The chapter presents a layered framework for the presented approach, and the four layers are elaborated separately under their specific headings. Subsection 5.1.1 first gives an overview of the CPS Layer, it's working for the primary production plan, and the situational awareness system. Subsection 5.1.2 presents the situational assessment layer that provides a method to assess the anxiety of braved situations. Subsection 5.1.3 provides the optimization technique for resource allocation to emerging situations; subsection 5.1.4 presents an overview of the decision-making system for catering to situations generating anxiety through available resources.

Chapter 6 presents the experimental case study for the proposed case and its validation. The case study includes implementing the proposed method in an industrial packaging scenario. The chapter incorporates the results from the case study, a discussion of the outcome, and a comparison of the proposed method with contemporary systems.

Chapter 7 presents the experimental validation of the proposed method through a second case study on an industrial assembly scenario. The chapter also includes a survey comparing the standard and proposed methods. The survey also contains two hypotheses one on the fluency of HRC and the second on perceived safety, comfort, and legibility during collaboration when using the proposed method.

Chapter 8 summarizes the major conclusions of this work and outlines potential areas of future work.

Chapter 2

Concepts, Technologies and Techniques

2.1 Overview of Industrial Revolution

The Industrial Revolution, which began in the 18th century, marked a period of profound technological, social, and economic change. This transformative era saw the introduction of mechanized production methods, the emergence of new technologies, and the transition from predominantly agrarian societies to industrialized ones. The Industrial Revolution unfolded in multiple stages, from the early proto-industrial revolution to the ongoing fifth industrial revolution. Each phase brought significant advancements and societal shifts. This premise aims to provide an overview of the major developments and transitions that characterized the different stages of the Industrial Revolution [21], [22], [23]:

2.1.1 Proto-Industrial Revolution (17th to 18th Century)

The proto-industrial revolution, also known as the cottage industry or the putting-out system, marked the initial stages of industrialization. During this period, rural households engaged in small-scale production, such as textile weaving, in their homes. Merchants would provide raw materials and collect finished goods for distribution. This phase laid the foundation for the mechanized production that would follow.

2.1.2 First Industrial Revolution (18th to 19th Century)

The first industrial revolution began in Britain and later spread to other parts of Europe and the United States. Key advancements included the mechanization of textile production through inventions like the spinning jenny and the water frame. Steam power, exemplified by James Watt's steam engine, revolutionized transportation, mining, and manufacturing. These innovations led to the establishment of factories and the rapid growth of industrial cities.

2.1.3 Second Industrial Revolution (Late 19th to Early 20th Century)

The second industrial revolution was characterized by significant technological advancements and industrial expansion. Notable innovations included the telegraph, the telephone, and the light bulb. The widespread use of electricity, along with the development of the internal combustion engine, fueled further industrialization and enabled the rise of the automobile and the expansion of rail networks. This era also saw the emergence of large corporations and the beginning of mass production.

2.1.4 Third Industrial Revolution (Late 20th Century)

The third industrial revolution, often referred to as the Digital Revolution or the Information Age, emerged with the advent of computers and electronics. Key developments included the invention of the microprocessor and the rise of the internet. These technologies revolutionized communication, computing, and information storage, enabling the automation of various processes and the emergence of new industries such as telecommunications, electronics, and software development.

2.1.5 Fourth Industrial Revolution (Late 20th Century to Present)

The fourth industrial revolution builds upon the third, characterized by the fusion of digital, physical, and biological systems. It encompasses advancements in areas such as artificial intelligence, robotics, automation, the Internet of Things (IoT), 3D printing, and nanotechnology. These technologies are transforming industries, enabling smart manufacturing, autonomous vehicles, personalized medicine, and the integration of digital systems into various aspects of society.

2.1.6 Fifth Industrial Revolution (Present and Future)

The fifth industrial revolution is an emerging concept that focuses on the potential of technologies like artificial intelligence, blockchain, quantum computing, and biotechnology to revolutionize industries and society further. This revolution aims to create a more interconnected, sustainable, and equitable world by leveraging advancements in digitalization, automation, and innovation. The fifth Industrial Revolution is still in its early stages, and its full impact is yet to be realized.

2.2 Industry 4.0

It was the beginning of automation, when computers controlled machines and later robots replaced human employees on production lines. The world entered the fourth industrial revolution known as Industry 4.0, where everything is connected, and AI-fed computers control robots and remotely placed machines without minute human intervention. Data exchange among the elements is essential in this latest trend of automated manufacturing technologies. The concept proposes the employment of IoT, CPSs, cloud computing, and cognitive computing [24].The fourth industrial revolution was initially considered for manufacturing; however, its context has evolved. A whole new concept has emerged: interaction and control of computer, operator, and robot now depend on machine learning [25].

The various collaborations between industry, government, and academia now belong to this terminology, leading to the new word "Industry 4.0". Broadly speaking, it is a manufacturing term that integrates smart factories, their related activities, production processes, and technology. However, Industry 4.0 does not simply involve a group of technical tools like the IoT. It may include quality-related functions like maintenance and consumer interaction/feedback. Quality improvement can be achieved by analyzing real-time information, reducing inadequacies, and eliminating mismatches in customer-focused environments where value-addition, cost-effectiveness, and swiftness are essential requirements. The idea is also linked to improving the supply chain, which is now digitally transformed. The idea is also beneficial for businesses where novel approaches are used for their transformation through feedback. The paybacks are profitability, budget reduction, value optimization, increased demand, and improved customer loyalty. One important facet is customer demand flexibility, which requires more innovative products in less time. The customer demand for the customization could be due to the service/product being part of the highest level, standardized low margin, or the one that will soon fade owing to "digital disruption" [26]. The German Federal Ministry for Education and Research refers: "The industry is on the threshold of the fourth industrial revolution. Driven by the Internet, the real and virtual worlds are increasingly coming together to form the Internet of Things. The industrial production of the future will be characterized by strong personalization of products in highly flexible production conditions (large series), the extensive integration of customers and business partners in the industry business through processes and value-added services, and the association between high-quality production and services leads to so-called hybrid products [2]".

2.3 Industry 5.0

The conventional manufacturing concept places tasks at the core of the production system, relegating workers to a passive role. However, future workplaces will prioritize workers, shifting from task-centric to worker-centric approaches. This paradigm shift anticipates an enhanced worker role, resulting in optimized production performance. The new concept emphasizes the significance of aligning job roles with individual workers' skills, experience, and characteristics. A worker-centric system fosters knowledge and capabilities among workers, irrespective of age or position. Consequently, the manufacturing sector must adapt to the emerging sustainability trend, encompassing environmental, economic, and social dimensions. Europe has issued a series of directives to enhance workplace safety and health to address these concerns. These directives seek to improve working conditions, reduce the risk of accidents, and ultimately create an environment that promotes a higher quality of life for workers. The principles of ergonomics are implemented to boost productivity, enhance worker health and safety, meet government regulations, or minimize worker claims. The ultimate objective is to attain greater job satisfaction. Companies increasingly recognize the importance of ergonomic adjustments in reducing injuries and costs while fostering employee motivation and satisfaction [27]. Currently, manufacturing companies find themselves in a transitional phase known as Industry 4.0. However, a new transformative wave called Industry 5.0 is emerging, which is often referred to as the "Age of Augmentation." In this phase, humans and machines work together in perfect harmony, achieving a symbiotic relationship. The concept of Industry 5.0 highlights the importance of human-centric design in Cyber-Physical Production Systems (CPPS), raising ethical concerns regarding the impact of technology on workers and society as a whole.

Industry 5.0, as an ideology, first surfaced in 2020 through a series of virtual workshops where ideas were exchanged and discussions took place. It gained official recognition in January 2021 when the European Commission (EC) formally introduced and published it [28], [29]. The European Commission (EC) introduced Industry 5.0 as a means to create more inclusive, resilient, sustainable, and human-centered workplaces. The transition from Industry 4.0 to Industry 5.0 marks a shift in the relationship between humans and intelligent systems. While Industry 4.0 mainly focuses on automating processes with digital technologies to improve efficiency, Industry 5.0 emphasizes the synergy and collaboration between humans and machines, giving priority to human desires and intentions. The goal of Industry 5.0 is to reintegrate humans into factories, leveraging their cognitive capabilities (creativity and knowledge) in collaboration with intelligent systems. Machines are employed for work-intensive or repetitive tasks, while humans oversee personalization and critical thinking.

Industry 5.0 empowers humans through the incorporation of innovative technologies and aims to place worker well-being at the forefront of production processes, maintaining a balance between human and machine systems and embracing resilience and sustainable development across ecological, economic, and social dimensions. While Industry 4.0 focuses on production efficiency and flexibility through digitalization and technologies, Industry 5.0 aligns with European societal goals, emphasizing job creation, resilient development, and industrial sustainability while respecting planetary limits and worker well-being [30]. Therefore, Industry 5.0 can be seen as an extension and progression of Industry 4.0, addressing the limitations of the latter in terms of industrial sustainability and worker well-being. Industry visionaries foresee Industry 5.0 as a means to reintroduce the human element into the manufacturing industry. The concept revolves around harnessing the creative capabilities of human experts and their collaboration with advanced, intelligent machinery. The idea is that Industry 5.0 will combine the speed and precision of machines with the critical and cognitive thinking of humans. Unlike Industry 4.0, which primarily focuses on large-scale production with robots, Industry 5.0 promotes more skilled jobs where intellectual professionals work alongside machines. Mass customization takes center stage in Industry 5.0, with humans guiding robots to meet customer satisfaction. While Industry 4.0 emphasizes connectivity in Cyber-Physical Systems (CPS), Industry 5.0 builds upon Industry 4.0 applications and establishes collaborative relationships between humans and robots, known as collaborative robots (cobots). Furthermore, Industry 5.0 brings additional advantages in terms of sustainability by offering greener solutions, which is not a primary focus of previous industrial transformations. The preservation of the natural environment is given greater consideration in the context of Industry 5.0 [31].

Industry 5.0 represents the latest industrial revolution which involves the integration of advanced technologies like artificial intelligence (AI), robotics, internet of things (IoT), and big data analytics with human capabilities in the manufacturing sector. While Industry 4.0 focuses on connectivity and digitization of machines and processes, Industry 5.0 builds upon those principles that recognize the value of human skills, creativity, and problem-solving abilities in driving industrial advancement. The aim is to balance automation and human intervention, fostering a harmonious coexistence between humans and machines within the manufacturing environment [32]. The concept of Industry 5.0 encompasses the integration of physical and virtual spaces with a human-centric approach, utilizing technologies such as the Internet of Things (IoT), cobots, and augmented reality to achieve a smart industry and digitally innovative society. Interactivity between humans and machines distinguishes Industry 5.0 from Industry 4.0, as increased interaction empowers operators to personalize products and services, creating synergistic relationships between technological and social systems. The principles of Industry 5.0 can be applied to cyber-physical production systems (CPPS), including conceptualization, learning, integration, data interoperability, information sharing, use of 5G and 6G networks, automatic identification and traceability systems, AI-based work assistance and supervision, industrial simulation, user application of augmented reality systems, and the utilization of cobots to achieve intelligent manufacturing systems [30].

The integration of robotics into production systems not only improves productivity but also enhances worker well-being and creates safer work environments. Robots, when operating within collaborative environments with humans, leverage the strengths of both individuals and technology. This partnership enables the overcoming of limitations associated with awkward, repetitive, and potentially hazardous tasks. As a result, workplaces are improved, and processes become more repeatable and reliable [23]. The coupling of robots with the human mind through brain-machine interfaces and advancements in artificial intelligence is gaining significance. This development allows for the emergence of cobots that are aware of human presence and prioritizes safety and risk considerations. These robots have the ability to perceive, comprehend, and even anticipate not only human actions but also the goals and expectations of human operators. Similar to apprentices, these collaborative robots observe and learn from individuals as they perform tasks. Once the learning process is complete, the cobots can execute tasks in the same manner as their human counterparts. Consequently, working alongside cobots gives humans a distinct sense of satisfaction and fulfillment [21].

Moreover, industry 5.0 emphasizes the manufacturing of robots and industrial robots as a future direction. To fully harness the potential of emerging technologies, it is crucial to design new solutions, such as sociotechnical systems that incorporate various human actors, cobots, and AI-based systems for assistance or supervision. Implementing smart solutions that leverage collaborative robots and AI can greatly alleviate physically and mentally demanding tasks. However, it is important to address workers' dual experience with such solutions. On the one hand, workers may perceive their work as passive and monotonous, reduced to mere monitoring tasks. On the other hand, they may face significant challenges when troubleshooting issues with smart machines.

It is evident that there is a need to enhance work allocation and foster teamwork within human-machine teams. This will ensure that human workers remain engaged and perceive their roles as meaningful and manageable. In the design of human-machine systems, careful consideration should be given to worker roles and the associated skills requirements. This will create an environment where human workers feel integrated into the loop and can actively contribute to the overall process [33].

2.4 Manufacturing Transformation in Industry 4.0: Digital, Intelligent, Smart

Digital Manufacturing, Intelligent Manufacturing, and Smart Manufacturing are closely related concepts that represent the evolution of manufacturing processes through the integration of advanced technologies. While digital manufacturing focuses on leveraging digital technologies, intelligent manufacturing incorporates advanced computational intelligence and automation, and smart manufacturing integrates digital technologies, intelligent systems, and real-time connectivity to create a highly adaptive and efficient manufacturing ecosystem in the context of Industry 4.0 [34], [35], [36], [37], [38], [39]:

2.4.1 Digital Manufacturing

Digital Manufacturing is a field that utilizes digital technologies and computer-based systems to enhance different aspects of the manufacturing process. It encompasses digitizing and integrating information, processes, and systems across the entire product lifecycle, including design, production, and supply chain management. Digital Manufacturing in Industry 4.0 focuses on digitizing physical assets, connectivity across the production line, and utilizing real-time data for decision-making and process optimization. Digital Manufacturing incorporates various technologies such as Computer-Aided Design (CAD), Computer-Aided Manufacturing (CAM), simulation tools, and digital communication networks to improve manufacturing operations' efficiency, accuracy, and productivity.

2.4.2 Intelligent Manufacturing

Intelligent Manufacturing takes manufacturing systems to the next level by integrating cutting-edge computational intelligence and automation technologies. Intelligent Manufacturing in Industry 4.0 combines the power of Artificial Intelligence (AI), Machine Learning (ML), the Internet of Things (IoT), and other intelligent systems to enable machines, robots, and manufacturing processes to acquire knowledge from data, independently make decisions, and adjust to dynamic environments. The ultimate goal of Intelligent Manufacturing is to enhance adaptability, responsiveness, and quality while simultaneously lowering costs and resource utilization.

2.4.3 Smart Manufacturing

Smart Manufacturing is an evolution of Digital Manufacturing and Intelligent Manufacturing, capitalizing on advanced connectivity, real-time data analysis, and cyber-physical systems. Its primary objective is establishing a fully interconnected and exceptionally efficient manufacturing ecosystem. Smart Manufacturing in Industry 4.0 integrates several elements like sensors, actuators, robotics, data analysis, cloud computing, and the Industrial Internet of Things (IIoT) to enable seamless information exchange and decision-making throughout the manufacturing value chain. This approach emphasizes continuous real-time monitoring, analysis, and optimization of processes to improve productivity, flexibility, and environmental sustainability.

2.5 Evolution of Smart Manufacturing in Industry 5.0

Industry 5.0 is a rising paradigm that aims to combine cutting-edge technologies with human expertise within the manufacturing industry. The significance lies in the synergy between humans and machines, allowing them to work in tandem to achieve increased productivity, innovation, and customization. Smart Manufacturing plays a pivotal role in facilitating Industry 5.0 by establishing the necessary technological infrastructure to develop manufacturing systems that are more adaptable and responsive [40], [41], [22], [42]:

2.5.1 Collaborative Robotics

Smart Manufacturing incorporates collaborative robots, commonly referred to as cobots, which collaborate with human workers to enhance their abilities and complement their skills. These cobots are capable of performing repetitive or hazardous tasks, enabling humans to concentrate on intricate and innovative activities.

2.5.2 Data-Driven Decision-Making

Smart Manufacturing utilizes real-time information gathered from sensors, machinery, and interconnected devices to facilitate predictive and prescriptive analytics. This data-centric strategy enhances decision-making, optimizes production operations, and enhances overall efficiency.

2.5.3 Adaptive Manufacturing Systems

Smart Manufacturing enables manufacturing systems to adapt quickly and seamlessly to changing product specifications, customer demands, and market conditions. Through advanced automation, AI-based algorithms, and flexible production technologies, smart manufacturing facilitates agile and customizable manufacturing processes.

2.5.4 Digital Twins

Smart Manufacturing integrates the innovative concept of digital twins, which serve as virtual replicas of physical products, processes, or systems. By leveraging digital twins, manufacturers gain the ability to continuously monitor, analyze, and optimize their operations in real time. This technological advancement contributes to enhanced quality control, predictive maintenance capabilities, and minimized downtime.

2.5.5 Cybersecurity

With the growing interconnectivity and data-driven nature of manufacturing systems, ensuring cybersecurity is of utmost importance. Smart Manufacturing emphasizes the implementation of robust cybersecurity protocols to safeguard intellectual property, sensitive information, and the overall integrity of the manufacturing ecosystem.

2.6 Internet of Things

"Internet of Things" (IoT) is an arrangement where a hefty amount of integrated elements communicate with each other using internet protocols [43]. The devices employed in IoT are also called "smart objects" owing to their connectivity through the internet. Devices employed in the IoT and are not necessarily directly operated by humans, e.g., different vehicle systems or smart devices employed in buildings, are not directly operated but rather remotely commanded by the operator. The IoT provides a concept that extends networking to commonplace items integrated with sensing capabilities. The computational ability of these systems, which is not mandatory to be central, permits the remotely placed devices to use, produce, and transfer the information without any human intervention [44]. The execution of the IoT is accomplished using various communication modes, all having distinct characteristics. The four widely used modes are device interacting with devices, devices interacting with a gateway, devices interacting with the cloud, and rear-end information sharing. The variation in these modes provides users with value-added services and connectivity flexibility [45]. It means that information transfer is sometimes direct amongst them, via a central computer over a wired/wireless network with unique identification, or can be from the cloud integrated with sensors. IoT devices include traditional personal computers, supercomputers, and universal devices such as smart home appliances, cellular phones, embedded sensors, and wearable devices (smart watches, sports/health sensors), all equipped with unique IP addresses. The connection between the devices can be through a WiFi network or an Ethernet [46]. The type of networks commonly used in the industry are Wireless Sensor Networks (WSNs). Their use especially in manufacturing industry can provide information on progress of work, physical status of products, tools and machinery, quantitative properties, information on supply chain etc. Frequency recognition devices are commonly employed to assist in capturing the status of above mentioned properties and ascertaining the performance of manufacturing systems e.g. Radio Frequency Identification (RFID) devices [47].

2.7 Smart Factories

It is a factory that learns from emerging requirements and then adapts itself accordingly, where a continuous stream of information comes from production and operations in real time. These factories are further advanced from existing automated systems; their elements are wholly interconnected and have flexible processes [48]. Information assimilation in a smart factory is system-wide collected from humans, physical components, and control. The goal is to complete the production process using digital technology, mainly for inventory tracking, maintenance monitoring, ongoing testing, or any act that happens through the process cycle. The expected result is developing a more efficient and flexible system that may lower the execution cycle, adapt to internal/external situations, or even predict them to create a better position in a competitive market [49].

FIGURE 2.1: The Smart Factory.

As stated, the smart factory is flexible; it can self-manage the processes of the entire production system. The system can adapt self-optimization and self-correction dictated through a more extensive network in real time. While factories had a certain degree of automation in the past, the concept states that every task should be considered a single entity with a higher degree of automation. Older machines used linear logic to make decisions, e.g., getting started or shutting down based on logic. Another example is the opening or closing of valves. However, when AI is induced in CPSs, the computational ability makes complex decision-making possible, just like humans. AI is also incorporated into the automation processes to increase optimization. On the other hand, connectivity has changed the production processes; technology-based physical assets are now integrated through digital entities. The two essential connectivity platforms are operations technology (OT) and information technology (IT). The IT/OT connections make it possible to integrate the decisions taken at the lowest task level with the production system in a large-scale smart factory context. The change in connectivity from linear operations to interconnected open processes also affects the supply chain networks and impacts production through improved customer interaction with suppliers. The new concepts changed the way corporations compete, which requires various abilities such as integrated manufacturing systems (vertical integration), countless operating systems (horizontally integrated systems), and comprehensive end-to-end integration (holistic integration), ultimately improving the organization of a complete supply chain [50]. Thus, the new concept is a step ahead of traditional automation, which has transformed into a fully integrated and flexible system where a continuous flow of data comes from the production and processes. These systems operate in real-time and can adapt to unforeseen emerging situations.

2.8 Cyber-Physical System

Helen Gill of the National Science Foundation in the United States introduced the terminology of Cyber-Physical systems in 2006. Cyber-Physical system (CPS) includes physical and computer, and network subsystems. A typical model of a CPS usually contains these elements; however, humans also exist in most. These systems generally embody dynamic and static characteristics both during operation. Thus, a CPS can be described as an intelligent system consisting of physical components and computer components (hard and soft), deeply connected while sensing the varying conditions of the real world. The control of the processes is done through network monitoring, and embedded computations, deployed with feedback that affect the computations, and the computations affect the feedback in a continuous loop.

The concept also refers to today's popular terms Industry 4.0, Fog (comparatively a closer Cloud), Internet of everything, IoT, Internet of industry, the TSensors (trillion sensors), and Machine to Machine connectivity (M2M). The terminologies mentioned above reflect technological advancement that intertwines the information domain with the physical domain [51]. A CPS can also be defined as the product of a trans-disciplinary mechatronics design that integrates electronic control, software, computers, and mechanisms, as shown in Fig. 2.2.

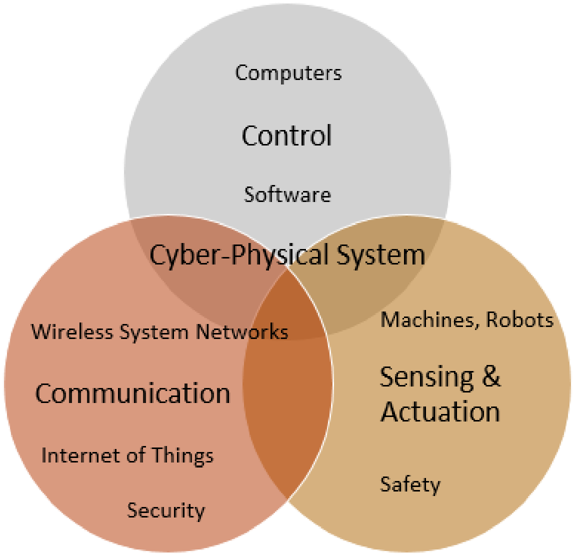


FIGURE 2.2: Cyber-Physical Model.

By nature, it is complex as it involves elements at multi-dimensional and chronological levels. Examples of CPS applications include smarts system in transportation, structures, electric networks, health monitoring and recovery, precision agriculture, air fleet control, advanced manufacturing, etc. [1]. An excellent example of CPS is an intelligent production line, where machines are supported by communication with their dependent components. In terms of structure, all the CPS models share four main layers: the sensors layer, the network layer, the analysis layer, and the application layer. Generally, the layers incorporate additional security and confidentiality mechanisms. The four-layer architecture is shown in Fig. 2.3.

Wu et al. [52] further added that in the case of the CPS, close association and co-operation among the computational and physical components is extra significant, shown in Fig. 2.4. The CPS connects the networked domain (i.e., information, intelligence, and communication) with the physical domain via various sensing and actuating devices which may be mobile or static. From the figure, it is clear that many problems require solutions at various architectural levels and distinguished design perspectives for achieving the coherence commonly observed in mechatronics applications. Critical success factors for CPS include transverse domain information management, embedded and portable sensor technology, flexible computational/storing technology, and privacy and security framework.

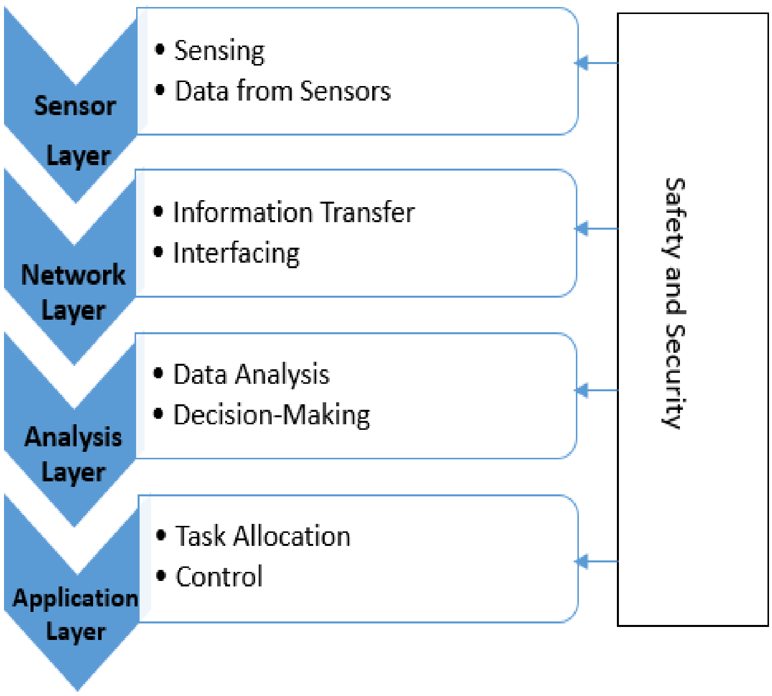


FIGURE 2.3: Four Layer Architecture of CPS.

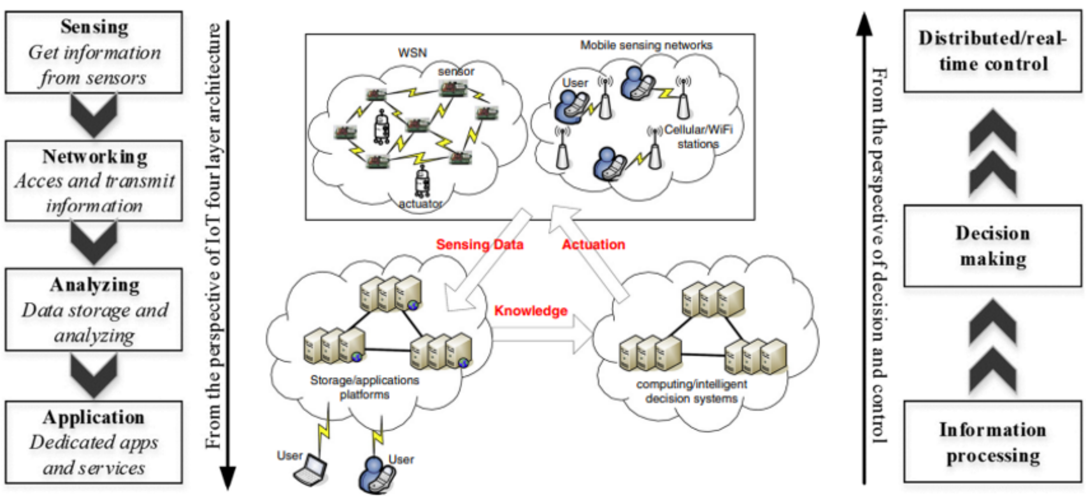


FIGURE 2.4: A CPS Architecture. Adapted with permission from Yu-Chee Tseng [52].

From the above, the four layers are defined as:

- Physical layer - includes sensors and actuators and is employed to obtain information. Data is gathered from the network monitoring sensors and human activity in the workspace.
- Network layer - The vital element in this layer is a node resulting from composite design integrating hardware and software. A combination of different nodes forms a network.
- Decision layer - advanced technology, such as artificial intelligence, can be used to obtain optimal decisions. This layer generates, memorizes, analyzes, and processes distributed information through computations related to the applications. In addition, it allows visualization, understanding, and interpretation of data.
- Application layer – Tasks are generated to handle confronted issues that depend on the information attained and analyzed, and the knowledge acquired on similar problems from other cases. Various parameters are monitored in this manner of interest, and appropriate decisions are taken to enhance a CPS's efficiency.

More recently, the CPS has emerged as a promising solution to augment human-to-human, human-to-machine, human-to-object, and machine-to-machine interactions in the physical and virtual worlds. The combination of cybernetic and physical systems now has numerous rewards over conventional embedded and control systems. All accessible data, information, and services can be deployed and used anytime and anywhere in the system. Today's manufacturing industry faces several challenges, such as the upcoming custom manufacturing requirements that force them to move to a new Flexible manufacturing system (FMS) concept. The questions then arise; what could be an appropriate set of methods and tools to enable the realization of reliable adaptive production systems for dynamic manufacturing processes that can be adjusted during implementation to ensure the high availability of these adaptive production systems? An enhanced FMS must include network, physical, and cyber functions, ensuring maximum efficiency and availability. This is achieved by the optimization capabilities built into the cyber, network, and physical functions. Such capabilities are desirable in a vast range of applications: e.g., custom manufacturing, maintenance operations, and more. CPS embedded in production systems provide new opportunities to deliver real-time information needed to effectively define the dynamically changing context in these systems [53].

2.9 Cyber-Physical Production System

CPS has the huge potential to change day-to-day aspects of human needs. Conceptions of self-driving cars, smart surgical applications, smart structures, smart electric networks, smart manufacturing, and smart medical implants are quite a few existing examples of the real-world [54]. Production Systems, which build on recent and predictable developments in computing science (CS), information and communication technology (ITC), and manufacturing science and technology (MST), are an opportunity for the fourth industrial revolution and are known as Cyber-physical production systems (CPPS) [55]. The first industrial revolution contributed to the first mechanical loom in 1764, the second to the Ford assembly belt in 1913, and the third to the first PLC in 1968. It is expected that CPPS can bring about a great leap forward on par with the breakthroughs mentioned above [2]; see Fig. 2.5.

CPPS consists of autonomous and collaborative elements connecting all production levels, from process to machine to production network. The connectivity of the elements is in a situation-dependent manner. Modeling their activity but predicting their emerging behavior poses a wide range of fundamental and applied research tasks without forgetting control at all tiers. The primary query is discovering the relationships between autonomy, collaboration, response, and optimization. The simulation and analytical methods are seen as of greater importance than ever.

It is necessary to meet the application's requirements in a case, developing sensor technology, large volumes of data manipulation, information analysis and elucidation, and safety and security aspects. Expectations for this new engineering system are very high, requiring exploitation of the developing capabilities and intelligence in the latest emerging devices. However, success depends on collecting information on the activities and the surroundings around the devices in which they are submerged.

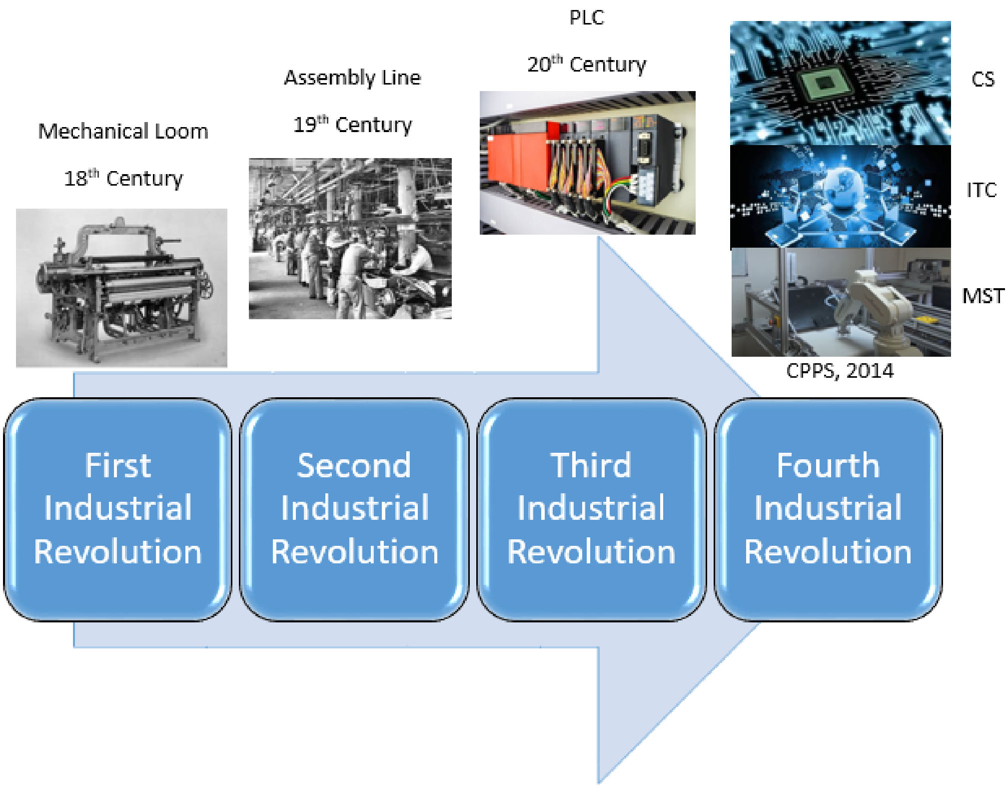


FIGURE 2.5: CPPS and Fourth Industrial Revolution.

CPPSs are anticipated to involve human-machine collaboration in unprecedented means. They describe a production system involving computers and physical systems and a place where humans and machines collaborate. While robots and machines take on most of the work in manufacturing, medical applications, and more, workers should always be in the work area as supervisors or for other tasks that aren't in the reach of the robots. Therefore, the robots and machines share the same workspace with their human counterparts [20].

The connectivity of the ”real” physical world with the corresponding representation of the ”virtual” cyberspace provides great potential for various applications. In one paper, Ribeiro et al. [56] defined a CPPS as a combination of humans, production tools, and composite products that incorporate numerous communication interfaces. The interfaces are built according to the cyber-physical interactions formula designed according to the manufacturing process. They exploit the information humans, machines, and products produced during the process loop and the historical knowledge base to monitor and control the CPPS activities. This insider awareness can be utilized at regular intervals for continuous improvement and appraisal of the consumption of resources. Products built with cyber-physical systems may create significance for external systems within the service-oriented networks’ framework.

If we summarize the above, the advantage of the connectivity is additional access to information whose analysis is valuable for further improvement of CPPS operations. CPPS elements capable of collecting and processing data, self-monitoring specific tasks, and interacting with humans through interfaces are shown in Fig. 2.6.

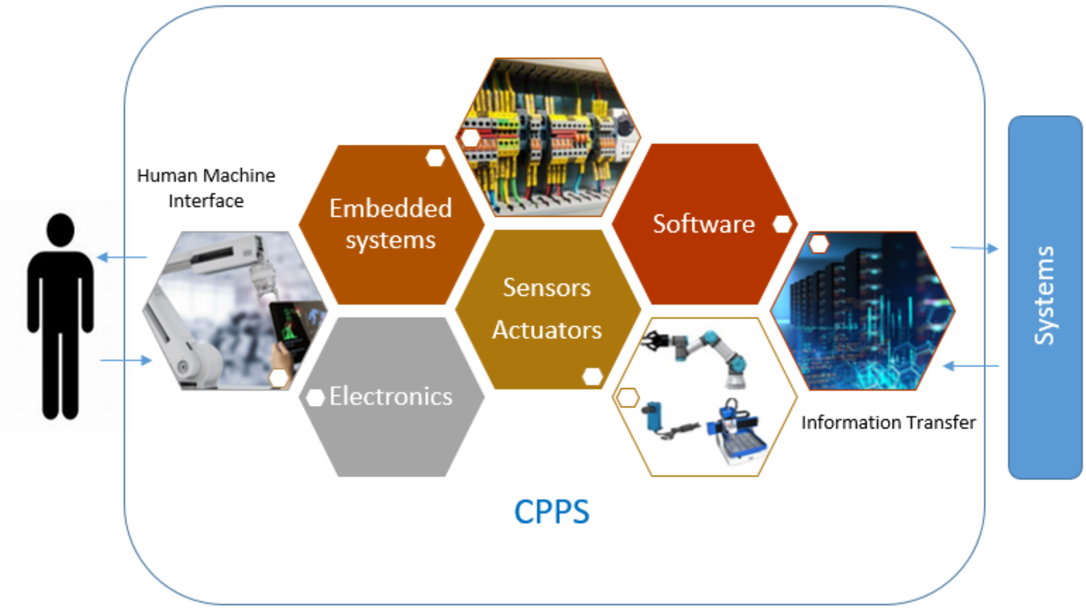


FIGURE 2.6: Interaction between Human and Machine in a CPPS.

2.10 Human-Robot Interaction

As stated above, implementing CPS technology in production systems leads to CPPSs. In Fig. 2.7, it is shown that the CPPS consists of a physical component (machines, robots, etc.) and a digital component (simulations, computations, etc.) and their association with the human, considering the concerned domain parameters.

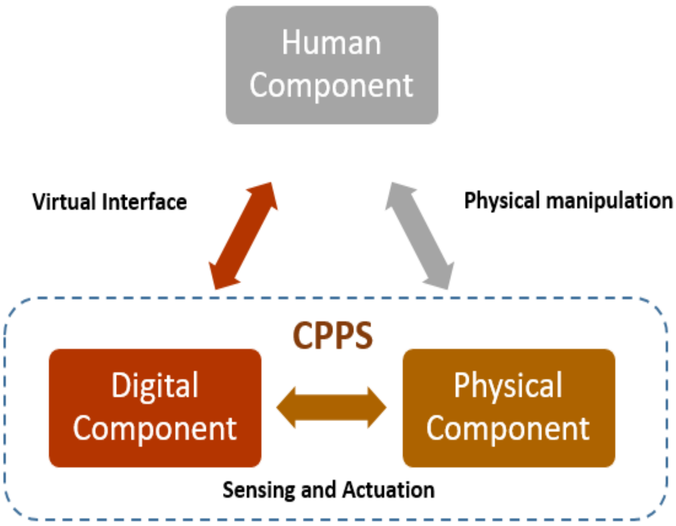
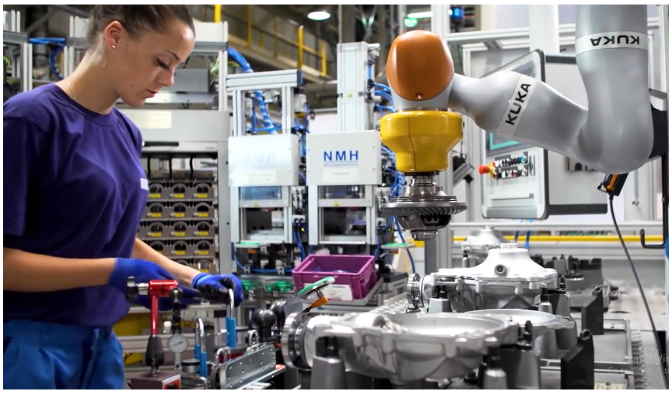


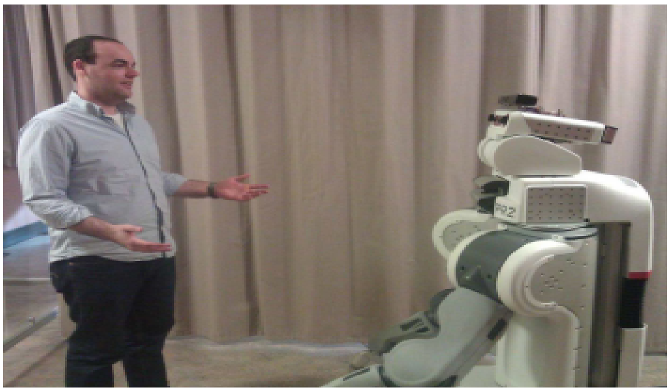
FIGURE 2.7: CPPS and its Components Interaction with Humans.

The layout and latest technological tools enhance production, quality, and efficiency. Other uses of these interactive CPPSs involving humans are supervision and analytical upkeep. The physical and digital worlds' connectivity depends on information transfer between both worlds in a closed loop [57]. The human and machine interface is called "human-machine interaction (HMI)." The concept is also associated with Human-Computer Interaction (HCI), which is dependent on computer technology. On the one hand, HCI is concerned with the techniques with which computers interface with humans; on the other, the innovative design of technology allows its implementation [58]. The field that incorporates all the aspects of humans while interacting with robots is Human-Robot Interaction (HRI). HRI in different fields is shown in Fig. 2.8.

(a)



(b)



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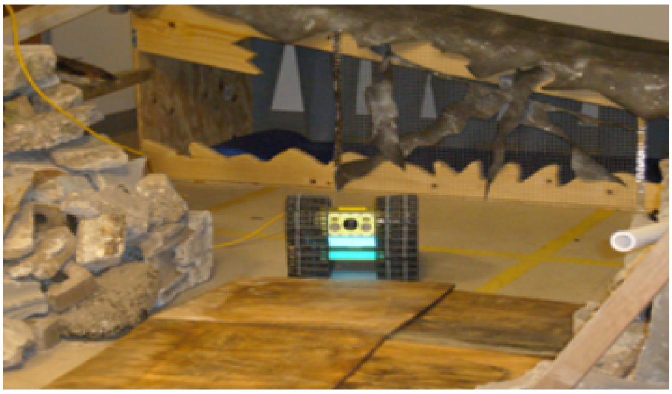


(d)

FIGURE 2.8: HRI in Advance Systems; (a) HRI in Surgery; (b) HRI in Manufacturing [63]; (c) HRI in Assisted Living, adapted with permission from Ross Mead [64]; (d) HRI in Emergency explorations, adapted with permission from Cindy L Bethel [65].

Therefore, HMI is a multidiscipline area enabling human-machine interface, which comprises the fields of HCI, robotics, humanoid robotics, AI, exoskeleton control, and human-robot interaction (HRI) [59]. It is a dynamic engineering scheme implemented through humans' direct or indirect manipulation of machines; these machines can be machine tools, conveyors, robots, etc. [56]. Technological developments like natural language processing, AI, and machine learning have significantly impacted HMI in recent years. Furthermore, HMI encompasses the study of human factors and ergonomics, considering human abilities, limitations, and preferences in the design of machines.

Robotic systems are now an essential layer of CPPS. The robot's intelligent interaction with the world relies on embedded computing, communication, and the ability to control and perceive the environment in real-time. Future robotic systems that will realize CPS vision include intelligent robotics in production systems, life support systems in smart homes, surgery systems, exploration and emergency response systems, and space exploration systems.

Karami et al. [60] envision that robots can effectively complete a joint task with their human partners if they collaborate better. For better collaboration with the human partner, the robot must be able to predict the partner's intentions. The robot can decide better for the collaborative mission using the information on the collaborator's intentions, providing comfort to its human counterpart.

Robin and Debra [61] devised HRI metrics under a taxonomy and classified them into humans, robots, and systems. Many of these attributes have been inferred from psychophysical indicators for the human type. For the robot, the HRI metrics are: how long the robot can stay without direct supervision (Neglect tolerance), the robot's progress on assigned task (Plan state), awareness of own position/orientation (Self-awareness), time in manual, autonomous, and unscheduled manual operations. For the system, the metrics include five distinct sub-sections: the participant's coactivity and the system's safety, reliability, efficiency, and productivity. The depiction of it can be seen in Fig. 2.9.

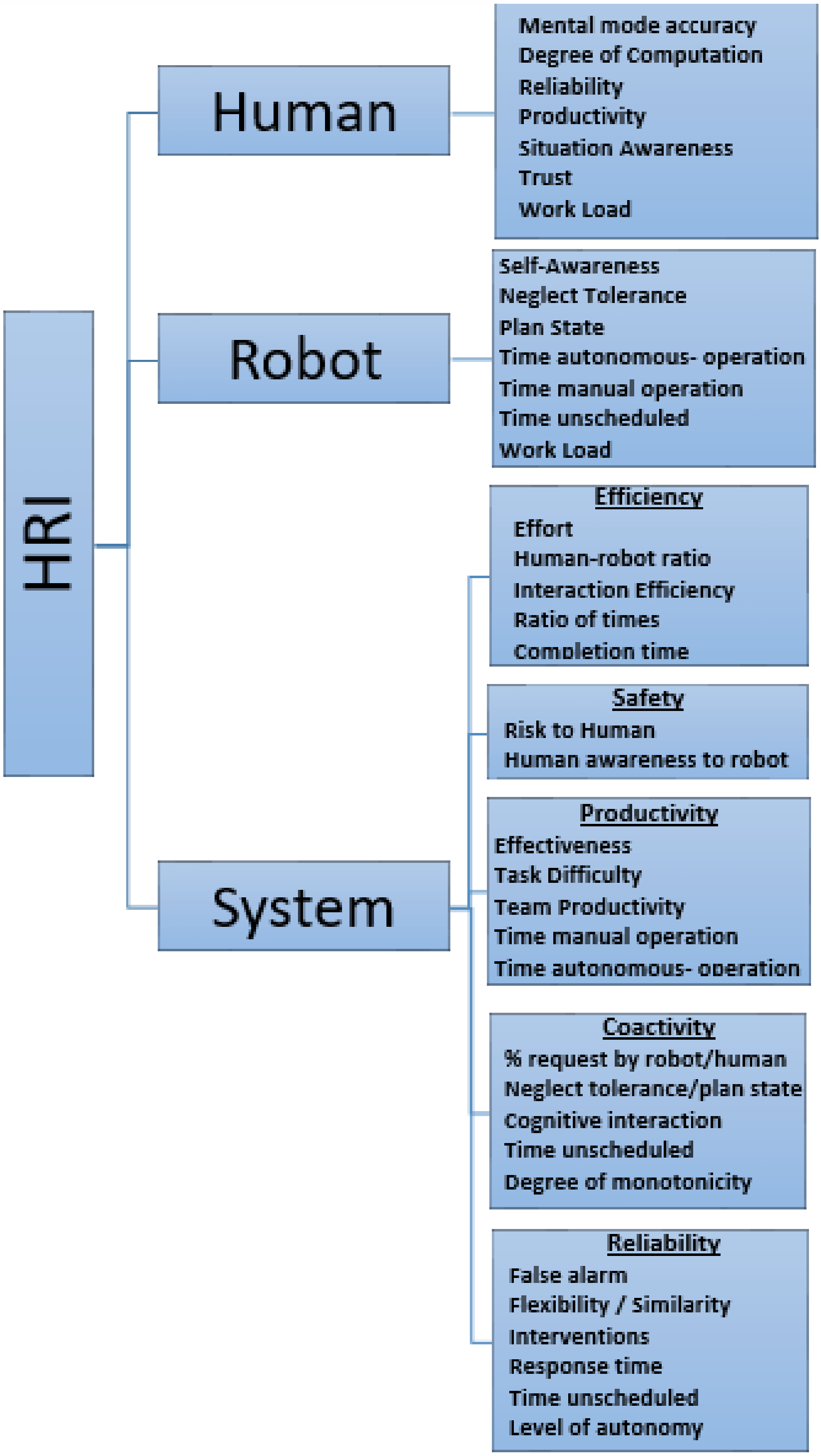


FIGURE 2.9: Taxonomy of HRI Metrics [61].

2.11 Human-Robot Collaboration

Human-centered systems are now considered necessary in the industry because they improve productivity and ergonomics in complex dynamic situations. This is why humans now perform collaborative tasks with the robots and machines in the industry that require constant guidance. Collaboration is "cooperation with counterparts, essentially in intellectual endeavors" [66].

A new term of Human-Machine Collaboration (HMC) arises in this context and Human-Robot Collaboration (HRC) specifically for robots. Chandrasekaran et al. [62] describe HRC as a measure for improved robot performance and reduced tasks for humans. The aim is to see how machines and robots can be made more interactive with humans for better task performance. More recently, the difference between collaboration, coexistence, and safety involved in human-robot interaction has been described by Villani et al. [67]. According to them, HRC no longer restricts sharing physical space but spans from task to cognitive engagement. In any engagement, safety needs assurance and accomplishment. The authors suggested a nested hierarchy containing three stages of human and robot interface, wherein a more significant commitment calls for functions of lower stages, as described in Fig. 2.10.

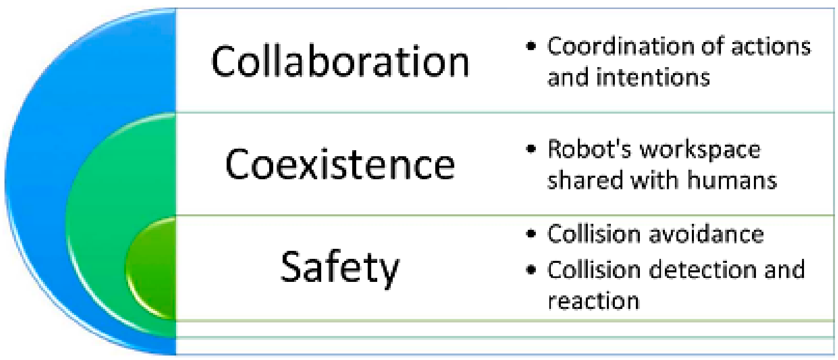


FIGURE 2.10: Nested levels for HRC, Adapted with permission from Valeria Villani [67].

Physical safety is the most inherent and important characteristic of robots working closely with humans. The existing cobots are medium payloads generally used for the cellular phone and electronics industry. The main functions induced in these cobots are collision detection and immediate hold-on detection, human employee contact avoidance, and reduced speed on workspace violations.

Coexistence is the robot‘s quality to share the common workspace with different entities, maximum applicable to human beings wherein human protection needs to be continually guaranteed during coexistence. Coexistence is often referred to as coaction; an instance of it is when a robot and a human operator are performing collectively for the same task; however, no mutual contact or coordination of intentions and movements is required [68].

Collaboration is the characteristic of a robot to perform a complex task in coordination and direct interaction, however, in two distinct ways. One is the physical aspect, where there is a clear intention of contact for exchanging forces between robots and humans [68]. By estimating or measuring these forces, robots ascertain the intents of human counterparts and respond in turn [69, 70]. Second is contactless collaboration, without physical interaction: coordinated actions directed through connectivity and data transfer, such as by vocal commands, gestures, etc. [71] or indirect communication, that is by perceiving intention [72] or attention [73], for example, reading intentions through eye gaze.

Villani et al. [67] presented four collaboration schemes dictated by ISO 10218-1/2 robotics standard: Safety-rated Monitored Stop, Hand Guiding, Speed and Separation Monitoring, and Power & Force Limiting. The levels with respect to safety provided by these schemes and their graphical depiction of each is shown in Fig. 2.11.

Recently, Mukherjee et al. [74] identified various levels of HRI, which ranges from fully programmed robotic systems to coexistence, assistance, cooperation, collaboration, and autonomous system. Autonomous systems are the ones that make independent decisions based on learning and intelligence, and accordingly they take necessary actions.

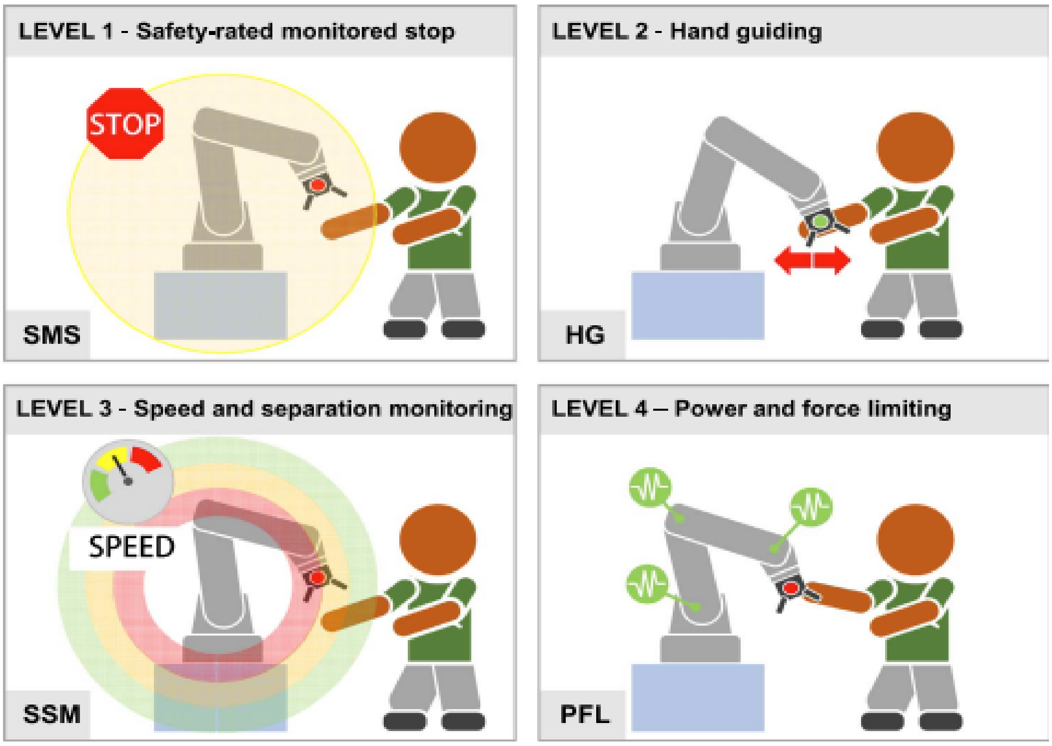


FIGURE 2.11: The Four Collaborative Operative Modes identified by Robot Safety Standards. Adapted with permission from Valeria Villani [67].

2.12 Cobots in Industry

'Cobot' is a short acronym for a collaborative robot that operates in conjunction with a human counterpart. For the safety and ergonomic improvement of the workspace, cobots are the best contenders for vigorous, non-ergonomic, repetitive, and monotonous tasks [75]. Awkward posture, repetitive, and heavy physical work are among the main causes of work-related musculoskeletal disorders (WMSDs); the most common health problems affecting roughly three out of every five workers in the EU-28. WMSDs can potentially lead to pain, functional limitations, impairment, absence, as well as a significant socio-economic impact. The incidences of WMSDs can further be aggravated due to workforce aging. Cobot assists its counterpart by manipulating jobs, considering the constraints and directives defined by the user. The directives and constraints are represented through user-defined virtual interfaces [76]. Colgate and Peshkin [77] established the concept of a Cobot, which is primarily a programmable instruction-providing robot. The cobot recognizes the virtual guide surface and positions the parts accordingly.

The significance of cobots to automated robots in the industry is that while interacting with the counterpart, the former shares space and the same payload; instead, the latter remains isolated from humans to ensure safety. Surdilovic et al. [78] developed a new production system to bridge the gap between fully automated robots and passive handling devices. The advantage of these systems is that they combine the qualities of both systems. These collaborative robots will help humans instead of replacing them. Features of this new system are direct HRI, computing power, and robot response based on detection ability, intelligence, experience, and skill. He termed them intelligent power assist devices (IPADs). A depiction of IPADs is shown in Fig. 2.12.

From a CPS perspective, integrating humans and intelligent robots is crucial to achieving better collaboration, cooperation, and organization to overcome complex tasks. This HRC is at a revolutionary stage, and the robots are expected to act as companions to humans, ascertain the behavior in real-time and react to deviations. The continuous presence of robots and humans has brought safety issues, and the latest cobots are designed to consider safety requirements. Khalid et al. [10] presented a survey on the capabilities of the latest cobots, including safety.

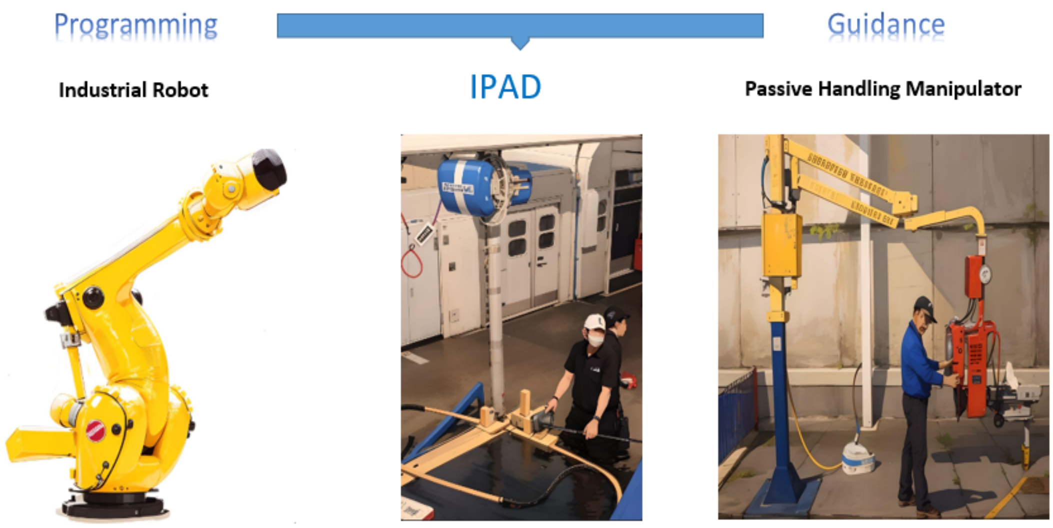
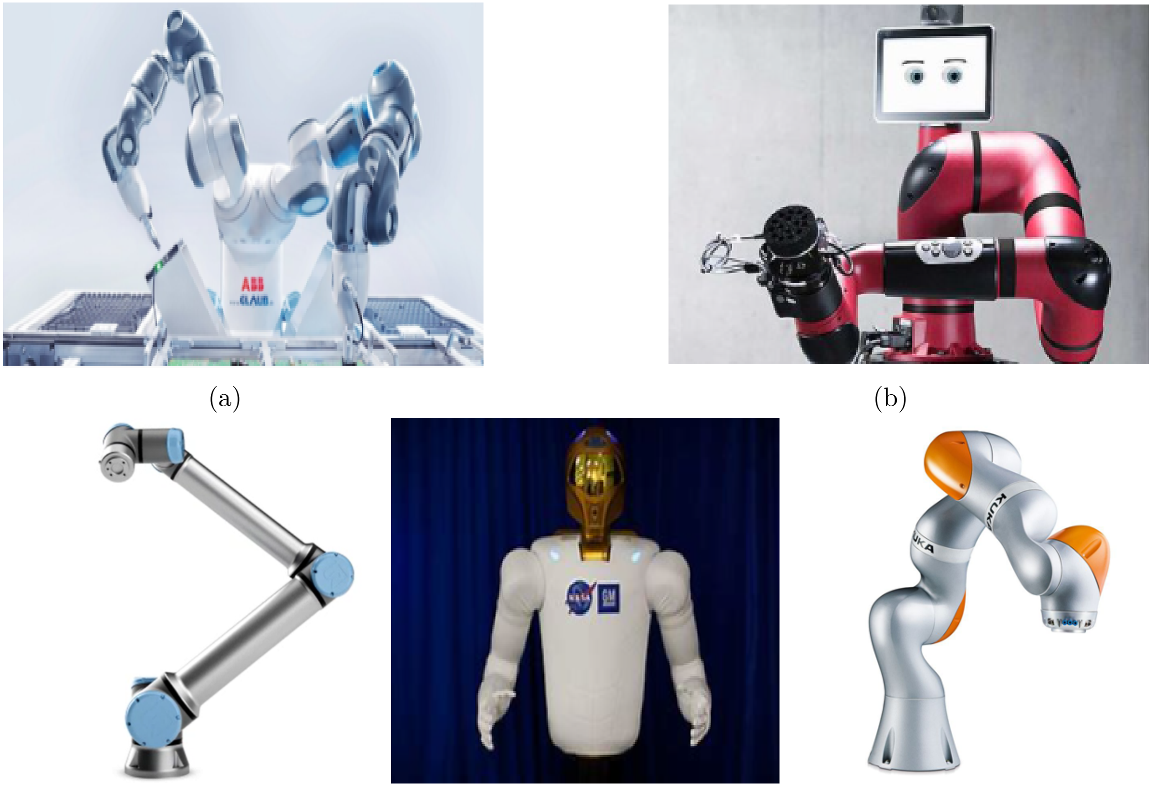


FIGURE 2.12: Intelligent Power Assist Device.

TABLE 2.1: Example of Collaborative Robots, adapted with permission from Azfar Khalid [10]

Robot	Application Area	Specifications	Main Sensors	Capabilities
ABB Switzerland, Yumi—IRB 14000	Mobile phone, electronics and small parts assembly lines	• Payload—0.5 kg • Reach—559 mm • Repeatability — 0.02 mm • Foot print size — 399 mm x 497 mm • Weight — 38 kg • Velocity — 1500 mm/s • Acceleration —11 m/s^2	• Camera-based object tracking • Collision detection through force sensor in joint	• Dual arm body Pause motion upon collision • Action resumption only by human through remote control • Collision free path for each arm
Rethink Robotics, Boston, USA, Sawyer	Machine tending, circuit board testing, material handling, packaging, kitting etc.	• Payload — 4 kg • Reach — 1260 mm • Repeatability — ±0.1 mm • Weight — 19 kg	• Camera in wrist Wide view camera in head • High-resolution force sensors embedded at each joint	• Force-limited compliant arm • Seven DOF single arm robot • Touch screen on the main column for instructions • Context-based robot learning
Universal Robots, Denmark, U10 robot	Packaging, palletizing, assembly and pick and place etc.	• Payload — 10 kg • Reach — 1300 mm • Weight — 28.9 kg • Velocity— 1000 mm/s Repeatability — ±0.1 mm • Foot print size — Ø190 mm	• Force sensors embedded in joints • Speed reduction is directly programmed	• Six DOF in single arm • Collision detection Robot stops upon collision • Speed reduction to 20% on workspace violation
NASA, USA, Robonaut 2	International Space Station, space robotics	• Payload — 9 kg • Reach — 2438 mm • Weight — 150 kg • Velocity —2100 mm/s • Finger grasping force — 2.3 kg	• Stereo vision camera Infrared camera • High-resolution auxiliary cameras • Miniaturized six-axis load cells • Force sensing in joints	• Dual arms with complete hands and fingers • Each arm has seven DOF • Each finger has three DOF Elastic joints
KUKA, Germany, LBR iiwa 14 R820	Machine tending, palletizing, handling, fastening, measuring	• Payload —14 kg • Reach —820 mm • Weight —30 kg • Repeatability — ±0.15 mm	• Torque sensors in all axis • Force sensors in joints	• Contact detection capability • Reduction in velocity and force upon collision • Single arm robot with seven axis



(a) (b)

(c) (d) (e)

Figure 2.13: Example of Cobots [10], (a) ABB Yumi—IRB 14000; (b) Rethink Robotics, Sawyer; (c) Universal Robots, UR10; (d) NASA, Robonaut 2 ;(e) KUKA, Germany, LBR iiwa 14 R820.

In Table 2.1, some examples of dexterous collaborative robots are shown that include single or double arms with multiple degrees of freedom (DOF). It can be seen that most of the cobots have high repeatability, depicting the ability of these latest machines to manage complex jobs. The available cobots allow gentle collisions with counterparts in the workspace through joints incorporating internal force sensors. The head and arms of these cobots can accommodate high or low-resolution machine vision cameras for monitoring. Visual markers are included to quickly identify and track each tool the robot needs to perform its job. All robots are programmed-compliant to be trained for a new task in the production center. However, the maximum payload has a limitation that ranges between small to medium, i.e., 0.5 to 14 kg. Immediate stop on impact, collision detection, and deceleration on workspace violations are commonly implemented technology features. There seems to be a paradigm shift in the industry and services concerning the role of robots, moving from conventional non-intelligent robots to collaborative robots.

2.13 Social Human-Robot Interaction

When considering any novel technology, social and technical aspects are associated with its application in industrial practice. One of the key challenges facing CPPS applications is designing a strategy that is safe, secure, anomalous resistant, and resilient to a variety of rapidly changing unforeseen environments [20]. Social science is the discipline dedicated to the learning of societies and the relations between individuals in these societies. The term was referred to earmark the "science of society," the sociology field founded in the 19th century. Within society, social interaction is a building block of that society which is an exchange of interaction among individuals. Social interaction can be studied between social groups of two people (dyads), three people (triads), or larger social groups. People design rules, regulations, foundations, and systems in which they want to exist while interacting with each other [79]. It is defined as "any event in which one party has a tangible influence on the overt actions or state of mind of the other" [80]. Gillin [81] defined social interaction as "the mutual or reciprocal influence leading to behavioral change due to social contact and communication that is established by alternating stimulus and response." Therefore, it is an interdependent and reciprocal activity. As stated earlier, people design rules for interaction with others, and social standards are accepted guidelines of conduct tolerable within a cluster or society; they ensure order and predictability in society. Social norms can also be changed or modified over time. We can say that social interactions comprise all physical and psychological aspects. One of these social interactions' prime facets and requirements is safety, including physical and psychological safety. For example, in a scuffle, a person involved in it feels safe from another until he is out of the range of the other person's limbs: this is physical protection, and until one feels secure from other words or facial expressions: psychological protection. The safety hazard not only includes a current activity but a potential threat that is also attributable to psychological issues, e.g., anxiety.

Conventionally, robots were used with nominal sensors and intelligence capabilities in the industry. The tasks assigned to them were usually repetitive [82]. However, recent developments in the industry have spawned a wide range of robots. The up-gradations are common in services [83, 84], exploration and rescue [85, 86], and therapy operations [87, 88]. The advent of human and robot interaction in the aforementioned fields has given rise to the specialized area of HRI [89]. The field of HRI is now transforming into social HRI and is of particular importance. The interactions in this field include cognitive, social, and emotional activities with the robots. [90]. Since these interactions occur continuously during collaborative human and robot tasks, they place intense demands on collaborators' personal and environmental safety. In addition to physical contact, the control system of the human-robot collaboration system must cater uncertainties and ensure stability.

Nass et al. [91] observed that the social factors which govern human-to-human interaction also apply to human-computer interaction. This particular knowledge necessitates robots to accustom themselves to a range of populace, and several human requirements and behaviors. Moreover, as the concept of social interaction in HRC matures, robots are now designed to be aware of social norms commonly known as Social cobots. The outcome of this addition is further synchronization of the collaborative tasks, thereby increase in the overall efficiency of the process [92]. A social robot is a self-governed robot which obey social norms while interacting with humans and other physical entities in the workspace [93]. In a broader sense, a society in a CPPS can be said to consist of social human and non-human members who contribute to the system's structure, connotation or dynamism in number of ways. Robotics design in the social domain is especially difficult because the robot has to accurately interpret human actions and react appropriately. Robots in the social domain must attain a common understanding of communication using conversational gestures, similar to the ones humans are capable of, like eye contact, finger pointing, and hand and face gestures.

Lemaignan et al. [9] emphasized the architecture of the decision layer of social robots. The work was an endeavor to characterize the issues faced and present a series of critical decision problems that must be solved for cognitive robots to share space and tasks with humans successfully. The authors identified essential personal, collaborative, and cognitive skills, which were logical reasoning and perception-based situational assessment, affordability analysis, representation and acquisition of knowledge-based models for multiple actors (humans and robots with their specific characteristics), multimodal dialogue, human conscious mission planning, and HRC task planning. Görür et al. [92] suggested a robotic decision-making mechanism that predicts the human state of mind and responds accordingly in an HRC task. The robot intervenes and helps the operator when required. The primary aim of the robot is to accurately and non-intrusively estimate when to intervene and when to help. The robot was designed to intervene and assist by estimating the operator's states (e.g., inattention, fatigue); however, when available for the task, the operator notifies the robot to leave the task.

De Jong et al. [94] improved the perception, behavioral robustness, and interactive social robots' ability by incorporating a state-of-the-art visual and speech recognition system. They presented a multimodal approach to enhance social interaction between robots and humans by integrating inputs from vision, gestures, voice, and control devices (onboard tablets, mobile remotes, and external microphones). Khoramshahi et al. [95] proposed a mechanism that adjusts generated movements to match the required (i.e., desired speed) with those intended by the operator (i.e., actual speed), thus moving along to accomplish the same task. They provided a rigorous analytical review of their method for stability, convergence, and optimality, thereby generating safe and intuitive interactive behavior for humans.

Galin et al. [96] proposed an indexing technique for collaborative interaction between humans and robots. This index, combined with AI, will help to review the effectiveness of HRI. Organizing the effective interaction between humans and robots will achieve high economic efficiency and improve the quality of the production process.

One of the leading roles of social robots is to understand and manipulate proxemics using natural communicative gestures within the framework of the social domain. Behaviors in proxemics are governed by sociocultural norms that govern the sensory experience of each participant [97, 98]. It is necessary to understand how social cues (speech and gestures) are generated and perceived by humans so that cobots can perceive and use them similarly. Schegloff [99] suggested the major usable cues: separation distance, the orientation of the hips and shoulders, head posture, stance, and eye gaze. These gestures can be used to show interest in starting, accepting, maintaining, ending, or avoiding social interactions. Mead et al. [64] identified three types of feature representations for HRI commonly used by computer models of proxemics:

- physical, dependent on collaborators' separation and positioning;
- psychological, dependent on the collaborators' affiliation; and
- psychophysiological, dependent on the sensing through social cues

The physical depictions of proxemics are related to the occupation of space by two or more objects, connecting them through orientation and separation. Proxemics' psychological manifestations involve interactive relationships amongst different entities. There is little research linking the physical and psychological manifestations of proxemics. Mead et al. [100] suggested the application of psychophysiological representation for proxemics activities to model the agent's state in the environment. It would involve linking physical and psychological manifestations, and the agent's representation in inter-agent interaction and the environment. Psychophysiological manifestations are now thought to affect the perception of the interaction between multiple agents and the social stimuli produced by them. In a nutshell, psychophysiological representations are the ones that associate the sensual involvement of social cues (voice, posture, gestures, etc.) with physical bounds (location, positioning, etc.). In other words, man's perception of sound, smell, or sight tells him how far away the object is.

Mead et al. [64] presented a computational framework for psychophysiological proxemics in autonomous systems that control social robots. A proxemics trajectory planner evaluating "interaction potential" on a cost basis and a responsive controller were deployed at each pose and time along a path. The aim was to maximize the potential alongside the path conversant of the objective's pose.

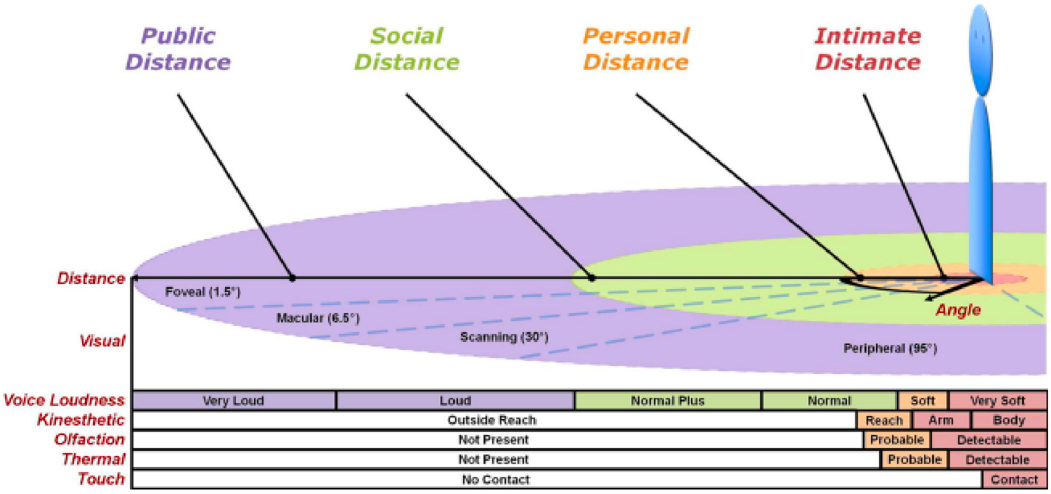


FIGURE 2.14: The psychophysical representation of proxemics. Adapted with permission from Ross Mead [100].

Koay et al. [101] presented the proposal, application, and experimental validation of the proxemics planner that relies on situational awareness intending to increase the social interaction of robots by adjusting their distance and the pose with the target. It tells the operator about the interactive distance based on sensory data obtained from the operator, the robot, and the task. The case presented was; the operator may stipulate that the robot may or may not be present at a particular location while he is doing some activity or while he is at some location like watching TV (activity) or in the kitchen (location).

Social intelligence in the history of AI and robotics appeared relatively recently. However, it is becoming evident that social and interaction abilities are essential in any context where human-to-human interaction or HRI is possible. The Human-Robot Collaboration (HRC) currently demands a lot in terms of the peculiarity of interactions among the elements and the behavior posed by them. The complex dynamic environment coupled with uncertainty, anomaly, and threats raises questions about the safety and security of the CPPS in which HRC is involved. Interactions in the social sphere include both physical and psychological safety issues. An integrated approach that integrates AI and the knowledge domain is needed to solve all problems collectively.

2.14 Conclusion

This chapter reviewed the latest concepts in the ambit of Industry 4.0, an emerging trend for the automation of production systems using real-time communication. The Internet of things (IoT) is the best mode of communication due to its access to a range of devices, whether sensors, actuators, or control systems. The chapter then highlighted the importance of smart systems in this domain, which are autonomous and flexible systems that use IoT and AI. Cyber-Physical Systems (CPS) are highlighted to be an essential ingredient of these smart systems, which incorporate the physical, computational, and networking elements. The literature review highlighted that the inclusion of CPS in the industry 4.0 domain has emerged as a novel Cyber-Physical Production System (CPPS) concept. The CPPS is the main essence of Industry 4.0 which encompasses manufacturing science and technology (MST) in addition to physical, computational, and network layers. It was observed that the latest CPS now includes human elements as there is still no substitute for their intelligence and supervision capabilities. These systems are termed Anthropocentric Cyber-Physical Production Systems (ACPPS). Due to the integration of human systems, the latest systems are now facing the challenges of Human Machine Interaction (HMI). Robots are an essential element of CPPSs, and the focus of the latest research has now shifted to Human-Robot Interaction (HRI). Due to the participation of robots and humans in collective tasks to achieve a common end-state goal, the concept has changed to collaboration rather than interaction. The term Human-Robot Collaboration (HRC) is the talk of the town. The latest robots are now designed to work with humans to perform collaborative tasks and are known as Cobots. Humans being social animals, feel comfortable when social norms are being followed during human-human interactions. Research has shown that the same is equally suitable for HRI and has increased the productivity and efficiency of systems. Robots are now being designed as social elements of CPPSs and must adhere and adapt to the social rules by getting firsthand information through social communication skills.

We may summarize the requirements of a smart robotic factory ascertained from the literature. In that case, we can say that high productivity and flexibility are essential to operate in the context of Industry 4.0, and to accomplish this, robots may take on most of the work. Still, human workers must stay on the shop floor as supervisors or for tasks out of reach of the robots. The continuous presence of humans near the intelligent robots in the confined workspace also changes the level of safety. The usual approach is to have human exposure with the robot within a limited range and with proper safety controls resulting in a complete shutdown (safekeeping) in the event of a worker encroachment in the robot workspace. It causes disruption and resets processes, reducing productivity. The approach of the future is to deploy CPPS where humans and robots safely co-exist and collaborate. Collaborative robotics technology is developing rapidly; however, research has oriented itself to HRI in the social domain. Robots, now part of the social systems, are equally affected by social safety issues, including physical and psychological problems.

Chapter 3

Safety in Collaborative Robotic CPS

Direct deployment of the robots in fully shared workspaces increases the possibility of accidents. The large amount of impact force created during an accident can create minor, moderate, and major injuries to the human worker in case of robot failure. A list of reported accidents includes fatality and non-fatality cases in developed countries such as China, Japan, the United States, and Germany, where robot use is widespread in the industry [102]. The nonfatal cases observed include injury and pain using complete safety protocols and isolated work environments. Environmental conditions, human error, and engineering error might be the reason for the accidents during HRI. Jiang et al. [103] reported thirty-two fatal and non-fatal accidents that happened due to maintenance and programming errors. Charpentier et al. [104] reported thirty-one cases in which workers were injured because of operator errors and maintenance errors, whereas eight were fatal injuries. Therefore, in the future factory, safety will be an intrinsic part of the Collaborative Robotic Cyber-Physical Systems [105]. Safe HRC can be classified into two categories: the first and most apparent is physical safety. Maintenance of physically safe HRC requires avoidance of unwanted contact between humans and robots. The second, however often overlooked, is psychological safety, ensuring HRC, which does not cause undue stress and discomfort.

3.1 Physical Safety in Collaborative Tasks

With the numerous abilities of CPS to exhibit systematic guidance in a coupled environment and the reality that human-robotic collaborative structures must deal with and satisfy industrial safety necessities, there is a specific need to develop safety systems for such CPPSs. Azfar et al. [10] introduced two distinct concepts of safety and security, which are interrelated and fall within the physical safety scope of collaborative tasks. Security protects the system from humans acting as invaders, and safety physically protects humans from the system, such as contact avoidance. The author further makes it clear that security also incorporates avoidance of cyber-issues despite the physical dangers. However, these terms are considered a collective requirement for the CPS and are not differentiated in this thesis. Safety is a vital requirement in the design of systems, machine tools, and products, especially in collaborative environments where humans and robots work together. Accordingly, new methodologies and instrumental support are needed to develop human-robot collaborative safety schemes for industrial tasks [105]. Traditional working strategies do not permit safety measures due to dynamic changes as they lack the capability to react intelligently to adaptive processes. Hence, most of the existing safety systems that separate workers from machines (e.g., through safety barriers) are inadequate to enable effective HRC [68].

FIGURE 3.1: Evolution of Safe Human Robot Collaboration. Adapted with permission from Azfar Khalid [6].

The CPPS working environment must adapt to work conditions and situations in real-time. Contextual systems are on the rise to provide integrated, active, and pervasive human protection, leading to novel and improved ways of interacting and collaborating.

Collision avoidance is a common solution to provide physical safety, including avoiding unwanted contact with people or environmental obstacles. It is one of the largely studied fields in robotics, and plenty of designing and control strategies have been suggested [106]. These techniques depend on the measurement of the distance in-between the robot and the obstacle [17, 107]. Motion planning techniques are one of the key strategies to estimate the collision-free trajectories like configuration $\times$ time-space method [108], collision-free vertices [109, 110], representation of objects as spheres, and exploring collision-free path [111], potential field method [112], and virtual spring and damping methods [113]. Unfortunately, collision avoidance can fail because of the sensors and robotic movement limitations, as sometimes human actions are quicker than robotic actions. However, it is nevertheless feasible to sense the bodily collision and counteract it [114–116], which allows eradicating the robot from the contact area. In such circumstances, robots can use variable stiffness actuation [117, 118] while effectively controlled [119, 120], and light-weight robots with compliant joints [121] may be used to lessen the impact forces on the contact. Lately, a multi-layered neural network method involving dynamics of the manipulator joints (measurement of torque through sensors and intrinsic joint positions through kinematics) has been used [122] to discover the location of the collision on the robot (collided link).

While accidents due to sudden contact between humans and robots may be restricted by designing lightweight/compliant mechanical manipulators [119] and collision detection/response strategies [116], collision avoidance in complex, unpredictable, and dynamic environments mainly depends on the employment of exteroceptive sensors. A real-time collision avoidance technique consists basically of 3 parts: (1) Perception, (2) Collision avoidance, and (3) Response. Perception is related to the environment, collision avoidance is mainly incorporated through algorithms, and the robot generates a response. These strategies generate parameterized collision-free paths using trajectory calculations, and as the perception of the environment is modified through sensors, the trajectory parameters are updated at runtime.

Green et al. [66] highlighted two essential components of an active HRC-based system. First, adjustable autonomy is a crucial part of an effective collaboration that allows changing the degree of autonomy of the robotic system, which increases productivity. Second, awareness of situations or knowledge of happenings in the workspace is necessary for collaboration. The members must know what is happening in the working space of robots to evade collision or accidents with the robots. Researchers have proposed that mutual understanding is necessary for robots to partner with humans effectively, i.e., the interaction must be meaningful. The effectiveness of collaboration relies on awareness of collaborators and environmental activities, intelligence to predict and control these activities, and mental states to which humans may have contributed to the task. An HRC system must benefit from adjustable autonomy and interfaces that allow the robots to operate self-sufficiently and request help from their partner in case a problem arises. Azfar et al. [10] recognized that traditional robots couldn't be replaced with new collaborative robots in the industry due to the massive economic fee involved. However, existing can be transformed into intelligent for more collaborative tasks by converting their surroundings through setting sensors across them and sensing the human employee's activities. Communication signals significantly improve the performance in collaborative tasks; they must be deployed to detect the center of attention. An essential component of the collaborative model is grounding, which can be achieved through meaningful dialogue and interaction.

3.1.1 Sensing and Interfaces

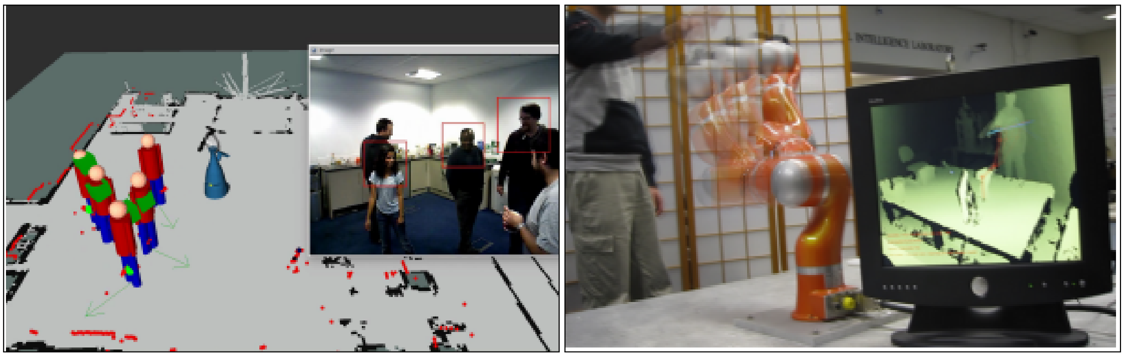
Regardless of the approaches used to program the robot, sensors are frequently applied to improve the operator's interaction with the robot. Indeed, in addition to the aspects related to safety functions, the use of additional sensing techniques has been seen to make the human-to-robot interaction just like a human-to-human interaction, which in turn supplements the human capabilities because of favorable interaction. The aforementioned eases the burden of communicating with the robots; thus, people with no prior HRI knowledge or experience can easily and effectively interact with the robots. The ultimate aim is to program and control a robot through high-level behaviors abstracted from the robot language ensuring effective collaboration [67]. It may be done by keeping in mind socially interactive modes, like eye tracking, voice and speech recognition, gestures, facial expressions, and haptic technology, further to the conventional ones like a mouse, keyboard, touchpad, monitor, and touchscreen.

It is worth noting that in a few applications combination of these interactive modes is used, and in some, they are integrated with augmented reality. Vision and voice sensing structures are usually applied more in collaborative tasks.

Voice guidance is useful when hand-free interaction is required, e.g., when the operator's hands are not free or when the standard interaction system cannot be adapted to the situation, as in the case of interaction with a mobile service robot. The main advantage of voice communication is that it does not restrict the operator's mobility, and the operator can concentrate on their task without taking their eyes off it. However, industrial scenarios use rare voice recognition and language processing systems. Indeed, the poor popularity of voice control systems in the industrial environment is due to the lack of reliable solutions and the fact that any recognition error in this context will have a negative impact. Significant side effects are in production, efficacy, and safety [67]. Generally, when considering the use of voice interfaces, two main aspects need to be addressed: speech recognition, which involves word recognition or phoneme, and language processing, which includes sentence construction and semantic analysis. These approaches are typically based on elementary voice commands. Many researchers deal with voice control of assistive and mobile robots [123]. The ultimate goal is to establish two-way communication that allows the robot to understand and generate natural language. Pires [124] used a voice interface to control robotic production cells. He used the speech recognition interface for two particular industry illustrative examples, pick & place and welding. The strategy was intended to clarify the potential interest of these HMIs for industrial applications. Similarly, remote web-based voice control for robotic cells was proposed by [125] that was based on near natural language strategy. A combination of automatic speech recognition and remote web-based control of robotic cells attained this goal. Voice commands were used [126] in conjunction with pointing commands. Recognized voice commands activate the visual module that captures what the user pointed at.

Visual sensing is one of the best adoptions today for incorporating sensor-based collision avoidance strategies into robotics control systems. In addition, developing cheap sensor technology, such as low-cost machine vision cameras, depth sensors, etc., meets many requirements and provides economic and potent sensor systems. Typically, vision systems are used to recognize objects/environments, make gestures and detect human facial expressions. In a nutshell, we can say they are used to identify the demonstrator's actions and then transfer the decisions based on these actions to the robot for the response. Sometimes, the recognized scene is shown to the human operator in terms of appropriate visual feedback to make the operator aware of the situation. Numerous works exist focusing on localization and recognition of the humans and the objects around the robot using machine vision technology. Dondrup et al. [127] used human-aware navigation for safe human-robot interaction by detecting and tracking humans through Red Green Blue-Depth (RGBD) cameras and lasers. Flacco et al. [17] used a fast sensing method based on spatial depth to assess the distance between a robot and conceivably moving obstacles (including humans). The robotic arm reacts instantly to human movements and other dynamic obstacles identified in the depth space, thus avoiding collisions. Morato et al. [16] have established a mechanism for evaluating the separation between humans and robots in 3D Euclidean space, which can be used to generate safe movements for robots. To this end, an N-Kinect system has been developed to construct an unambiguous model of spheres representing human body parts. A simulation was used to evaluate the interference between humans and robots in the field. Sharma et al. [18] used a random decision forest (RDF) classifier with a conditional random field (CRF) to label the pixel-based class for real-world scenes. The aim was to segment real-world objects and pre-emptive motion planning for safe human-robot collaboration (SHRC). Bogun et al. [128] identified objects using 2D cameras and algorithms based on machine learning. The authors used the Washington Scene Dataset and achieved a high success rate (up to 82%). A comparable system using object detection developed by Google achieved an 83% success rate [129]. Safeea and Pedro [107] used a laser distance finder and inertial measurement unit (IMU) to detect human-robot collisions in a human-robot interaction application. Humans and robots were represented by capsules, which allowed authors to calculate the minimum distance between humans and robots in the workspace. A recent review by Junming et al. [130] focused on gathering holistic vision-based information of objects, humans and environment in a scene for better HRC. Choi et al. [131] used a mixed reality system integrating deep learning and digital twin to measure safety distance between the operator and the robot for ensuring safe HRC. Similarly, in another paper Choi et al. [132] descried that how an extended reality approach can be used for safe HRC. Rodrigue et al. [133] used deep learning segmentation methods for collision detection and to check whether the operator is wearing personal protective equipment (PPE) or not. Secil et al. [134] used a skeletal tracking algorithm on the capsules used by [107] for measuring their orientation, this was then used for measuring the minimum distance between human and robot for safe HRC. Karagiannis et al. [135] divided the space around the robot into different security zones using vision-based monitoring for collision avoidance and adaptive robot's speed. Yi et al. [136] proposed a digital twin for collision avoidance using depth camera-based human skeleton recognition.

Collectively, the performance of these visual techniques requires deliberate calibration procedures, complex algorithms, and line-of-sight conditions. However, the main strength of vision-based techniques is that they do not require any environmental alteration. Moreover, low-cost devices and open-source algorithms have made it easy to apply these techniques to desired strategies. In addition to the above-mentioned voice and visual sensing techniques, several physiological monitoring systems were proposed by researchers that extract the operator's information on response to robot movement or behavior. These physiological indicators include skin electrical conductivity, heart rate, pupil dilation, and brain & muscle nerve cell activity.



(a) (b)

FIGURE 3.2: Vision based applications for Safety; (a) Tracking of Humans for safe HRI [127], adapted with permission from Marc Hanheide; (b) Collision avoidance using depth space, adapted with permission from Alessandro De Luca [17].

3.2 Psychological Safety in Collaborative Tasks

From the perspective of HRI, psychological safety means ensuring interactions that do not cause undue stress and discomfort in the long run. For example, a robot capable of moving a sharp end-effector device at very high speeds within a few inches of the operator's arm may cause extreme stress to the operator. Although the system may prevent unwanted contact injuries, a person working with such a system is likely to experience a constant state of discomfort and stress, which can affect the health of the operator long term. Papetti et al. [75] identified ergonomics as one of the major pillars for the design of human-oriented safe HRC systems. Therefore, methods of ensuring both physical and psychological safety must be developed and designed to meet the safety requirements of collaborative CPS [7]. A robot that can sense worker fatigue with whom it works in the workshop will be able to take the essential safeguards to avoid accidents [137]. Recent advances in robotics and sensors have spawned many robots and their applications. Robots are now found to be increasingly used with humans in the service industry, search and rescue operations, and therapeutic applications. These applications require researchers to build machines that identify, model, communicate, express, and respond to emotional information, also known as ‘‘affective computing.’’ Understanding emotional cues in human communication are essential to comprehend and interpreting emotional information. Accordingly, the robot must respond by perceiving the emotional levels of the operator. Picard [138] states that "emotions play an important role in shaping, learning, and deciding a variety of cognitive functions." Research in affective computing pioneered by Picard exploits this relationship to assess human affective states [139]. In psychology, affect refers to the fundamental knowledge of feeling, emotion, or mood. In affective computing, we look at the emotional features that are connected to human expressions. In the case of machines, their expressions are separate from feelings; they can ignore the presence of emotions pretty well. Machines that would have emotions are the concerns of affective computing for psychological safety. However, with a machine, it is simple to assess how expression does now no longer infer the underlying feeling [140]. Consequently, endowing robots with a degree of emotional intelligence will allow HRI to be more meaningful and natural. Moreover, in addition to normal operations such as detecting obstacles or following walls, the robot, based on emotional inputs, must perform actions related to approaching closer or exchanging dialogue with humans [62]. An illustration of it was demonstrated earlier in a human-computer integration where biosensors were mounted on the operator, and physiological signals such as anxiety were measured in real-time and transmitted to the robot [137]. Latent operator states such as frustration, fatigue, anxiety, and commitment were incorporated. Therefore, a robot that can sense these internal psychological states can immediately take purposeful action to help the operator. Fig. 3.3 shows the affective-sensing-based HRI architecture. The physiological cues of a person participating in a collaborative task were recorded. The related cues were then analyzed to determine the person's emotional state. The controller used the associated affective information and other environmental data to decide on the subsequent course of action. The controller then command the robot to perform the desired actions. In fact, the human work is also affected and influenced by the robot operation and the cycle must be renewed. It was noted that physiological responses are often spontaneous such as facial expressions or tone of voice and have less reliance on culture, gender, and age.

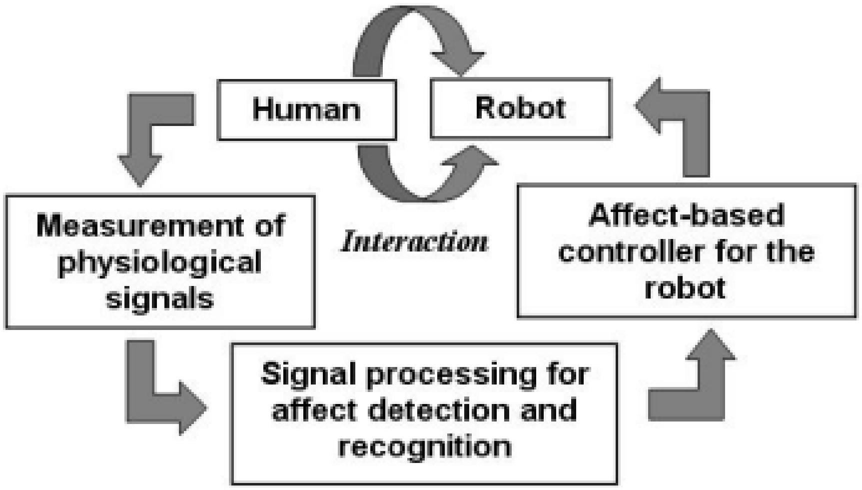


FIGURE 3.3: Psychological Interaction Framework for HRI, adapted with permission from Nilanjan Sarkar [137].

In another paper, biofeedback sensors were placed by [139] to calculate a person's affective state. The experimental setup is shown in Fig. 3.4.

FIGURE 3.4: Physiological Monitoring of Human Operator, adapted with permission from Nilanjan Sarkar [139].

3.2.1 Sensing and Interfaces

Several methods, such as voice intonation, gestures, facial expressions, and posture, can be used to determine the underlying emotions of a person interacting with the robot. Physiology is another effective and promising way to assess a person's emotional state. It is related to biological signals such as heart activity, muscle tension, blood pressure, skin conductivity, etc. Psychophysiology is the branch of psychology concerned with the physiological basis of psychological processes. In psychophysiology, emotions and physiology are closely related and affect each other, hence have an excellent potential for affective computing. Sarkar [141] proposed using multiple physiological cues to estimate the emotional state of humans for subsequent modification of robot actions to make the user more comfortable. Kulic and Croft [142] showed that measurement of cardiac activity, skin conductivity, and eye muscle activity in conjunction with fuzzy inference tools could be used to estimate physiological states. The physiological conditions can be anxiety, calm, and surprise to further monitor human response and subsequently change the robot's trajectory in real time for safe HRI. A similar set of physiological cues and inference tools have been used in [143] for intention estimation and [144] for anxiety perception to provide safe HRI in the industry. Instead of examining sudden changes in physiological cues, a hidden Markov model detector (HMM) based on gradual physiological changes has been proposed by Kulic and Croft [145] for HRI. The authors have demonstrated that the HMM approach gives better results than the previous technique that used fuzzy inference tools. Various psychophysiological sensing techniques, skin conductance response (SCR), blood-volume pulse, electronic cardiograph (ECG), and abdominal and thoracic respiration were used to measure the emotional state of the participants on robots actions who were performing search and rescue operations [146, 147]. The robots performed differently when in emotive mode; they approached slower, lower to the ground, and focused on the ”victim” to show caution, care, and concern. A novel framework for HRI is proposed in [148], wherein a robot seamlessly adjusts its behavior based on the physiological monitoring of humans. Physiological processing combined with machine learning was used to model the affective state for an adaptive HRI.

The robot-based basketball (RBB) mission, an HRI mission, was designed as an experiment. The authors have shown that the robot can detect human psychological states such as anxiety and joy in real-time through psychophysical feedback and respond appropriately during an interactive task. The transition from one emotional state to another, such as from an anxious state to a relaxed state, is accompanied by dynamic changes in the indicators of the autonomic nervous system (ANS).

3.3 Combined Safety Systems in Collaborative Tasks

Lasota et al. [7] have introduced a distinct concept of combining physical and psychological safety for safe human-robot interaction. They presented a safe real-time system capable of allowing safe human-robot interaction at low separation distances without needing to modify or replace anything in the robot's hardware. By knowing the position of the robot and the human in the workspace, it is possible to precisely adjust the robot's speed using real-time separation distance measurements. This will help prevent collisions in a way that is comfortable for the operator. The authors developed a low latency, real-time protection gadget to transform an existing industrial robot into a safe human-robot platform. The system now guarantees the physical and psychological (comfort) protection of the human collaborator without the need for specialized actuators or hardware additions. The developed system permitted HRI at a separation distance of as little as 6 cm. They had proven that in the context of psychological safety, only collision avoidance is not enough to preserve human comfort for safe HRI. Furthermore, it's been highlighted that numerous parameters, consisting of end-effector speed, separation distance, and advanced intimation of robotic motion, have a substantial impact on the psychological pressure of human operators, although there may be no contact between humans and robots. A virtual environment was used to calculate the separation distance between the operator and the robot. As soon as the configuration of the human operator and the robot is refreshed inside the virtual field, the distance of separation between both is estimated and communicated to the central program, which calculates the speed for adjustment and updates the controller. The experimental and the virtual setup is shown in Fig. 3.5. In another paper, Lasota et al. [15] showed via quantitative metrics of the same experiment that human-conscious motion planning leads to more effective HRC.

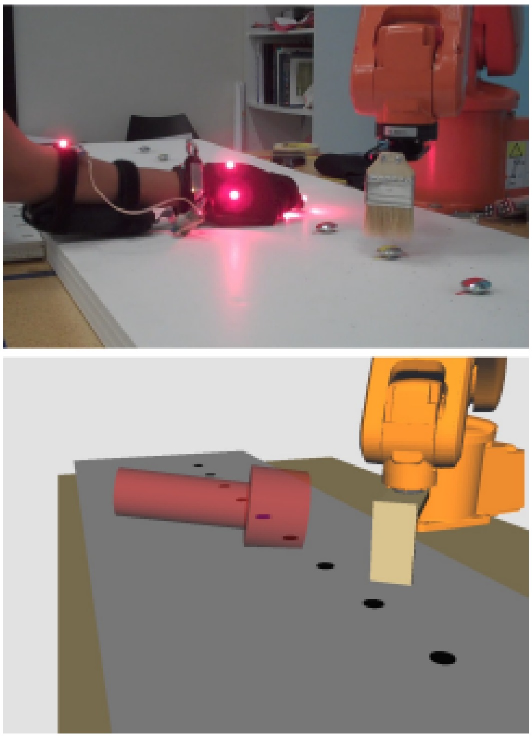


FIGURE 3.5: Concept Encompassing both Physical and Psychological Safety, adapted with permission from Julie A Shah [15].

Dragan et al. [19] described that psychological safety is ensured by legibility; the operator feels more comfortable if he can judge the robot's target by its intended motion. The legibility further ensures physical safety as the intent of the robot's motion is known to the operator. The authors analyzed the advantage of robot motion planning, which allows collaborators' inferences for the success of a physical collaboration. An experimental setup has been designed in which the robot and the operator had to prepare tea orders in collaboration. The robot grabs the cup in line, and the operator collects the corresponding ingredients. Three types of robot movements were compared in the paper based on human comfort criteria. The three types presented are functional motion, predictable motion, and legible motion. The main comparison was made between predictable motion and legible motion since both are functional motion types. Legible motions were given preference over predictable motions. The work, as a whole, supported the legible motion and its employment in collaborative tasks, signifying that collaborators had ease while coordinating with the robot. Functional motion is when the robot approaches the target avoiding collisions but inefficiently. A predictable movement corresponds to the collaborators' expectations, given that the goal is known in advance. A Legible motion is a readable movement in which the operator infers the robot's target continuously from its current motion. In the paper, the concept of legibility proposed by the authors says that knowledge about an upcoming task improves comfort and safety; they demonstrated in the experiment that the operator could easily infer the robot's target due to its intended motion, making her more comfortable and safe in the collaborative tasks. While in a predictable motion, the target is known prior to the robot's movement, the operator still feels uncomfortable due to the initial trajectory of the robot. The experimental setup and the virtual representation of robot carrying task using the three types of motions are shown in Fig. 3.6. The concept of legibility outlined above was only applied to the robot's motion; there is a need to design a system that may ensure the legibility of all processes involved in a CPPS.

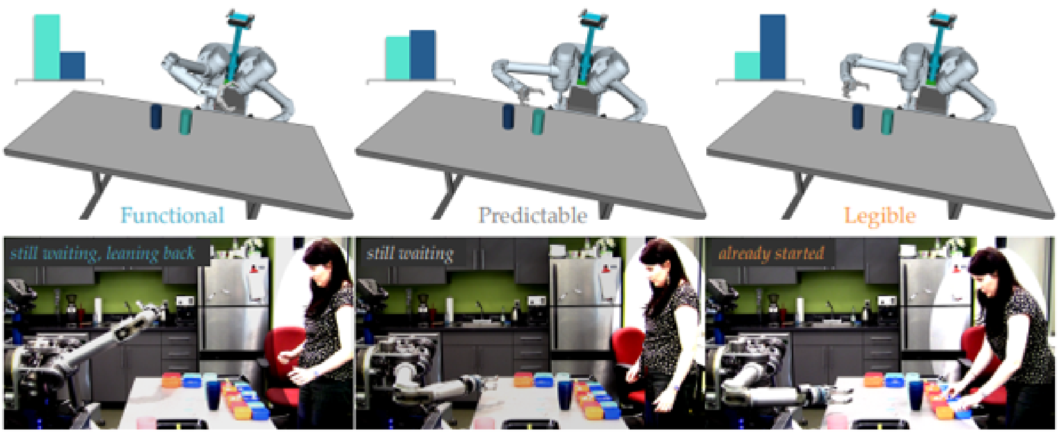
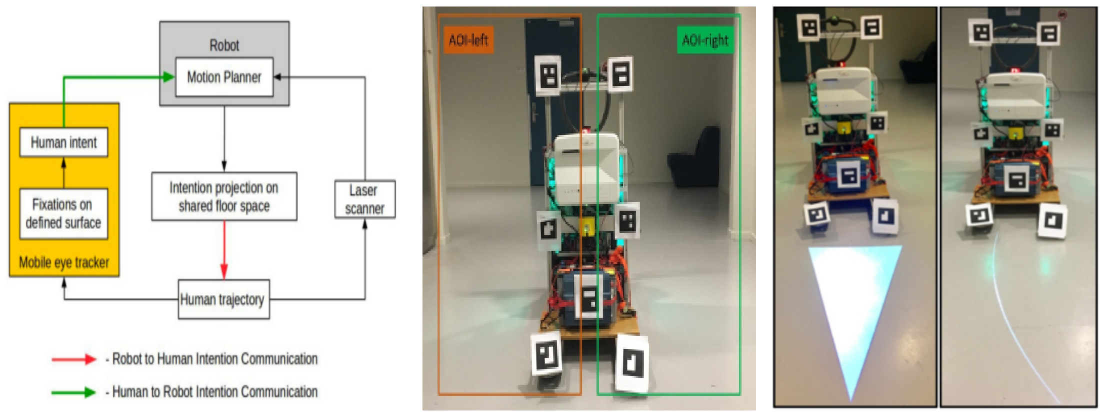


FIGURE 3.6: Functional motion is deceptive; Predictable is efficient but ambiguous; Legible motion makes intent more clear. Adapted with permission from Anca Dragan [19].

Recently, Chadalavada et al. [149] evaluated two-way communication for robot and human navigation purposes. The study focuses on an industrial logistics application wherein people interact with automated forklifts. The authors demonstrated how a robot could show its intentions using spatial augmented reality (SAR) so that humans can visually understand the robot's navigational intent and feel safe next to it. To determine the human intent, the authors analyzed the human operator trajectories and viewing patterns when interacting with automated forklifts. They analyzed that people who are mostly looking at the particular side of the robot ultimately decide to move on. On analysis of recorded trajectories, they discovered that a mobile robot that projects its intentions (as in the case robot's intentions were projected onto the floor) encourages humans to proactively choose safer paths and reduce shortest distances during interactions. The concept and the setup is shown in Fig. 3.7.



(a) (b) (c)

FIGURE 3.7: Two way Communication for Intent Determination; (a) Implicit Intention Transference Concept; (b) Human's Intentions; (c) Robot's Intentions. Adapted with permission from Ravi Chadalavada [149].

A latest paper by Hanna et al. [150] gave a new concept of deliberate safety, which proposes that a HRC based system must be able to switch between different safety measures spanning from rigid parameter safety to close interactive safeties like active and planned safety measures. The switching would depend on the requirement of flexibility and efficiency.

3.4 Conclusion

The literature review highlighted that the HRI in collaborative tasks poses many safety challenges. These safety issues can be subdivided into two domains which are physical and psychological safety issues. Extensive research is underway to address the physical safety issues that mostly include contact and collision strategies in the realm of collaboration and co-existence. However, there is rare research on psychological safety issues in collaborative tasks that mostly relies on proxemics and is limited to human operators' psychological aspects. A recent literature survey by [151] has also confirmed this fact. It is also noted that in the related works, part of the robot's cognitive abilities constitutes their capacity to understand the impact of their presence on the human's companions and regulate their behavior and reaction respectively. Psychophysiological systems are being incorporated to bridge the gap between physical and psychological systems. This requires knowledge of social senses in addition to estimates taken from physical parameters. Here we are ignorant of a crucial aspect; while talking about the issues in the social domain, the researchers only focus on the issues pertinent to human beings. As industry 4.0 recommends using intelligent robots, the concept of comfort to human users is equally pertinent to intelligent robots, i.e., physical and psychological safety. However, being the contributors to the common end state, the safety issues must not be limited to humans and robots; rather, the complete system is vulnerable and has to be intelligent to address the social safety issues. Let us consider an intelligent system working for the desired end state, which, if unable to achieve it due to uncertainties, may face psychological stress if we relate it to humans. On the other hand, the uncertainties may encompass physical safety issues, meaning the stress can be due to any physical or psychological issue. In this work, intelligent systems are meant as 'ACPPS,' which incorporates all physical, computational, and human elements. Our research focuses on addressing both physical and psychological issues faced by CPPS. This can be done by increasing the flexibility in the system; first, get aware of uncertainties in the task, then analyze, decide and perform corrective actions. As evident from the literature review, despite some literature on proxemics, there is a lack of an integrated approach that addresses both the physical and psychological safety issues of a collaborative CPPS. Therefore, a connective framework should encompass the detection, assessment, decision-making, and countermeasures of social safety issues. In other words, we can say that a CPPS has to be flexible enough that it may handle the braved uncertainties in a way to achieve the desired end state optimally.

Chapter 4

Anxiety of Cyber-Physical Systems

4.1 Anxiety in Human Beings

The natural reaction of human beings to stress is anxiety. It can be said it is the sense of worry or apprehension of what will emanate. The central task of the overall system in the brain is to relate, real with anticipated stimuli, and then operate in two roles. If the real situation is in accordance with the anticipated stimuli, the brain operates in a "checking" role. In this case, behavioral control of the body remains with the dormant portion of the brain. However, if the situation is aversive, i.e., there is a mismatch between the real and the anticipated, the brain operates in a "control" role. The brain, in this case, takes direct control of the behavior. In this mode, there will be two courses of action. The first one is the instant hang-up of any running motor program. Second, the motor program is marked with the label "faulty," which must be inspected for the mismatch. This emanates two more concerns, (a) The detected program may be performed with larger restrictions in the future (slower, intermittent, quickly disregarded, etc.), (b) The labeled program is dealt with more caution whenever it occurs in the impending times, the brain will exercise its task with particular care; matching real with anticipated.

It is assumed that the brain subjects each situation to an examination that spawns over various parameters (e.g., brightness, hue, position, size, and relation to other stimuli). The relationship between the subject's response and behavior outcomes can similarly be exposed to this type of multidimensional evaluation. In addition, the brain also recruits explicit probing and investigation to draw deductions, which gave rise to the mismatch. Among the probes, the brain explores for a specific class that predicts disorder, i.e., situations linked with punishment, no reward, or failure. Moreover, it is presumed that the brain identifies certain situations as important and requires careful investigation [152]. Different classes of mismatches/anxiety disorders are identified in medical science [153], [154], [155], [156], [157]. The broader categories are:

- **General Anxiety Disorder** is a day-to-day routine situation for which refined solutions exist.
- **Panic Disorder** is a situation to which the affected person is not accustomed and has a serious impact on the affected person, being instantaneous.
- **Obsessive-Compulsive Disorder** is a repetitive thought that leads to ritual, and due to this disorder, a false alarm is generated.
- **Post-traumatic Stress Disorder** is a serious incident of the past that causes disorder, and the affected person remains under constant stress that it may occur again.
- **Specific-Phobia/Agoraphobia** is a specific situation that is critical but known; anxiety may be relieved based on the situation's knowledge.
- **Social Anxiety** is a communal problem not liked by humans and assessed through observations like cleanliness, cluttering of objects in the environment, etc.

4.2 Anxiety of Cyber-Physical Systems

A novel concept, Anxiety of a CPS, is proposed to assess physical and psychological issues. Anxiety is the unpleasant state when an expectation is not achieved due to any stressful, dangerous, or unfamiliar situation. The term anxiety needs to elaborated more and should not be confused with risk. Risk is based on hazard, whereas "anxiety can be defined as an urge to perform a particular job to avoid a hazard or even to do a righteous job." In real life, different situations are faced while performing a certain task. It is pertinent to differentiate between a scenario and a situation. A scenario is defined as the amalgamation of different situations at one time, whereas a situation is one state of condition faced by the system. Every situation will generate anxiety, but there would be limited resources to handle each situation. However, there are different levels of anxiety generated by situations, either to perform the intended task or a task to avoid any hazard. Therefore, anxiety is defined and scaled for CPSs.

The technique presented in this work estimates the braved anxiety due to the current situations. The module is initialized by the results of the Ishikawa analysis that assigns an index to each anticipated situation. After initial indexing, a novel and intelligent technique based on medical knowledge categorize situations into different anxiety types. Each type relates to a particular level of severity.

4.3 Categorization of Anxiety

Certain considerations are taken into account to categorize and quantify the situations. The categories are named concerning the characteristics matched with the medical anxieties. Each category defines severity, which shows one's priority over the other and declares its significance for counterstrategy. Thereby keeping into consideration the category, the severity is calculated, and it can be said that 'Quantification' of psychological safety for the CPS is being done. The categories will be re-evaluated on every subsequent iteration of a process. Change of category is the discretion of the human supervisor and depends on the severity and the repeatability of a situation. For this, a log is maintained for a particular situation's severity and category whenever it emerges. Anxiety for a situation is the sum of the lowest severity limit and Ishikawa's index I. The value of I ranges from 0 to 100.

A detailed description of each category is explained in the subsequent paragraph. Panic is defined as a severe unknown incident. Panic is denoted by P, and it is considered the highest level of anxiety. Any new situation causing defined severity is considered panic, hence, identified from the impact of a severe unknown situation. Examples can be a 'collision of participants' or a 'power failure'. For panic, action is to be taken by all stakeholders; however, it must be handled by a human operator being the most intelligent resource. In the mentioned case, all stakeholders of the CPS must stop the operation while the human may observe the cause and rectify the issue.

Specific-phobia/Agoraphobia is the third level of anxiety that comprises the situations previously defined by the user. Agoraphobias are denoted by K. They may be related to a particular resource and may not be affecting others, like user interference in the cobot's task may not affect the user; however, they affect the cobot. Initially, all defined situations not considered in panic/obsession/social norms be included in specific phobia. They may be transferred to the obsession or post-traumatic category on confirmation of a false alarm or emergency/damage caused by some situation. However, the final decision is the privilege of the human supervisor.

The second-highest level of anxiety is Post-traumatic. The assessment criterion can be the emergency stop button pulled by the operator and the declaration of the situation as post-traumatic. In case post-traumatic is declared, the complete system must stop, and the operator must rectify observations. After certain repetitions without any damage, the same may be transferred to Specific-Phobia with the consent of the human supervisor. This category is denoted by T, and the value within the category depends upon I.

The fourth level of anxiety is General anxiety which is denoted by G. The ideal/intended situation is considered for general anxiety that will act as a reference to categorize other situations.

Social norms are warnings that may not affect the current scenario; however, they may affect the performance at a later stage. They are the fifth level and denoted by N. They are the social aspects disturbing both humans and the system. Raising observation to humans can remove such errors, e.g., raising caution for an expected decrease in the distance between the operator and the cobot. The threshold level of this distance is to be defined. Similarly, time delay while completing the intended task is to be displayed. The value within the category is dependent upon I.

Obsessions are related to false alarms. These are previously defined/declared false through Ishikawa, and a null value is given to them. They are the last level of anxiety and are denoted by O. Repetition and continuity are the indicators of the recognition of obsession. Feedback from the human supervisor is taken if a situation from a specific phobia is repeated several times. For example, a foreign object appearing in the work area does not affect operations and can be considered an obsession. Three consecutive repetitions and authentication by the human supervisor is the criterion defined to declare obsession. The leverage always remains with the human supervisor to declare any situation into an obsession at any time. Further identification in the category will be through the data collected/stored through sensors, like the image of the item that appeared may be stored as an obsession. Total severity is also calculated for a particular instance, and an alarm is raised if it crosses a certain limit. It is the sum of every current emerging situation in a single iteration, whose severity is already defined.

$$\text{Total severity} = G + P + O + T + K + N \tag{4.1}$$

The criterion for categorizing and indexing anxiety in different situations faced by the CPS is defined in Table 4.1.

Table 4.1: Anxiety Categories

Level	***Name***	***Description***	***Severity***	***Equation***	***Detailed Description***
1	Panic	Emergency	80 to 100	*P=80+ I× 20/100*	**Medical**: a situation to which the affected person is not accustomed and has a serious impact. **CPS**: a severe unknown incident identified by impact, action be taken by all stakeholders; however, it must be handled by HC being the most intelligent resource.
2	Post-traumatic	Trauma/ Fear	60 to 80	*T= 60+ I× 20/100*	**Medical**: serious incident of the past, the affected person remains under constant stress that it may occur again. **CPS**: assessment criterion is an emergency declaration by HC on occurrence. The complete system must stop, and observations must be rectified by the operator. After certain repetitions without any damage, the same may be transferred to Specific-Phobia.

3	Agora-phobia/ Specific-Phobia	Known Specific Situation	20 to 60	*K= 20+ I× 40/100*	**Medical**: a specific situation that is critical but known may be relieved based on available knowledge. **CPS**: known situations previously defined and not considered in panic/obsession/social norms. They may be transferred to the obsession or post-traumatic category on confirmation of a false alarm or emergency.
4	General Anxiety	Intended Situation	20	*G= 20*	**Medical**: the day-to-day routine situation for which refined solutions exist. **CPS**: ideal/intended situation. Act as a reference to categorize other situations.
5	Social norms	Etiquettes	0 to 20	*N= 0+ I× 20/100*	**Medical**: a communal problem not liked by humans. **CPS**: warnings that may not affect the current scenario, however, may affect the performance at a later stage.

6	Obsession	False	0	$O = 0$	**Medical**: repetitive thought that leads to ritual or a false alarm. **CPS**: previously declared false alarms through Ishikawa, and a null value is assigned. Repetition and continuity are indicators; however, confirmation from HC is required.

The detailed procedure for calculating index I is explained here. The requirement is that in case of multiple situations, the CPS must act on the situation having maximum anxiety. When it comes to problem-solving in the behavioral and social domain, there exists no capability in computers to overcome the human mind due to its intrinsic properties of consciousness, perception, judgment, and thinking. The problem is to establish a criterion to rank each situation's priority. Therefore, a management technique based on a brainstorming tool is used to cater to the scenario faced by a CPS in the social domain. Ishikawa analysis is used to find situations' anxiety and further allot weight to each situation. A number of experts in the domain may be consulted for brainstorming and assigning weights to situations compared to others. Ishikawa is a team brainstorming tool that offers an analytical and methodical technique of viewing the effect and the causes that bestow that effect. Due to its cause-and-effect framework shape, it is also mentioned as a Fishbone diagram [158]. The benefit of adopting Ishikawa analysis is an organized approach that uses group knowledge for consultation to determine the root causes of a problem [159]. In a typical Fishbone diagram, the effect is usually a problem that needs to be resolved and is placed at the "fish head". The causes of the effect are then laid out along the "bones", and classified as different types along the branches. The anxiety, which is the effect in our case, is placed at the head of the fishbone, whereas the situations leading to anxiety are placed as main headings along the bones. A method of assigning weights to each situation is proposed; all other identified situations are placed as sub-headings under the considered situation, and weights are assigned to them in relation to the main heading, which could be 1 or 0. '1' is assigned to other situation if it is decided to have low priority than the main heading and '0' if it has high priority. The weight is assigned based on the voting of experts. The ranking of the situation (index I) is the total of weights assigned under it. An illustration of the method is shown in Fig. 4.1.

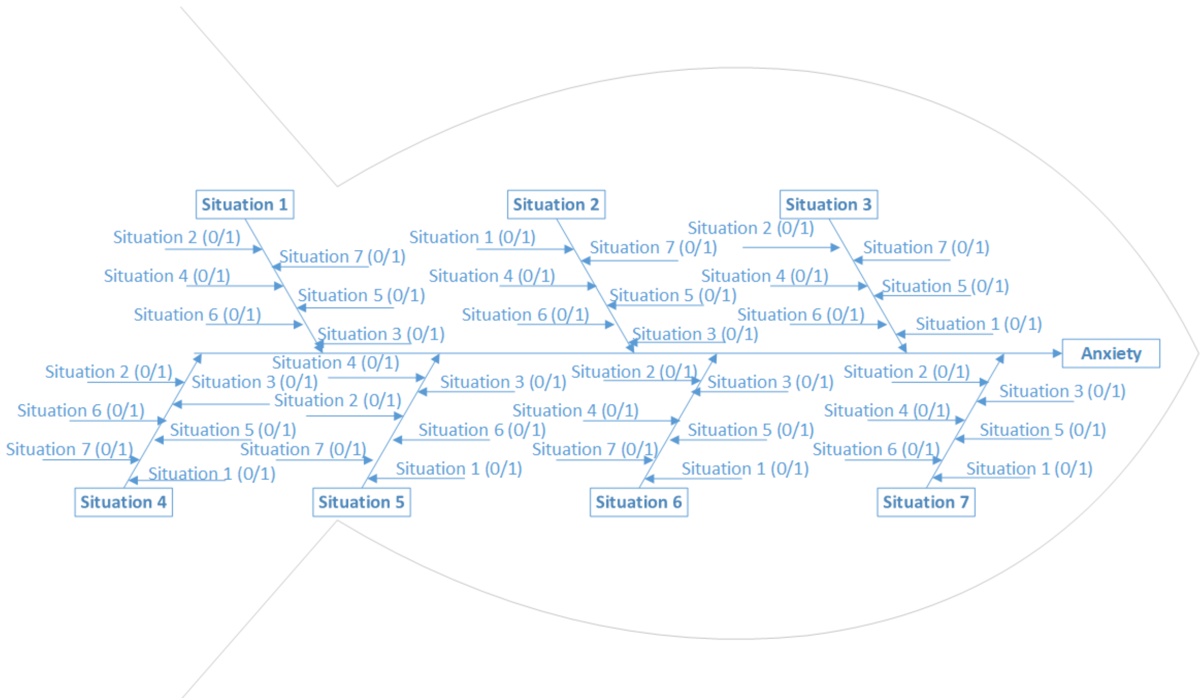


FIGURE 4.1: Method for Calculating Index I of Situations.

4.4 Anxiety Factor

The CPS may have several resources to handle various situations; the calculation of matching scores through a mathematical model is proposed to estimate the suitability of each resource to handle each situation, and termed as an anxiety factor. The anxiety factor, i.e., the matching score, is specific to a particular situation and resource and is dependent on the category and the variables related to tasks/resources. Various key variables are proposed to calculate the anxiety factor through a mathematical formula. These variables denote the relation of situations with resources.

4.4.1 Key Variables

A parameter is a set that lays out the conditions of a system's operation. The parameter defined for the problem is anxiety and denoted by A. Its value is defined by the category of the particular situation, that is, G, P, O, etc., and calculated as explained in Table 4.1. If there are S number of situations, we can relate them with the values of anxiety. The other variables are also dependent on the knowledge of experts. These values will subsequently be used in the solver mathematical model to calculate the matching score of situations vs. resources. Now it is to be declared which resource is most suitable to handle a particular situation. It requires the assignment of each situation's anxiety to one resource. For this, a task variable is introduced in the calculations. It defines which task can better be performed by which resource. It is denoted by t. The prior resource is assigned a lower value and subsequently ascending value for lower priorities. e.g., two resources are considered in this work, then '0' is assigned to the prior resource and '1' to the least prior resource. A preference variable is the ascending order of anxiety level sorted for different situations; it can also be referred to as a priority index number and denoted by p. Few tasks cannot be performed by some of the resources or are not preferable to be handled by some. For example, a foreign object in the workspace may not be handled by a cobot due to its limited maneuverability, or a cobot's power failure cannot be handled by the cobot itself. To define this, the resource-suitability variable is introduced, which has the value '1' if a resource is suitable and '0' if not suitable. It is denoted by Q. To solve this assignment problem, we need to identify which resource is assigned to which situation. A decision variable X is introduced for each possible assignment of resources to the situation. In general, it can be said that any decision variable X_{rs} equals '1' if resource $r \in R$ is assigned to the situation $s \in S$ or '0' otherwise. The anxiety factor a is the value of anxiety calculated through the above variables for a particular situation tackled by a specific resource.

4.4.2 Anxiety Factor Calculation

The anxiety factor for a corresponding resource and a situation is calculated as follows:

$$a_{rs} = Q_{rs}[A_{rs} + (p_{rs} - t_{rs})] \tag{4.2}$$

A is the parameter, p is the preference variable, t is the task variable, and Q is the resource suitability variable. To simplify the mathematical notation of the model formulation, indices for resources r and situations s are defined. The expression for a can be written as:

$a_{rs} \in [0, 100 + S]$ for all resources $r \in R$ and situations $s \in S$

$r \in R$: index and set of resources.

$s \in S$: index and set of situations. S is the total no of situations. The value of p ranges from 1 to S, hence the range of anxiety factor is from 0 to $100 + S$.

The value of t depends upon the number of resources. As two resources are considered, then $t = 0, 1$. The value of Q will either be 0 or 1.

In equation (4.2), it can be seen that the first variable that affects the anxiety factor is Q. This means that the foremost thing that defines the anxiety factor is resource suitability. The second variable that dominates the equation is the parameter A, which actually is the category of the situation under consideration and itself dependent on the index I. This means the higher the parameter A; the higher will be the anxiety factor. The third variable that has an influence on the anxiety factor is the preference variable p. The variable p is also dependent on the anxiety level I of the situation in consideration. As p is the ascending order of variable I, therefore higher the anxiety level higher will be the variable p, and subsequently higher will be the anxiety factor. The fourth variable is the task variable. It is defined to differentiate the priority of suitability among different resources. The higher the priority, i.e., the lower t as it is negative in our case, the higher will be the anxiety factor.

If we analyze equation (4.2), there are two portions. The first one defines the priority of situations that is the parameter A, and the second portion within the parenthesis actually defines the priority of resources in relevance to the situation. The second portion calculates a sub-value dependent on the task suitability to the resource. The equation (4.2) is defined to accommodate two resources, as highlighted earlier. In case more resources need to be accommodated, the matching scores, i.e., the anxiety factors calculated from this portion, have a limitation in that they should only be compared within the bracket of the single situation in relevance to the available resources, i.e., the anxiety factors calculated from the ts of a single situation. It is to mention that the number of ts is equal to the number of available resources. The limitation is because; as the number of resources increases more than the situations, the value of this sub-portion may become negative, or if the value of situations increases than the upper limit of the anxiety category, the anxiety factor may coincide with the next category range. To overcome this limitation, equation (4.2) may require necessary modification. First, the anxiety factor may be limited to one decimal place only, e.g., 57.8; secondly, the preference variable may be omitted, and only the positive task variable in the second portion may be defined to spread in the succeeding decimal limits. The suggested changes are highlighted in equation (4.3).

$$a_{rs} = Q_{rs}[A_{rs} + (t_{rs}/R \times 0.1)] \tag{4.3}$$

Where R is total number of resources. In this case range of variable t may start from 1 to R.

Chapter 5

Proposed Method

The complex real-world industrial scenario comprises a large number of elements that interact in a non-linear way with each other and exhibit the emergence of unplanned activities, lack of complete knowledge, and ethical and safety issues. This is a new domain of CPPS in which physical and psychological safety issues are apparent. CPPS's architecture and characteristics show that connectivity, sociability, flexibility, adaptability, and highly automated nature are an inherent part of its operation. These characteristics and properties clearly indicate that a complex industrial CPPS cannot fully operate based on a conventional mathematical control model. Our research focuses on addressing both physical and psychological issues faced by a CPPS.

A layered framework is proposed for knowledge-based decision-making in a CPS, as shown in Fig. 5.1. The method decides on the confronted situations to mitigate their anxiety. The CPS, at the core, performs the desired operations through the interactions between its physical component (PC), computer component (CC), and human component (HC). Real-time sensing is incorporated through Visual, IR cues, and other sensing methods for simultaneous detection of various situations. A situational assessment layer is proposed above the central layer to assess the anxiety of the situations faced. This layer uses the knowledge base of HC to assess the anxiety generated by confronted situations. For this, indexing of anxiety for expected situations and calculation of matching scores through a mathematical model is proposed for each resource vs. situation, as described in Chapter 4. The matching score, i.e., the 'anxiety factor,' is the relevance of each situation's anxiety to each resource.

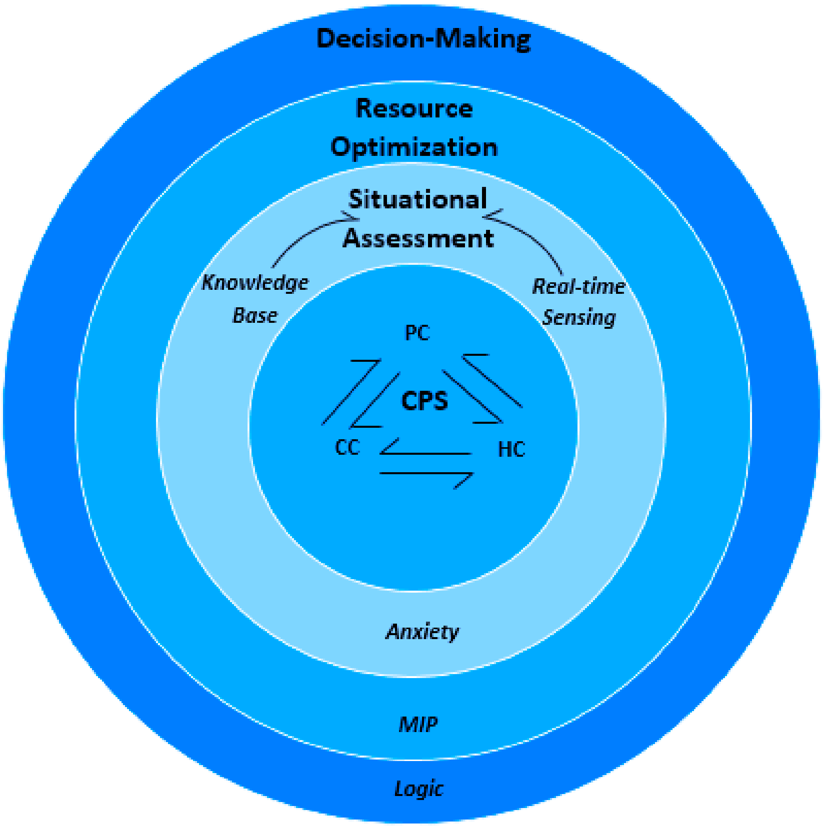


FIGURE 5.1: A Decision-Making Connective Framework for Anxiety Mitigation.

The third layer is the resource optimization layer, above the situational assessment layer. A Mixed-integer programming (MIP) technique is proposed to formulate an optimization model. This layer optimizes the allocation of available resources through an optimization algorithm using the evaluated matching score, the objective function, and the defined constraints. The last is the logic-based decision-making layer. As a complex dynamic scenario involving unprecedented situations is faced, the solution for each situation is different and needs to be defined using the knowledge of experts, suggested optimization, and calculated anxieties. A decision-making layer is suggested that ascertains the task assessment of various resources according to desired metrics and employs the allocated resources to handle the complicated scenario. This layer embeds predefined logic to decide on complex situations and tasks with different resources using the experts' knowledge, evaluated optimization, and calculated anxieties. The logic remains specific to each identical case/situation embedded in a CPS scenario. The proposed framework is validated through an experimental case study of an assembly plant facing several situations.

5.1 Decision-Making Framework

The fourth industrial revolution relying on CPS-based automation represents the industry shift from centralized to decentralized, where autonomous and collaborative elements of a CPS are directly in communication with a computational element, and services such as monitoring, control and optimization subscribe to it in real-time. Therefore, a connective framework is proposed, and an overview of its execution is shown in Fig. 5.2. A knowledge-based modular software system is suggested where different modules represent different layers of the proposed framework. However, the number of modules is not recommended to be fixed and may vary as per the requirement of a particular case. The data of all the layers is stored in a central database.

The basic modules are; the main module for the sensing and process control layer of the CPS, the anxiety module for the situational assessment layer, the optimization module for the resource optimization layer, and the decision-making module for the decision-making layer. The main module holds the database and is connected to other modules through information transfer. As mentioned earlier, the logic remains specific for a particular case, and there could be several modules other than the basic modules to represent different situations. The main module works for the intended scenario and looks for the changes at every cycle of the operation. In case multiple changes are faced, the anxiety module ascertains the matching score for each situation. Accordingly, the situations with the higher anxiety factor are assigned the best possible resources through the optimization module.

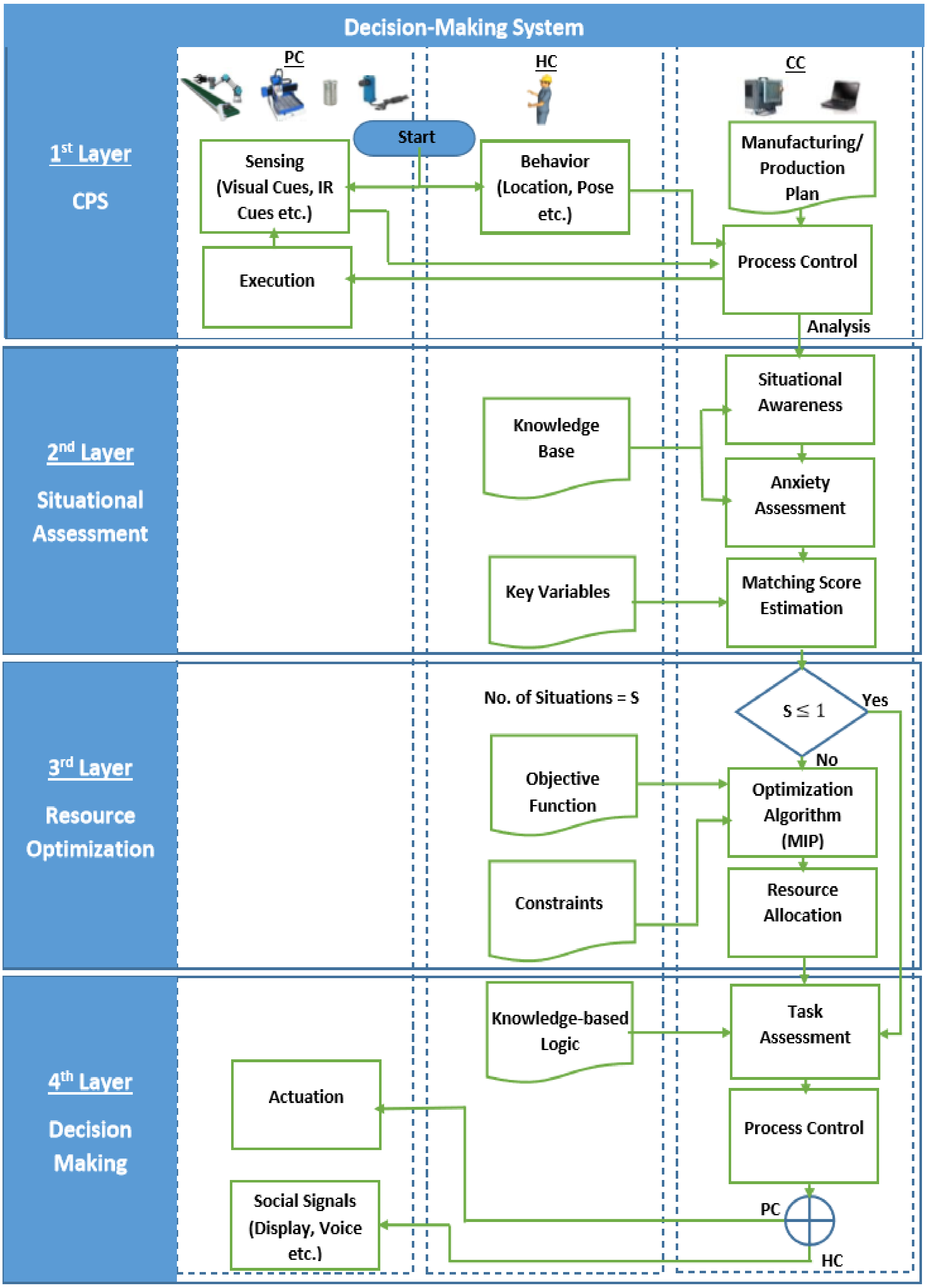


FIGURE 5.2: Decision-Making Framework Execution.

The decision-making module looks after the contingencies to handle the braved situations. In this context, outputs from the anxiety and the optimization modules are given to the start of the decision-making module, which decides on the assignment of resources to the tasks based on the defined logic. The general connectivity of the modules is shown in Fig. 5.3; however, the logic representation is shown for particular case studies in relevant chapters.

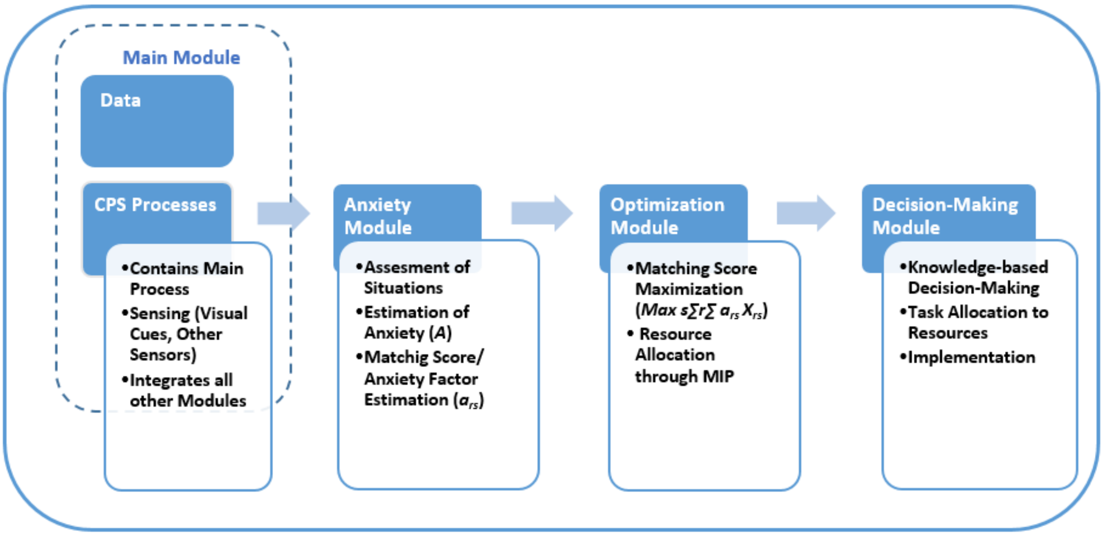


FIGURE 5.3: Module-based Software Implementation for Decision-Making.

The framework will now be explained layer by layer. The implementation of the proposed method includes two types of actions, one to be taken before activating the system and others are happening in real-time during the process cycle. Both the pre-process and in-process steps concerning each layer are shown.

5.1.1 CPS Layer

The CPs layer is the main layer that controls all physical and human elements. The physical component involves machines, robots, conveyors, sensors, display/output devices, input devices, etc. The main role of the layer is to execute the intended process for which the production plan is uploaded. The layer uses HC and PC status to aid the completion of desired tasks and ascertain any change in the process. For this, various sensing techniques, like proxemics, visual, physiological, or social cues, etc., may be used. Different situations which are expected to affect the desired output are registered and identified through sensing techniques if they emerge in the process. The preprocess formalities and the pseudo-code of the process involved in the CPS layer are shown in Table 5.1.

Table 5.1: Process for CPS Layer

Ser	***Layer***	***Pre-Process Formalities***	***Process Pseudo-Code***
1	CPS	Prepare Manufacturing/ Production plan	
2		Register expected situations	
3			Start
4			Upload Execution Plan
5			Initialize
6			Check the state of the human component
7			Check the state of physical components
8			While no uncertainty
9			Execute the process
10			If uncertainty
11			Go to the situational assessment layer
12			Else go to initialize
13			End

5.1.2 Situational Assessment Layer

The Situational assessment layer assesses confronted situations for anxiety by using the HC's knowledge base. Prior to the process, different pre-process formalities are performed. First, the expected situations index is calculated with HC's knowledge (Ishikawa analysis), as proposed in Chapter 4. The anxiety category of each situation is then identified, as anticipated by HC. And based on the category, the matching score for all expected situations is calculated, which states the resource suitability to the particular situation. On the initialization of the process, the layer first gets itself aware of the situations that are detected by the CPS layer. The layer then links the matching scores to the related situations and re-estimates if the category of the situation changed by the HC during the operation. Details of the process and pseudo code are shown in Table 5.2.

TABLE 5.2: Process for Situational Assessment Layer

Ser	***Layer***	***Pre-Process Formalities***	***Process Pseudo-Code***
1	Situational Assessment	Index the defined situations' anxieties through the Ishikawa method	
2		Categorize situations into the type of anxiety	
3		Assign weights to key variables for estimation of matching score	
4		Calculate the matching score (anxiety factor) with respect to resources	
5			Initialize
6			Upload the matching scores
7			Check the emerged situations
8			Check the matching score of emerged situations
9			If the category is changed by the operator
10			Re-designate the anxiety category of the situation
11			Re-estimate the matching score in case category is changed
12			Move to Resource Optimization

5.1.3 Resource Optimization Layer

A number of optimization techniques can be found in the literature that is applied to flexible CPSs. Li et al. [160] addressed the uncertainty issues generated in manufacturing plants by employing robust optimization for process scheduling. In [161], a CPS is deployed for an automotive electric part's selective and adaptive assembly; an optimization technique was applied by employing a holistic matching approach. In another paper [162], a flexible manufacturing CPS adopted self-optimization by learning real-time context sensitivity. Context extraction was used for learning the context sensitivity of the discrete flexible manufacturing system and the optimizer continuously improved the system's performance. In [163], a constraint-based approach was adopted to optimize the design parameters of an intelligent electric vehicle. A co-design optimization approach was used to determine how to automatically adapt the vehicle's control while adjusting to drivers' driving styles. The optimization problem was formulated for a multi-objective solution that caters to control and driving comfort requirements.

There is a need to identify the best resources that can handle the situations bearing major impacts. This layer optimizes the resource allocation through an optimization algorithm. The module checks the number of situations; if there is a single situation, the program directly moves to the decision-making layer, and if there are multiple situations, the program moves to the optimization algorithm. The algorithm employs the mixed-integer programming (MIP) technique, using the matching score (anxiety factor), objective function, and defined constraints. This resource assignment problem is defined as "To determine the assignment of resources which can deal with situations such that each situation is handled by one optimized resource and each resource is assigned to at most one situation while sequentially addressing the situations with maximum anxiety." Since the problem incorporates both integers and variables, thus making the problem complex; therefore, MIP is the best solution. The MIP can use both binary digits and whole numbers, which greatly increases the scope of optimization problems while satisfying the constraints and objective function. The Gurobi Optimizer [164] is one of the state-of-the-art solvers for mathematical optimization problems. The MIP model of the stated problem is implemented in the Gurobi Optimizer. The overall technique addresses all the situations sequentially in terms of priority. The preprocess formalities and the pseudo-code of the layer are shown in Table 5.3.

TABLE 5.3: Process for Resource Optimization Layer

Ser	***Layer***	***Pre-Process Formalities***	***Process Pseudo-Code***
1	Resource Optimization	Defining the optimization criteria for allocation of resources, the objective function, and the constraints, MIP in our case	
2			Initialize
3			Case 1: Single situation
4			Move to Decision-Making Layer
5			Case 2: Multiple situations
6			Allocate resources to situations through MIP
7			Move to Decision-Making Layer

A decision variable X for each possible assignment of resources to the situations is introduced. In general, we can say that any decision variable X_{rs} equals '1' if resource $r \in R$ is assigned to the situation $s \in S$ or '0' otherwise.

5.1.3.1 Situation Constraint

This sub-section presents the constraint associated with situations. This constraint ensures that each situation is handled by exactly one resource. This corresponds to the following:

$$for \quad r \in R \quad \sum_{r=1}^{R} X_{rs} \leq 1 \tag{5.1}$$

Less than < 1 is included to incorporate the null when no resource is assigned to the situation in an iteration.

5.1.3.2 Resource Constraint

The resource constraint ensures that, at most, one situation is assigned to each resource. However, it is possible sometimes that not all the resources are assigned. For example, if CPS encounters two situations and only one resource is suitable to handle both. Then the situations will be handled sequentially by the resource in order of anxiety. We can write this constraint as follows:

$$for \quad s \in S \quad \sum_{s=1}^{S} X_{rs} \leq 1 \tag{5.2}$$

This constraint is less than < 1 to allow the possibility that a resource is not assigned to any situation.

5.1.3.3 Objective Function

The objective is to maximize the total matching score (anxiety factor) of the assignments that satisfy both the situation and resource constraints. The objective function can be concisely written as follows:

$$for \quad s \in S \quad and \quad r \in R \quad \text{Maximize} \sum_{s=1}^{S} \sum_{r=1}^{R} a_{rs} X_{rs} \tag{5.3}$$

5.1.4 Decision-Making Layer

As the CPS, in reality, faces a complex dynamic scenario involving unprecedented situations, the solutions for different situations may vary and are required to be defined through logic based on experts' knowledge. The decision-making module encompasses the logic defined by experts to handle the braved situations and decides on the assignment of resources to tackle them. The main consideration for the assignment of resources is the allocation recommendation by the optimization module; however, the implementation is carried out by the decision-making module. Commands are then given to the physical resources, which could be a human operator, a cobot, a machine, etc., depending on the ascertained tasks. The human component is also given cautions through social signals on observation of social norms and obsessions. The preprocess formalities and the pseudo-code of the layer are shown in Table 5.4.

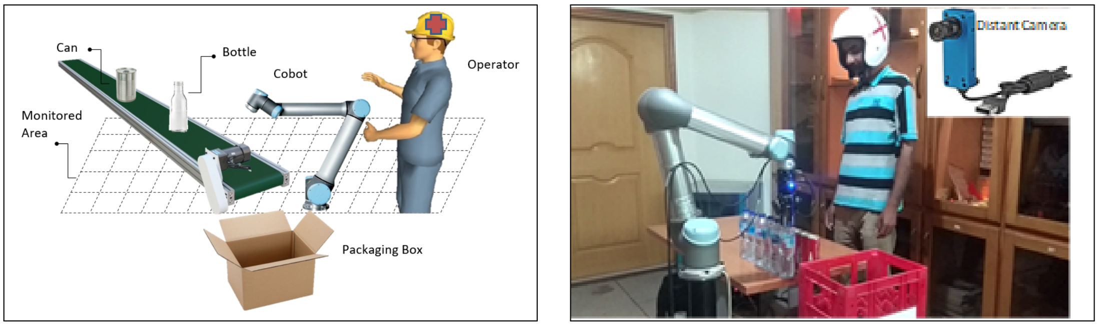
TABLE 5.4: Process for Decision-Making Layer

Ser	***Layer***	***Pre-Process Formalities***	***Process Pseudo-Code***
1	Decision Making	Define and design the logic for each situation with inputs from experts for an anxiety mitigation strategy	
2			Initialize
3			Upload resource allocation data
4			Check situations
5			Check resource allocation to situations
6			Assign a task to available resources based on allocation and logic
7			Execute the task through the PC
8			Exhibit social signals to HC
9			Move to CPS Layer

Chapter 6

Experimental Validation 1

In this chapter, the proposed framework is validated on a case study of an industrial scenario facing multiple situations at a time. An example of a beverages packaging industry is considered, as shown in Fig. 6.1. The industrial scenario is implemented through a collaborative CPS incorporating a cobot and a human operator. Bottles and cans arrive at a workstation from the production center in a sequence. A cobot has to pick these items and place them at the designated locations in a crate. A human supervisor monitors operations and places crates. Despite replacing crates, the supervisor is also monitoring operations for anomalies and erroneous activities, e.g., the supervisor will also look for defective items like broken bottles or dented cans. It means he is in both collaborative and supervisory roles. A total of twelve items have to be packaged, that is, six bottles and six cans. As the packaging process completes, the supervisor removes the crate, fills the space with an empty one, and gives a command for the next one; the cobot moves accordingly. The cobot performs specific operations in collaboration with the operator to complete the task, e.g., the robot picks bottles and cans in a sequence from specific locations and drops them in specific slots in the crate. The human supervisor is also responsible for corrective actions on wrong item arrival, wrong sequence, or absence of item from the location.



(a) (b)

FIGURE 6.1: Experimental Case 1, (a): Scenario; (b): Setup of Considered Case.

6.1 Experimental Setup

A setup is established to implement the case under consideration, which involves a universal robot (cobot) ver UR5, a machine vision camera, a Robotiq kit composed of a camera and a gripper, an IR proximity sensor, and an Intel Core i5-2430M CPU computer with 6 GB RAM. Python is used to run object detection/ pose detection algorithms and to connect the components/algorithms output with UR5 software (PolyScope). The control box of UR5 has both digital and analog inputs/outputs to interface with digital and analog devices. The interface amongst the elements of the CPPS is shown in Fig. 6.2. It also needs to be highlighted here that the complete setup is developed by using low-cost sensors/devices to implement the case study, meaning that the flexibility in the CPPS can be inculcated through low-cost devices for detection and implementation.

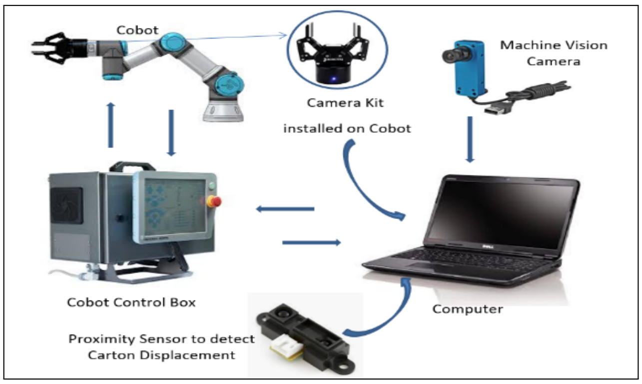


FIGURE 6.2: Interfacing of CPPS Elements.

The main scenario of packaging is programmed in PolyScope to pick bottles and cans from particular locations in a specific sequence and then place them in the crate at their dedicated locations. For this, the waypoints for each pickup and drop-off location are fed in PolyScope. Similarly, the waypoints for drop-off locations pertinent to the situations are set under the condition, the specific scenario is performed. A setup is established to implement the case study, shown in Fig. 6.3.

FIGURE 6.3: Setup and Implementation of Approach for Case under Consideration.

The connectivity of the HC, PC, and CC and their sub-components is shown in Fig. 6.4.

6.2 Scenario's Anxiety

There may be situations when the process may not proceed as intended, and it may face various unwanted and unforeseen situations. To cater to this, different situations were anticipated for both the cases that can emerge during a cycle; these include the intended situation as well as unwanted situations. The intended situation is the production plan and the situations that affect the production plan are unwanted situations.

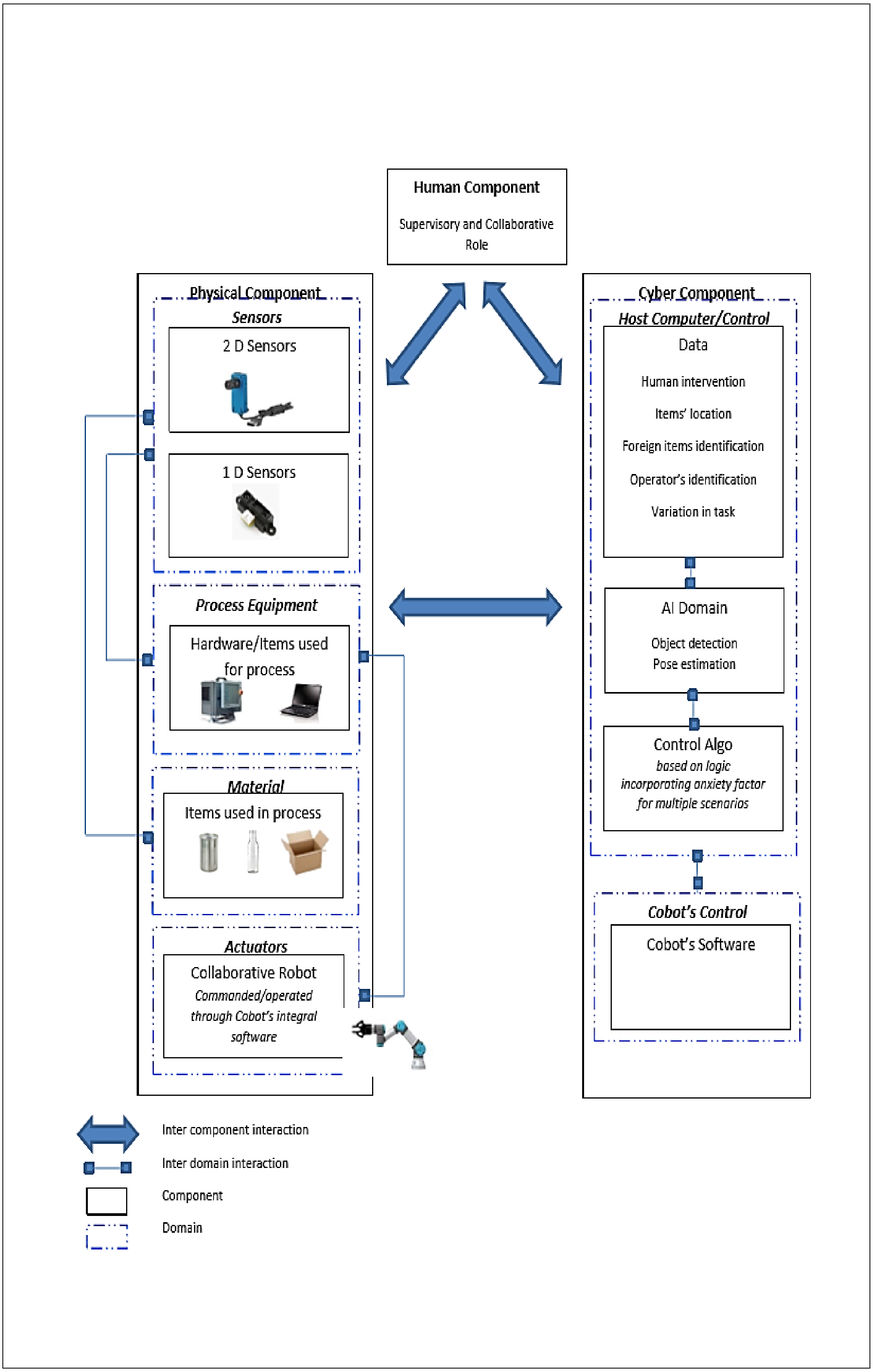


FIGURE 6.4: Connectivity of CPS Components.

The considered situations are: Right item: the main task/intended situation i.e. the right items (beverages) are in place for pick and place operations; the Wrong item: the item at the work location is either not in list or wrong in sequence; No item: when no item appears at the work location; the Human interference: when operator interferes in any task at any location, as he finds that the robot may not be able to perform the task or he finds any anomaly; Displaced Crate: the operation of packaging cannot be completed when the crate is displaced from the designated location; Unidentified person: any unknown person in the workspace is a hazard to the system and to himself; Foreign object: any object not required in the workspace is also a hazard to the system; Obsession: any situation actually not affecting but disturbing the outcome of the system; generally it is established after few iterations when the operator realizes that the situation is a false alarm e.g. in the case study the object detection algorithm detects the table on which the items are placed as a foreign object; Time delay: the completion time variance in the intended operation; Threshold Distance: the breach of minimum distance that is established to be safe for collaboration between the human and the robot; Cobot Power Failure: in case the cobot stops work due to power failure; Cobot Collision: in case the cobot collides with the human operator. As stated, situations that can emerge during this cycle include both anticipated and unforeseen. The situations with serious nature of impact were considered to judge the unforeseen. The two situations incorporated to differentiate unforeseen from anticipated are 'power failure of the cobot' and 'collision of the cobot'. To include social impact, situations; 'unidentified person', foreign object', 'human intervention in the task', 'decreasing distance between the cobot & the human', 'time delay in the work cycle', and 'obsession' were incorporated. Whereas the anticipated situations incorporated were the intended scenario, i.e., the 'right item', the situation when the 'wrong item' is present, when 'no item' is present, and the 'displaced crate'.

The question is how to map these situations to calculate the anxiety index and anxiety factor and then analyze and decide on requisite actions. As soon as any of the listed situations are detected through the visual sensing/other detection techniques, an input of detection is given to the main program. The situation's severity, anxiety index, variables relative to resources, and anxiety factor already evaluated before the commencement of the operation are taken into account. The severity I for each situation was assessed by the experts by assigning weights to each situation against all other situations in the Ishikawa diagram. '1' is assigned to the other situation that is decided to have lower priority than the main situation, and '0' if it has high priority. The weight is assigned based on the voting of experts. The ranking of the situation (index I) is the total of weights assigned under it. The estimate of severity posed by them calculated through Ishikawa is shown in Table 6.1.

TABLE 6.1: Possible Situations and their Anxiety Level

Ser	***Situation***	***Anxiety Level***	***Index***	***Severity(I)***
1	Cobot Power Failure	11	1	100
2	Cobot Collision	10	0.91	91
3	Foreign Object	9	0.81	81
4	Unidentified Person	8	0.72	72
5	Human Intervention	7	0.63	63
6	Displaced Crate	6	0.54	54
7	Wrong Item in Place	5	0.45	45
8	No Item in Place	4	0.36	36
9	Right item in Place	3	0.27	27
10	Threshold Distance	2	0.18	18
11	Time Delay	1	0.09	9
12	Table	0	0	0

The Ishikawa analysis for the considered situations involved in the packaging scenario is shown in Fig. 6.5. There are two resources, a human and a cobot, and the CPS anticipates twelve situations. The anxiety A was then calculated for each situation by putting in values of categories and severity as stated in Table 4.1. The matching score "a" was then estimated, as explained in chapter 4, for both the resources, i.e., a human and a cobot, vs. the situations and fed into the central database.

FIGURE 6.5: Ishikawa Diagram for the Anxiety Calculation.

The set of variables defined for the case is shown in Table 6.2.

TABLE 6.2: Variable Set

Situation	***As***	***Task Variable (t)***		***Preference Variable (p)***		***Resource suitability variable (Q)***		***Decision Variable (X)***		***Anxiety Factor (a)***	
		Human	***Cobot***	***Human***	***Cobot***	***Human***	***Cobot***	***Human***	***Cobot***	***Human***	***Cobot***
Right item	A_1	t_{11}	t_{21}	p_{11}	p_{21}	Q_{11}	Q_{21}	X_{11}	X_{21}	a_{11}	a_{21}
Wrong item	A_2	t_{12}	t_{22}	p_{12}	p_{22}	Q_{12}	Q_{22}	X_{12}	X_{22}	a_{12}	a_{22}
No item	A_3	t_{13}	t_{23}	p_{13}	p_{23}	Q_{13}	Q_{23}	X_{13}	X_{23}	a_{13}	a_{23}
Human interference	A_4	t_{14}	t_{24}	p_{14}	p_{24}	Q_{14}	Q_{24}	X_{14}	X_{24}	a_{14}	a_{24}
Displaced crate	A_5	t_{15}	t_{25}	p_{15}	p_{25}	Q_{15}	Q_{25}	X_{15}	X_{25}	a_{15}	a_{25}
Unidentified person	A_6	t_{16}	t_{26}	p_{16}	p_{26}	Q_{16}	Q_{26}	X_{16}	X_{26}	a_{16}	a_{26}
Foreign object	A_7	t_{17}	t_{27}	p_{17}	p_{27}	Q_{17}	Q_{27}	X_{17}	X_{27}	a_{17}	a_{27}
Table	A_8	t_{18}	t_{28}	p_{18}	p_{28}	Q_{18}	Q_{28}	X_{18}	X_{28}	a_{18}	a_{28}
Time delay	A_9	t_{19}	t_{29}	p_{19}	p_{29}	Q_{19}	Q_{29}	X_{19}	X_{29}	a_{19}	a_{29}
Threshold distance	A_{10}	t_{110}	t_{210}	p_{110}	p_{210}	Q_{110}	Q_{210}	X_{110}	X_{210}	a_{110}	a_{210}
Cobot Power Failure	A_{11}	t_{111}	t_{211}	p_{111}	p_{211}	Q_{111}	Q_{211}	X_{111}	X_{211}	a_{111}	a_{211}
Cobot Collision	A_{12}	t_{112}	t_{212}	p_{112}	p_{212}	Q_{112}	Q_{212}	X_{112}	X_{212}	a_{112}	a_{212}

The severity, categories, the value of anxiety evaluated for the cases, and the anxiety factors are shown in Table 6.3. It can be observed that the highest values are for the panic 'Cobot Power Failure' and 'Cobot Collision,' and the lowest value is for the obsession 'Table.' The 'Right item' is the intended situation; therefore, it is assigned G. 'Threshold distance' and 'Time delay' have lesser values as observed social norms.

Table 6.3: Data Set

Situation	***Cat***	***Par. (A)***	***Task Var.(t)***		***Preference Var. (p)***		***Resource Suitability Var.(Q)***	
			Human	***Cobot***	***Human***	***Cobot***	***Human***	***Cobot***
Right item	G	20	1	0	4	4	1	1
Wrong item	K	38	1	0	6	6	1	1
No item	K	34.4	0	1	5	5	1	0
Human interference	K	45.2	1	0	8	8	0	1
Displaced crate	K	41.6	1	0	7	7	1	1
Unidentified person	K	48.8	0	1	9	9	1	0
Foreign object	K	52.4	0	1	10	10	1	0
Table	O	0	1	1	1	1	0	0
Time delay	N	1.8	0	1	2	2	1	0
Threshold distance	N	3.6	0	1	3	3	1	0
Cobot Power Failure	P	100	0	1	12	12	1	0
Cobot Collision	P	98.2	0	1	11	11	1	0

If we analyze the Table 6.3, we see that the first basis for the resource assignment is the resource suitability variable Q. Suitable resources for a particular situation are shown against Q, where '1' describes the suitability of resources to tackle a particular situation; if it is zero the resource cannot be assigned to the situation.

The second basis is the task variable t. The task priorities are defined through t;

in our case, 0 is assigned to the preferred resource, and 1 is to the less preferred in the table. Hence the resource having t=0 is assigned if it is not already committed and if the resource suitability variable is not '0'.

The third basis is the preference variable p, the situation with the higher value will be addressed first by the two resources, and the remaining will be addressed subsequently after the disposal of the initial ones. The preferences of the situations defined are shown. The higher the parameter A, the higher the preference. The cumulative effect of all these variables is the anxiety factor.

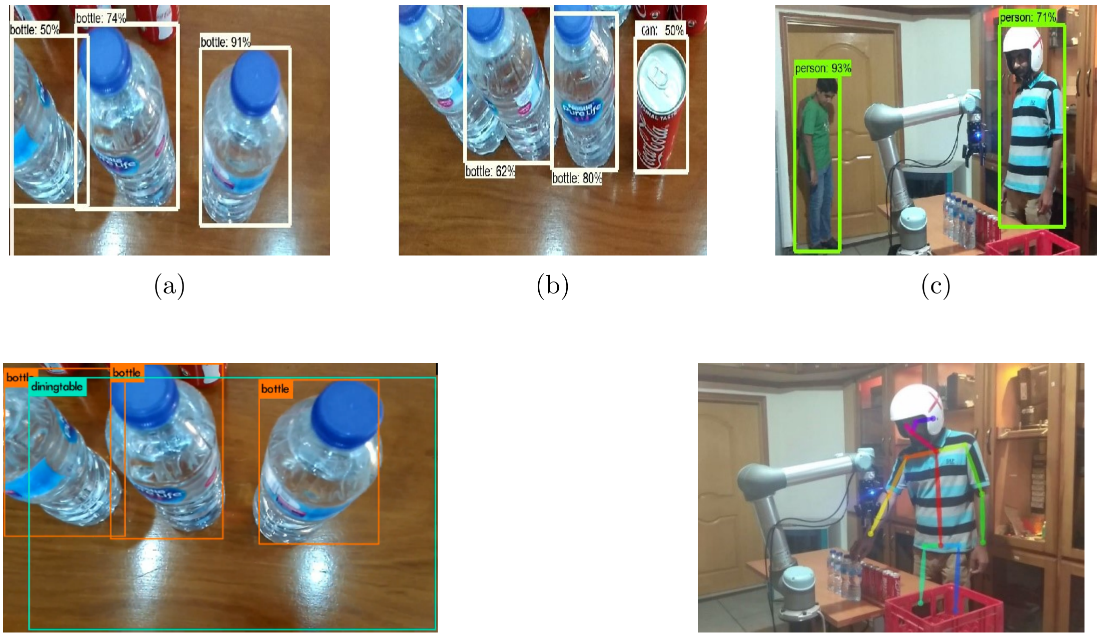
The anxiety factor calculated from the data set presented in Table 6.3 is shown in Table 6.4. The table gives a clear depiction of when any situation appears, which out of two resources can be assigned, which the prior resource is, and which situation will be addressed first.

TABLE 6.4: Anxiety Factors

Situation	***Anxiety Factor (a)***	
	Human	***Cobot***
Right item	23	24
Wrong item	43	44
No item	39.4	0
Human interference	0	53.2
Displaced crate	47.6	48.6
Unidentified person	57.8	0
Foreign object	62.4	0
Obsession	0	0
Time delay	3.8	0
Threshold distance	6.6	0
Cobot Power Failure	112	0
Cobot Collision	109.2	0

6.3 Situational Awareness

For situational awareness, different techniques are used, like a right item, a wrong item, no item, an unidentified person, and a foreign object are detected through a visual cue (object detection). Similarly, the authorized operator is identified by a mark (cross sign) on the helmet detected through the object detection module. The displaced crate is detected through an IR sensor. The human intervention situation is detected through another visual cue (pose estimation of a human operator) via a camera installed above the workspace. The assessment metrics for other situations: time delay is gauged through a clock measuring the complete cycle, threshold distance is assessed from the separation between the cobot and the object-detection-bounding-box covering the human supervisor, cobot collision through impact sensor of the cobot, and cobot power failure through the power of the cobot. A table was initially detected as a foreign object through object detection; however, it was later declared as an obsession, not obstructing the cobot's motion. Detection of various situations through visual cues is shown in Fig. 6.6.



(a) (b) (c) (d) (e)

FIGURE 6.6: Detection of Situations through Visual Cues; (a): Right item; (b): Wrong item; (c): Unidentified person; (d): Table; (e): Human intervention.

6.4 Optimization Criterion for the Case

For the optimization algorithm, the decision variables X_{rs} were defined, which shows the relationship for the assignment of available resources to the possible situations. As 12 situations are considered, and two resources are available for this particular case, therefore 24 decision variables were defined, which are to be used in equations (5.1), (5.2), and (5.3).

As an example, X_{21} is the decision variable associated with assigning resource '2' to situation '1', and X_{12} is the decision variable associated with assigning resource '1' to situation '2'. The situation constraints for this particular case were then defined. As equation (5.1) contains the summation of the term r that represents the resources, therefore, out of the available resources, i.e., 'resource 1' (Human) or 'resource 2' (Cobot), either one can be assigned to one situation, 1 to 12. Hence, 12 equations were formed for the 12 situations. As an example, the first equation for the resource constraint of 'situation 1' (Right item) can be written as (6.1). Similarly, eleven other situations' constraints were formulated.

$$X_{11} + X_{21} \leq 1 \tag{6.1}$$

In the same way, resource constraints were defined. Equation (5.2) for the resource constraint includes the summation of term s that represents the situations. As only one situation can be assigned to one resource, therefore two equations were formed for the two resources. The constraint for resource 1 (Human) can be written as (6.2) in which the first index of every decision variable represents the resource number and the second the situation number:

$$X_{11}+X_{12}+X_{13}+X_{14}+X_{15}+X_{16}+X_{17}+X_{18}+X_{19}+X_{110}+X_{111}+X_{112} \leq 1 \tag{6.2}$$

Similarly, the constraint for resource 2 (Cobot) can be written as (6.3):

$$X_{21}+X_{22}+X_{23}+X_{24}+X_{25}+X_{26}+X_{27}+X_{28}+X_{29}+X_{210}+X_{211}+X_{212} \leq 1 \tag{6.3}$$

The objective function (5.3) contains the summation of both the indices s and r; the equation contains the decision variable and the matching scores. Therefore, the complete equation will have 24 terms. For illustration, the first term for situation 1 (Right item) is written as $a_{11}X_{11}$ if resource 'Human' is assigned and the second term $a_{21}X_{21}$ if resource 'Cobot' is assigned, therefore the terms for the 'Right item' situation are given in (6.4), where only one term in this summation will be nonzero.

$$a_{11}X_{11} + a_{21}X_{21} \tag{6.4}$$

Similarly, other terms for each resource versus each situation were included in the objective function.

In totality, 15 equations were formed that, if calculated manually, are a cumbersome process and were included in the Gurobi optimizer for computation.

6.5 Decision-Making Logic for the Case Study

A logic-based approach is applied to implement the desired strategy for the considered case. The framework is subdivided into five modules and three frameworks for easy understanding. One additional module, 'item in place,' is incorporated, which is specific to the case. Each subdivision is represented using the Integrated Definition for Process Description Capture Method (IDEF) approach [165]. The five modules are the main module, item in place module, anxiety module, optimization module, and decision-making module.

The main module Fig. 6.7, integrates all the other modules; it keeps count of the intended task (Right item) and looks for the situations identified in Table 6.1 at every single iteration. On the assessment of single or multiple situations, the main module ascertains the matching score through the anxiety module. Subsequently, the optimization module identifies the highest matching score for the current situations vs. resources and allocates the resources accordingly.

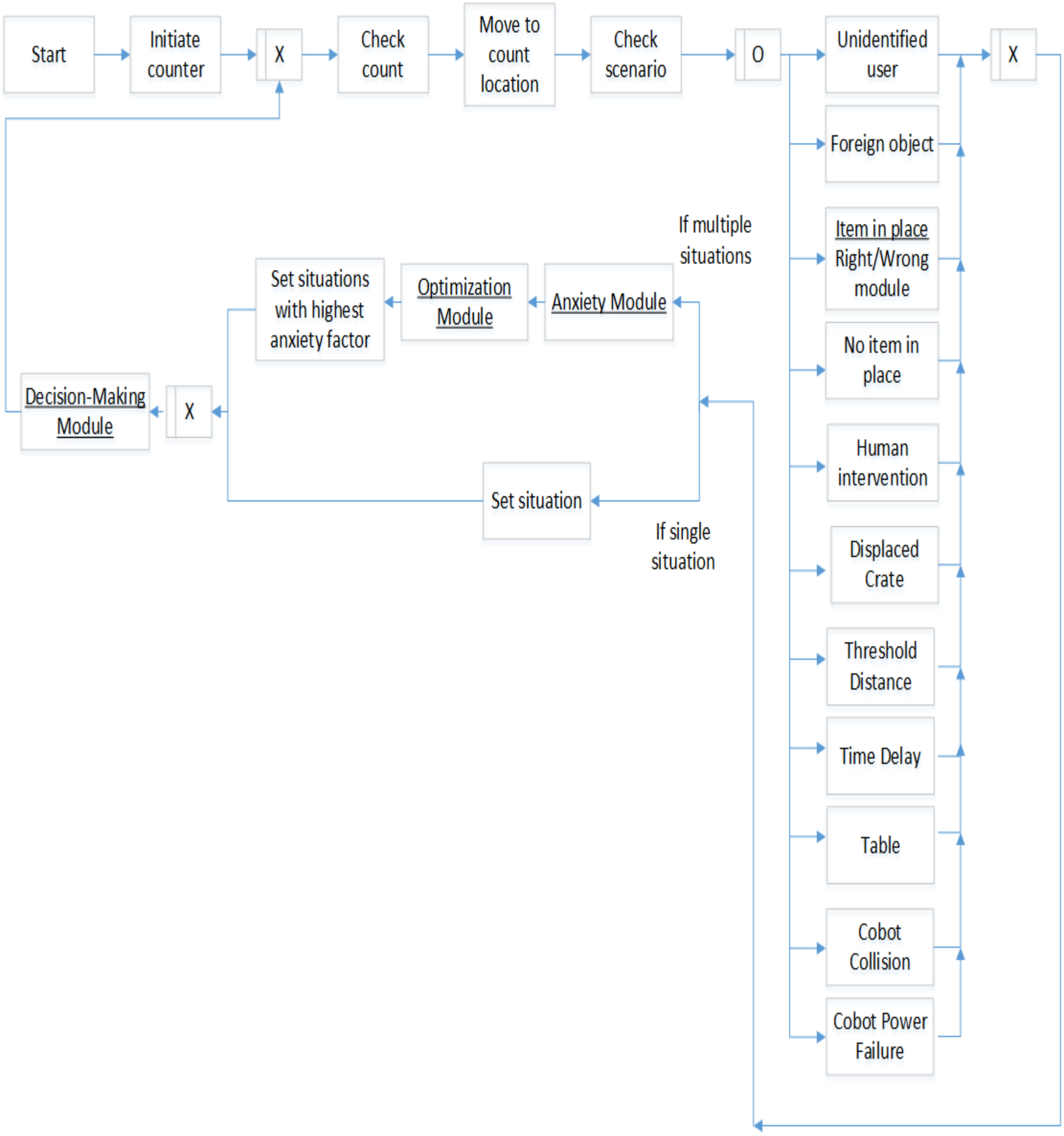


FIGURE 6.7: Main Module for Case 1.

The contingencies to handle other situations are also looked after by the decision-making module Fig. 6.8. The logic in the figure represents what actions are to be performed, whereas which resource must handle the task is decided on the recommendation of the optimization module. For understanding, the tasks which are to be performed by the human operator only are shown specifically in the diagram. The actions of the cobot are implemented through the cobot's software, PolyScope. The software provides leverage to designate waypoints to the cobot for each contingency and the count for the intended situation.

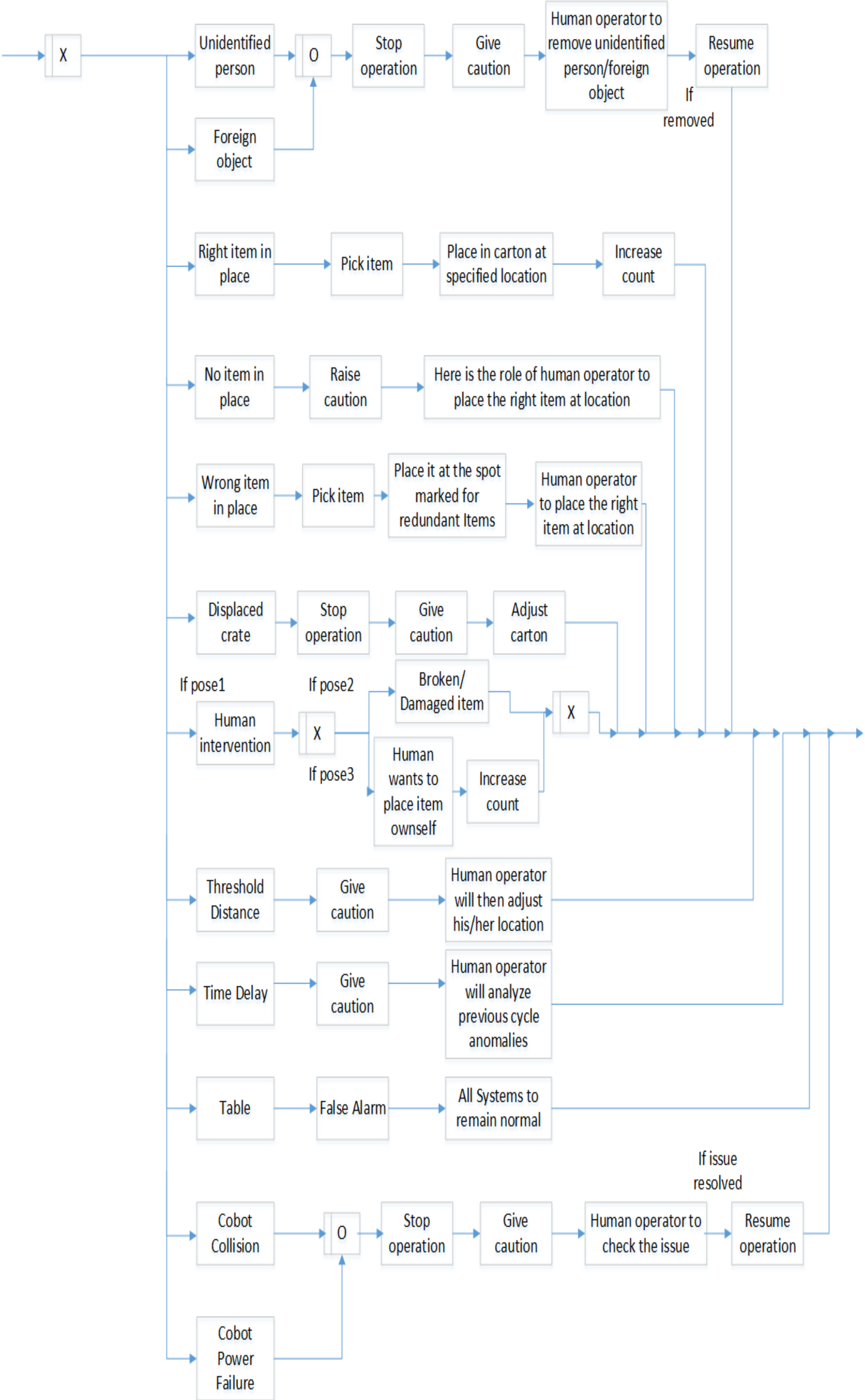


FIGURE 6.8: Decision-Making Module for Case 1.

The item in place module, Fig. 6.9, checks whether the right or wrong item is in place. The module verifies it through object detection and the item count. If some other item or the item not in a sequence is in place, the module adopts the contingency plan through the decision-making module; otherwise, it works as per the intended situation.

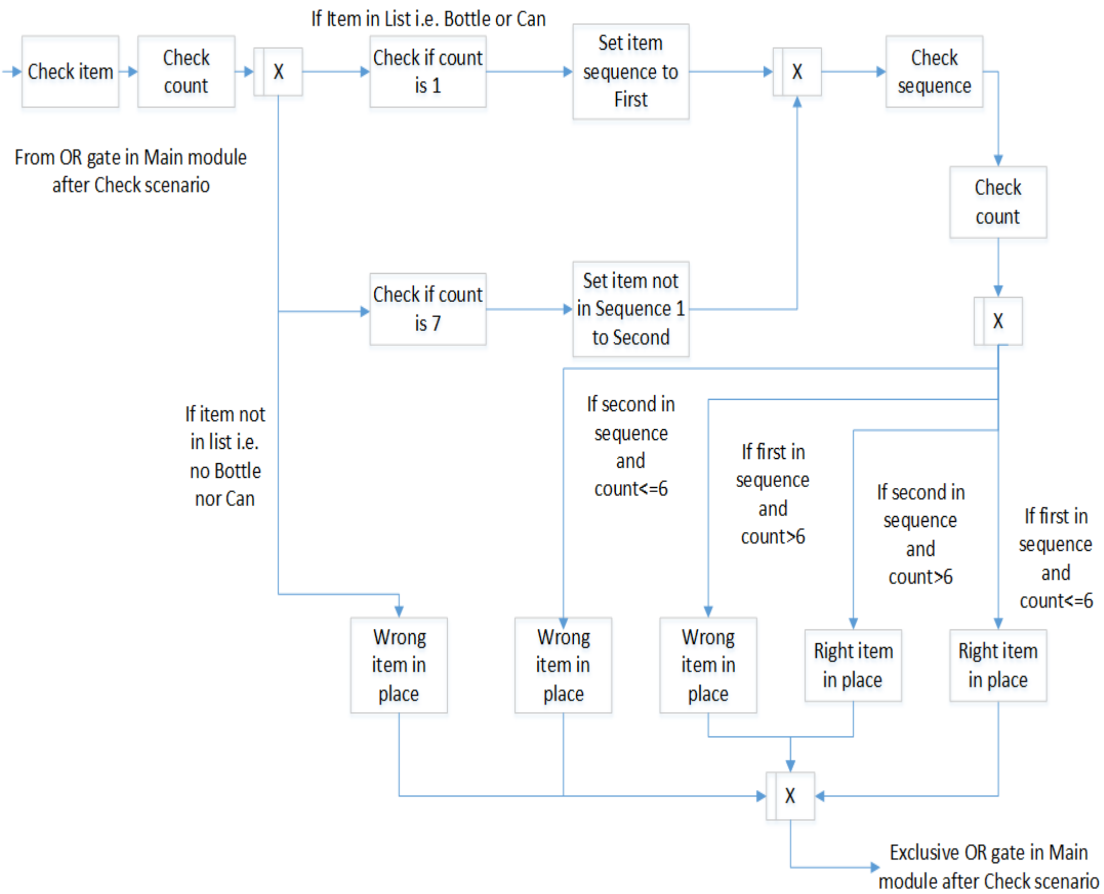


FIGURE 6.9: Item in Place Module for Case 1.

The decision-making module decides the contingencies for the identified situations through actions performed by the resources. The actions are either performed by the cobot or the human supervisor in our scenario, which is dependent on the specific role assigned to the resource for a particular case.

The roles assigned to the situations are: in case of right item the robot will pick and place the item at designated location, the human can do so but the preference is given to the robot; in case of wrong item the robot will pick the item and place it at the spot dedicated for them, the count however, will not be increased and the human has to place the right item at the location; in case of no item in location, the robot moves to the next location and the human places the item at the drop point; in case the human operator feels to interfere may be due to any anomaly in the process or defected item, he may drop the item at the drop point or the wrong item spot, the count will then be incorporated by checking the human pose when doing action; in case of displaced crate, the robot adjusts it by pushing it to the fixed enclosure and if the robot is not available then the human performs it; in case unidentified person enters the workspace, the human has to remove it from the area, a caution is displayed on the screen for the human to perform this action; similarly if a foreign object appears in the workspace, a caution is raised to the human to remove the object from the workspace, in both the last two cases the robot stops action until the human presses the button for resume operation; in case of obsession, none of the resources perform any action and perform the task as intended; in case of time delay and threshold distance is breached, a caution is given to the human operator to analyze and adjust accordingly; in case of cobot power failure, the human checks the reason, rectify it and resume the operation, however, the whole system is to remain at stand still; similarly in case of cobot collision, the whole system comes to stop and the human checks, resolve the issue, and then resume the operation.

If we may analyze, we see that all the actions are interlinked with the variables assigned in Table 6.3 and Table 6.4. The experts actually decide the values of the variables based on experience and consultation.

6.6 Results

Two machine vision cameras and a proximity sensor were used for the assessment of the situations and to detect changes in the scenario. On detection of the right item from the camera installed with the gripper, the item will be placed by the cobot at the dedicated place in the crate. On detection of the wrong item, the item will be picked up by the cobot and placed at a spot dedicated to redundant items. The vacant space will then be filled by the operator, and the cobot will move to the specific location. At every next location, the item is checked to determine whether right or wrong. In case no item is detected, the human will place the item at the designated location, and the cobot will then move to the next location. The system also requires protection from collisions like unidentified persons or any foreign object in the workspace. These situations will be detected through object detection techniques through camera input. On detection of any from both situations, the system will be stopped, and a caution is raised to the operator, who then has to remove the object or the person from the workspace; until then, the system will not resume. The dedicated operator is identified by the marked helmet he is wearing. The object detection of the operator through a distant camera and the items through a camera installed on UR5 gripper are shown in Fig. 6.10.

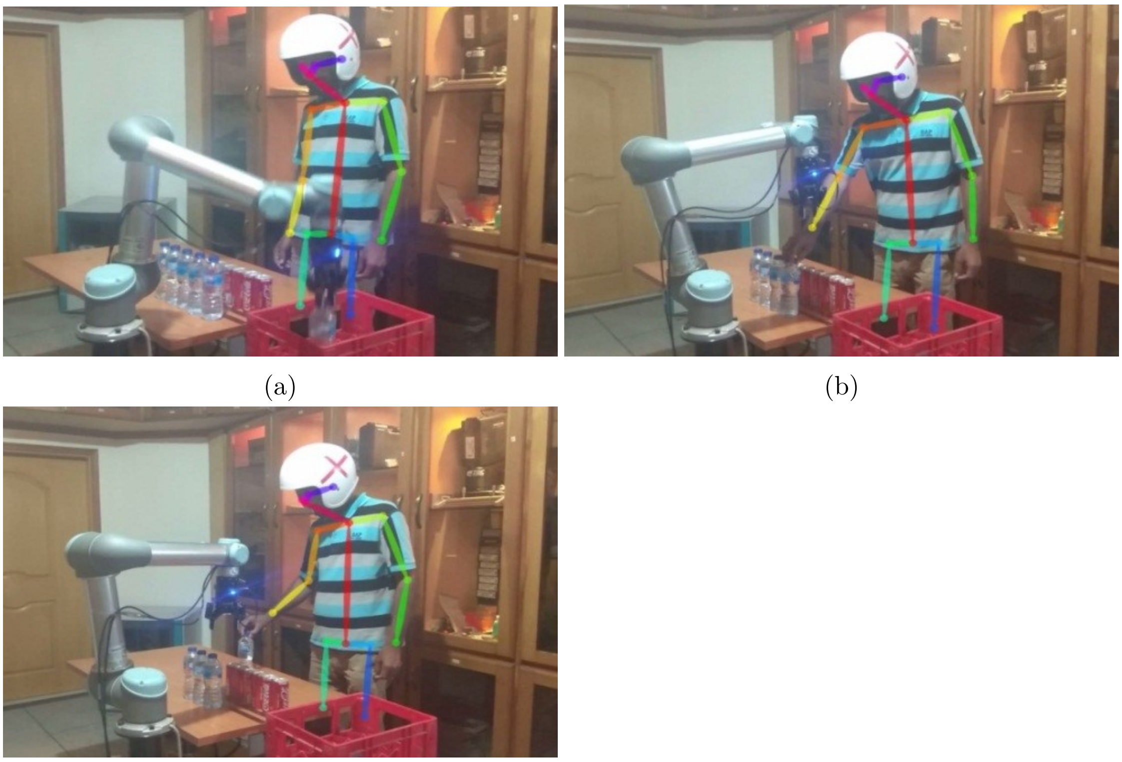
(a) (b)

FIGURE 6.10: Pictures showing Object Detection; (a) Detection of Operator; (b) Detection of Bottles.

The bounding boxes around the objects show the accuracy of a match with which the objects are detected by trained YOLOv3 [166]. Our object detection algorithm was not only trained for the detection of objects used in the scenario but also for the day-to-day general objects.

To judge the unforeseen, serious nature impacts are defined in the logic diagram, which is 'power failure of the cobot' and 'collision of the cobot'. The system will stop the operation, a caution will be raised by the system for the human operator, and the operation will not resume until the issue is resolved by the human supervisor. There could be different interventions by the human operator. The human intervention can be due to two situations; one is that the operator finds the item damaged/broken, and the second is that the operator assesses the cobot may not be able to pick up the object due to its intended movement/the placement of the object is not right. In the first case, the item will be placed by the operator at the damaged/broken items spot; however, the count will not be increased, and the cobot will return to the same location upon completion of the task. In the second case, the operator will pick the item himself/herself and place it in the crate, where the control system will increase the count so the cobot may move to the next location. The combination of two pose detections will verify these two cases, i.e., if pose 1 and pose 2 are in combination, then a damaged/broken item is removed, and if pose 1 and pose 3 are in combination, then the operator has interfered and placed the item in carton either to improve efficiency or bypass imminent error in the system. Pose 1 is the pose of the operator when picking items from the stage. Pose 2 is the pose of the operator when placing broken/damaged items at their spot. Pose 3 is the pose of the operator while placing an item in the crate, as mentioned in the second case. The particular pose of the operator is detected via a camera installed above the setup, covering the workspace. Detection of different poses of the operator through Open Pose [167] is shown in Fig. 6.11.

In case the crate is displaced from the dedicated location, it can be detected through a proximity sensor. The cobot will move the crate to its proper place in case of displacement by pushing it to the fixed enclosure. Considering the social impact situations, first of all, if the 'threshold distance' is breached, i.e., the distance between the cobot & the human has decreased, a caution is raised, and the operator must adjust his location. Similarly, caution is raised for the 'time delay' in the work cycle, and the operator must analyze the anomalies in the previous cycle. In case the obsession is declared and detected, the system will remain normal.

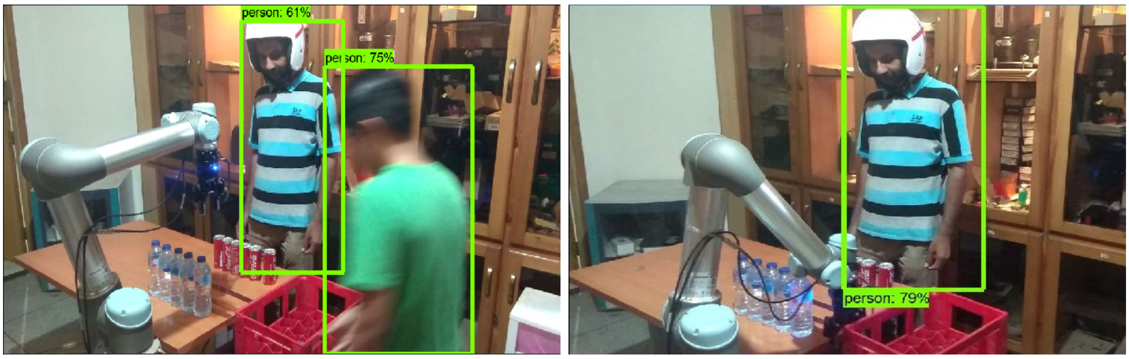


(a) (b) (c)

FIGURE 6.11: Detection of Various Poses (a) Normal pose, (b) Pose1, and (c) Pose2, of operator.

Our system is capable of detecting multiple situations. In case any two or multiple scenarios are detected/overlapped, the action to be taken is decided based on the priority set by the CPS. The priority, in this case, is set by the anxiety factor of CPS, whose indexing is explained earlier, and subsequently, the resources are allocated through an optimization algorithm.

As an example, two individual scenarios are shown, i.e., a displaced crate and an unidentified person's entry. An unidentified person is shown entering the workspace and has mistakenly displaced the crate from its original position (see Fig. 6.12). The unidentified person is detected through an object detection algorithm, whereas the proximity sensor gives the output of the displaced crate to the main program. As the two inputs are detected, the algorithm finds the anxiety factor of each situation. The optimization algorithm decides the resource 'human operator' for the unidentified person and the resource 'cobot' for the displaced crate. Based on the decision given by the decision-making module, the algorithm chooses the action for an unidentified person scenario, and the cobot stops working initially. Until the unidentified person is removed from the workspace by the operator, the cobot will not resume operation. The signal is then given to PolyScope for the displaced crate situation; the cobot resumes operation and moves the crate to its original location.



(a) (b)

FIGURE 6.12: Detection of Multiple Situations and Actions, (a) Detection of Unidentified Person and System Halt, (b) Detection of Displaced Crate and Crate being aligned by the Cobot.

6.6.1 Test Case

Two complete cycles, i.e., packaging of two crates/24 items, are considered for the test case. A detailed list of situations encountered at each iteration throughout the two cycles is shown in Table 6.5. Individual/total severity is calculated by the system, and resource assignments are shown accordingly.

The important situations are discussed here. The situations that appeared at the iterations are mentioned alongwith the decision taken by the system for each. At the 1st iteration, a foreign object, i.e., a table, appeared with the right item situation. The human supervisor assessed the table; as not an obstruction to the cobot's motion and declared it an obsession for subsequent iterations.

At the 2nd iteration, the table again appeared with the right item situation; however, considered an obsession this time.

Table 6.5: Situations vs. Resource Assignment

It.	***Situations***	***Individual Severities (a)***	***Resource Assignment***	***Total Severity***	***Decision Time (s)***
1	Foreign Object, Right item	62.4, 24	Human, Cobot	86.4	0.03
2	Table, Right item	0, 24	Cobot	24	0.02
3	Table, Right item	0, 24	Cobot	24	0.02
4	Table, Right item	0, 24	Cobot	24	0.02
5	Table, Right item	0, 24	Cobot	24	0.02
6	Table, Right item	0, 24	Cobot	24	0.02
7	Unidentified Person, Table, Right item	57.8, 0, 24	Human, Cobot	81.8	0.02
8	Table, Right item	0, 24	Cobot	24	0.02
9	Table, Right item	0, 24	Cobot	24	0.02
10	Table, Right item	0, 24	Cobot	24	0.02
11	Displaced Crate, Table, Right item	48.6, 0, 23	Cobot, Human	71.6	0.03
12	Table, Right item	0, 24	Cobot	24	0.02
13	Table, Wrong item	0, 40	Cobot	40	0.03
14	Table, Right item	0, 24	Cobot	24	0.02
15	Table, Right item	0, 24	Cobot	24	0.02
16	Table, Right item	0, 24	Cobot	24	0.02
17	Table, Right item	0, 24	Cobot	24	0.02
18	Table, Right item	0, 24	Cobot	24	0.02
19	Table, Right item	0, 24	Cobot	24	0.02
20	Table, Wrong item, Threshold Distance	0, 40, 6.3	Cobot, Human	46.3	0.02
21	Table, Right item	0, 24	Cobot	24	0.02
22	Table, Right item	0, 24	Cobot	24	0.02
23	Table, Right item, Cobot Collision	0, 24, 109.2	Cobot, Human	133.2	0.02
24	Table, Right item	0, 24	Cobot	24	0.02
25	Table, Right item	0, 24	Cobot	24	0.02
26	Table, Right item	0, 24	Cobot	24	0.02

At the 7th iteration, an unidentified person entered the workspace while the 'Right item' situation was encountered along with the table. The system chooses the human for the 'Unidentified person situation' and the cobot for the 'Right item situation'.

At the 11th iteration, a 'Displaced crate' situation appeared with a 'Table' and the 'Right item' situation. The system chooses the human for the 'Right item' and the cobot for the 'Displaced crate'. Human is chosen this time for the right item as the matching score for the combination (cobot, displaced crate) is more than (cobot, right item).

At the 13th iteration, a wrong item appeared along with the table. The system chooses the cobot to handle the wrong item situation.

Three situations that appeared at the 20th iteration were 'Wrong item', 'Threshold distance', and 'Table'. The system chooses the two most prior situations, i.e., the wrong item and threshold distance and assigned resources cobot and human, respectively.

In the 23rd iteration, the 'Right item' situation appeared with the 'Table'; however, during the cobot's operation, the human supervisor sneezed and contacted the cobot. This is the 'Cobot Collision' situation, and the system was bound to stop. The system assigned the human to the 'Cobot Collision' and the cobot to the 'Right item' situation. However, the cobot would not move until the human gives a clear to the system as indicated in the decision-making diagram (Fig. 6.8). The Right item situation will then be activated on the 'resume operation' command.

The maximum time taken to decide on a scenario is shown in Fig. 6.13, along with the anxieties for each iteration. The system took 0.03s at maximum to decide upon the high-impact situations and their assignment to the resources.

6.6.2 Discussion

Now the proposed method is compared with some contemporary systems in the field developed in the recent past. The systems are compared in terms of the safety parameters and the system's situational handling.

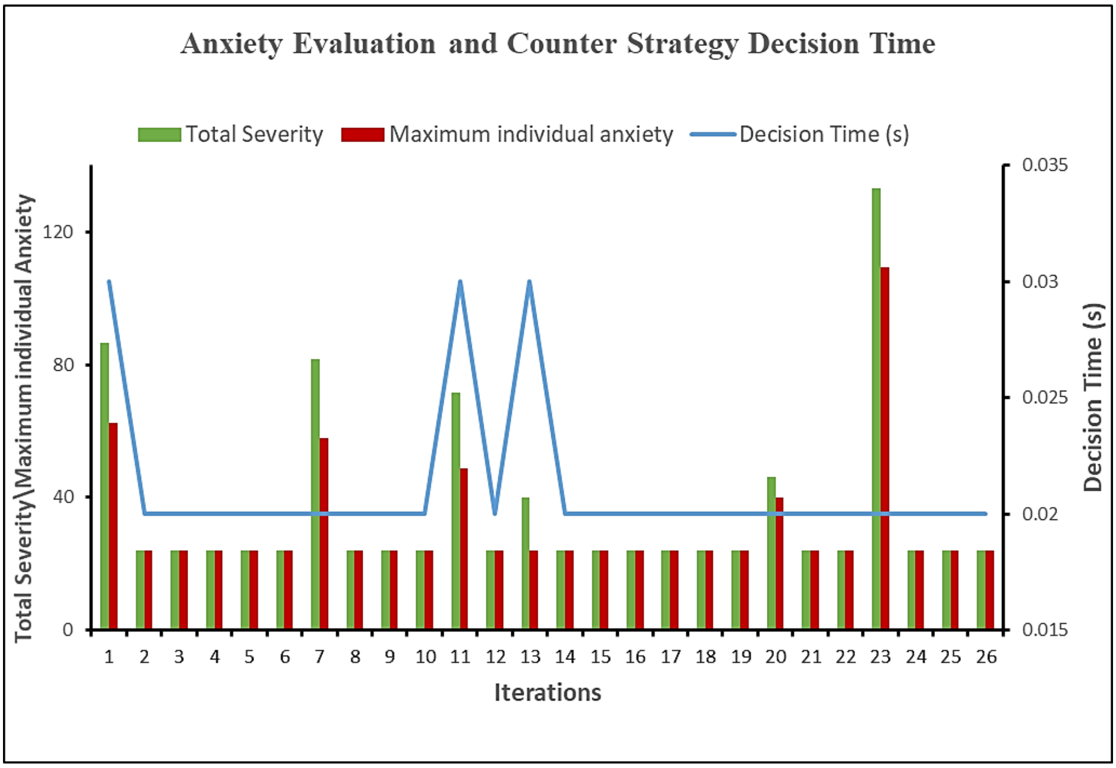


FIGURE 6.13: Anxiety Evaluation and Counter Strategy Decision Time.

It can be seen from Table 6.6 that the major contribution of the existing systems was to provide collision avoidance using different techniques. This assures one aspect of physical safety as seen in works of [17],[16],[107], and [122]. It can also be noted that these systems were catering to only one situation for which the system was designed. The minimal work for psychological safety assurance during HRI can be seen in the works of Bekele et al. [148] and Dragan et al. [19]. These systems were also designed to handle a single situation. The novel concept of legibility was given in [19]; the task assigned to the robot varies with the human intent, which is assessed during HRI. The situation confronted was single; however, the variation in approach to perform the task makes it hybrid. The outcome achieved was an early response and confidence to counter the confronted situation. Then, the system presented in [7], [149] assures both physical and psychological safety to the confronted single situation. The system presented in [149] also ensures bi-directional intent to assure legibility.

Table 6.6: Comparison of Proposed Method with Contemporary Systems

Authors	***Technique***	***Safety Parameters***	***Situation Handling***
Flacco et al. 2012 [17]	Collision avoidance using depth space	Physical Safety for safe HRC	Caters single situation
Morato et al. 2014 [16]	Kinect and sphere-based simulation model for collision avoidance	Physical Safety for safe HRC	Caters single situation
Safeea and Pedro, 2019 [107]	Laser scanner and Inertial measurement unit (IMU) based model for collision avoidance	Physical Safety for safe HRC	Caters single situation
Sharkawy et al. 2020 [122]	Neural network and Torque-sensing for collision detection	Physical Safety for safe HRC	Caters single situation
Bekele et al. 2014 [148]	Physiological monitoring for adaptive HRI	Psychological safety	Caters single situation (difficulty level)
Lasota et al. 2014 [7]	Monitoring of separation distance for collision avoidance and speed adjustment	Physical and psychological safety for safe HRC	Caters single situation
Dragan et al. 2015 [19]	Intent awareness for fluent HRC	Psychological safety (Legibility)	Cater single Hybrid situation
Chadalavada et al. 2020 [149]	Bi-directional intent communication using spatial augmented reality (SAR)	Physical and psychological safety for safe HRC	Cater single situation
Islam et al. 2019 [168]	Situational awareness through visual cues and indexing of multiple situations (Anxiety) for safe HRI	Physical and psychological safety for safe HRC	Caters multiple situations in order of priority (Handle highest priority situation at one time) Non-optimized Broad technique for indexing situations

Proposed Method	Connective Framework for Anxiety Mitigation by evaluation matching score (Anxiety factor)	Ensure both physical and psychological safety of the whole CPS for enhanced productivity (including Legibility)	Caters multiple situations at a time Any number of situations and resources can be incorporated Optimized Rationale-based indexing of situations

In our initial endeavor [168], despite ensuring physical and psychological safety, the approach caters to multiple situations; however, one situation was handled at a time in terms of priority. The anxiety of the system was ascertained to assess the priority of situations. The indexing of anxiety was carried out through a more generic approach which lacks a rationale for establishing different levels of anxiety. The approach also lacked optimization as different available resources were not utilized to cater to multiple situations, as only one situation was handled at a time. The situational awareness was acquired through cost-effective and off-the-shelf available sensors. The previous technique supports the current method, however, a logical approach having a connection to different types of situations is presented in the current approach. The technique makes it easy to differentiate and prioritize situations with varying anxiety levels based on knowledge acquired from nature. The current method employs all available resources to relieve the current state of anxiety, hence the current approach is optimized. In the considered case, two resources are available; we can see both are employed simultaneously to tackle the braved situations. The technique provides leverage to incorporate any number of resources by modifying the equations in the optimization algorithm, which decides on situations by calculating matching scores of corresponding resources vs. situations. There are times when only one resource is suitable to handle several situations. At this stage, the first situations with higher anxiety will be addressed, and the remaining will be catered for sequentially. For example, suppose two situations are encountered, i.e., 'Unidentified person' and 'Cobot

Power Failure'. In that case, the resource 'Human' is the only suitable resource to handle both situations one by one in terms of anxiety.

It is also observed that social cues ensured legibility for both the robot and the operator. In the case of the robot, it is ensured by object detection, displacement sensing, and pose estimation techniques, whereas in the case of the operator, through threshold distance, time delay, and other cautions mentioned in the logic diagram. It is also notable to observe the time taken by the setup in deciding on the braved situations. The system took 0.03s to decide upon the high-impact situations and their assignment to the resources. This shows that the method is not time-intensive, which can accrue benefits by combining human intelligence with AI techniques. It is seen from the results that the proposed method provides flexibility to the CPS by handling multiple situations at a time in an optimized manner. The method as a whole improves the decision-making of a CPS facing a complex scenario.

Chapter 7

Experimental Validation 2

In this chapter, the proposed framework is applied to a case study of a manufacturing scenario. An example of automotive industry parts assembly is considered, as shown in Fig. 7.1. The scenario involves a cobot and a human operator performing tasks depending on information through multiple sensors integrated with a collaborative CPPS. Different parts are manufactured at workstations and arrive at an assembly center. The outer case arrives through a conveyor at the center, where a cobot picks two gears in a sequence and places them on the case for assembly. A human supervisor performs assembly by aligning gears, placing the top plate, and tightening screws. In addition to the assembly process, the supervisor is also monitoring operations for anomalies and wrong operations, i.e., he is in both collaborative and supervisory roles. As the assembly process completes, the supervisor pushes the button for the next one, and the cobot moves accordingly. The assembly is then transferred for packaging through the conveyor. The experiment is designed to perform four assemblies in a cycle. The human supervisor is also responsible for corrective actions on wrong item arrival, wrong sequence, or absence of item from the location. This whole process is referred to as a standard procedure.

Five modules were formulated to represent the case: the main module, item in place module, anxiety module, optimization module, and decision-making module. The main module holds the other modules, keeps count of the operations in the cycle and performs the intended task. It looks for the situations during each iteration and ascertains the matching score through the anxiety module in case multiple situations emerge. The optimization module then assigns the resources to the situations by identifying the highest matching score through MIP using equations (5.1), (5.2), and (5.3). The decision-making module then decides the contingencies for the identified situations. The actions are either performed by the cobot or the human supervisor. The item-in-place module is specific to this case that checks whether the right or wrong item is in place through object detection and item count.

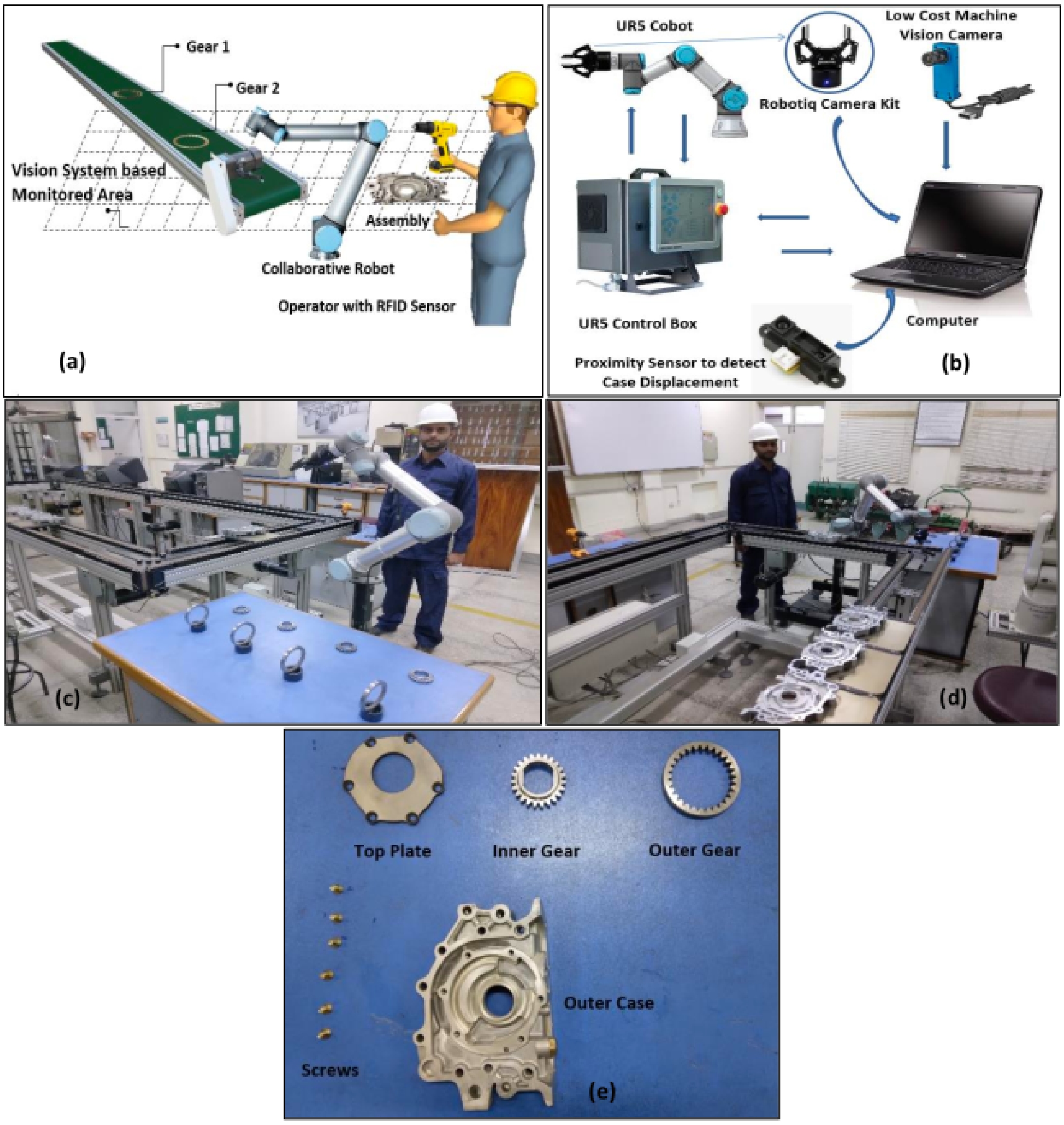


FIGURE 7.1: Experimental Case 2, (a) Scenario; (b): Interface; (c): Setup of Considered Case, (d): Setup from Different Angle; (e): Assembly.

7.1 Scenario's Anxiety

There may be situations when the process may not proceed as intended, and it may face various unwanted and unforeseen situations. To cater to this, different situations were anticipated for both the cases that can emerge during a cycle; these include the intended situation as well as unwanted situations.

The considered situations are: Right item: the main task/intended situation i.e. the right items (gears) are in place for pick and place operations/assembly; the Wrong item: the item at the work location is either not in list or wrong in sequence; No item: when no item appears at the work location; the Human interference: when operator interferes in any task at any location, as he finds that the robot may not be able to perform the task or he finds any anomaly; Displaced Case: the operation of assembly cannot be completed when the case is displaced from the designated location; Unidentified person: any unknown person in the workspace is a hazard to the system and to himself; Foreign object: any object not required in the workspace is also a hazard to the system; Obsession: any situation actually not affecting but disturbing the outcome of the system; generally it is established after few iterations when the operator realizes that the situation is a false alarm e.g. in the case study the object detection algorithm detects the table on which the items are placed as a foreign object; Time delay: the completion time variance in the intended operation; Threshold Distance: the breach of minimum distance that is established to be safe for collaboration between the human and the robot; Cobot Power Failure: in case the cobot stops work due to power failure; Cobot Collision: in case the cobot collides with the human operator. These situations and their anxiety index calculated through Ishikawa are shown in Table 7.1.

There are two resources, a human and a cobot, and twelve situations are anticipated. The matching score (a_{rs}) is estimated prior to the process for both the resources vs. the twelve situations. The severity, categories, the value of anxiety for the cases, were evaluated and the anxiety factors were then calculated. These were then fed into the central database. The variables to estimate these were thoroughly deliberated upon by the experts. The data set generated is shown in Table 7.2.

TABLE 7.1: Possible Situations and their Anxiety Index

Ser	***Situation***	***Anxiety Level***	***Index***	***Severity(I)***
1	Cobot Power Failure	11	1	100
2	Cobot Collision	10	0.91	91
3	Foreign Object	9	0.81	81
4	Unidentified Person	8	0.72	72
5	Human Intervention	7	0.63	63
6	Displaced Case	6	0.54	54
7	Wrong Item in Place	5	0.45	45
8	No Item in Place	4	0.36	36
9	Right item in Place	3	0.27	27
10	Threshold Distance	2	0.18	18
11	Time Delay	1	0.09	9
12	Obsession	0	0	0

If we analyze the Table 7.2, we see that the first basis for the resource assignment is the resource suitability variable Q; if it is zero, the resource cannot be assigned to the situation. The second basis is the task variable t; in our case, 0 is assigned to the preferred resource. Hence the resource having t=0 is assigned if it is not already committed and if the resource suitability variable is not '0'. The third basis is the preference variable p, the situation with the higher value will be addressed first by the two resources, and the remaining will be addressed subsequently after the disposal of the initial ones.

The cumulative effect of all these variables is the anxiety factor. The table clearly depicts when any situation appears, which out of two resources can be assigned, which the prior resource is, and which situation will be addressed first.

Table 7.2: Data Set

Sit.	***I***	***Cat.***	***A***	***t***		***p***		***Q***		***a***	
				Human	***Cobot***	***Human***	***Cobot***	***Human***	***Cobot***	***Human***	***Cobot***
Right item	27	G	20	1	0	4	4	1	1	23	24
Wrong item	45	K	38	1	0	6	6	1	1	43	44
No item	36	K	34.4	0	1	5	5	1	0	39.4	0
Human interference	63	K	45.2	1	0	8	8	0	1	0	53.2
Displaced case	54	K	41.6	1	0	7	7	1	1	47.6	48.6
Unidentified person	72	K	48.8	0	1	9	9	1	0	57.8	0
Foreign object	81	K	52.4	0	1	10	10	1	0	62.4	0
Obsession	0	O	0	1	1	1	1	0	0	0	0
Time delay	9	N	1.8	0	1	2	2	1	0	3.8	0
Threshold distance	18	N	3.6	0	1	3	3	1	0	6.6	0
Cobot Power Failure	100	P	100	0	1	12	12	1	0	112	0
Cobot Collision	91	P	98.2	0	1	11	11	1	0	109.2	0

7.2 Situational Awareness

Different situational awareness techniques were used to detect the listed situations. The object detection technique detects a right item, a wrong item, no item, an unidentified person, and foreign objects. YOLOv3 [166] is trained to detect gears along with day-to-day general objects. RFID sensor in the helmet is used to identify the authorized operator, an IR proximity sensor to detect the displaced case, impact sensors in the cobot to detect cobot collision, a power sensor to detect cobot power failure, and the clock to gauge the time delay.

The human interventions are detected through a pose estimation algorithm which takes the feed through a camera installed above the workspace. Open pose [167] is used to detect different human poses. The separation distance between the cobot and the operator is used to evaluate the threshold distance; this was done by calculating the distance between the center of the cobot and the operator detection bounding box. A machine vision camera is placed to detect the objects, which are two different types of gear. The gears were trained for detection using an online platform Roboflow [169], and subsequently used in YOLOv3. The module adapts the contingency plan if the right item is not in place through the decision-making module.

7.3 Optimization Criterion for the Case

Twenty four decision variables are stated to formulate the optimization criterion for this case, as there are twelve situations and two resources. Then the situation constraints were defined using equation (5.1); either 'resource 1' (Human) or 'resource 2' (Cobot) can be assigned to a situation. Similarly, the resource constraints using equation (5.2) were defined. In this way, a total of 14 equations were formulated. Consequently, the objective function incorporating the matching scores for the situations was developed as stated in (5.3). Situations constraints for the situations were defined as:

$$r \in R \quad \sum_{r=1}^{R} X_{rs} \leq 1 \tag{7.1}$$

$R = (1, 2)$

$S = (1, 2, ..., 12)$

The constraint for resource 1 (Human) is:

$$X_{11}+X_{12}+X_{13}+X_{14}+X_{15}+X_{16}+X_{17}+X_{18}+X_{19}+X_{110}+X_{111}+X_{112} \leq= 1 \quad (7.2)$$

The constraint for resource 2 (Cobot) was defined as:

$$X_{21}+X_{22}+X_{23}+X_{24}+X_{25}+X_{26}+X_{27}+X_{28}+X_{29}+X_{210}+X_{211}+X_{212} \leq= 1 \quad (7.3)$$

The matching scores for the situations to formulate the objective function were defined. Consequently, the objective function incorporating the matching score for the situations is:

$$s \in S \quad r \in R \quad \text{Maximize} \sum_{s=1}^{S} \sum_{r=1}^{R} a_{rs} X_{rs} \quad (7.4)$$

$R = (1, 2)$
$S = (1, 2, ..., 12)$

7.4 Decision-Making Logic for the Case Study

The decision-making module decides the contingencies for the identified situations through actions performed by the resources. The actions are either performed by the cobot or the human supervisor in our scenario, which are actually dependent on the specific role assigned to the resource for a particular case.

The roles assigned to the situations are: in case of right item the robot will pick and place the item at designated location, the human can do so but the preference is given to the robot; in case of wrong item the robot will pick the item and place it at the spot dedicated for them, the count however, will not be increased and the human has to place the right item at the location; in case of no item in location, the robot moves to the next location and the human places the item at the drop point; in case the human operator feels to interfere may be due to any anomaly in the process or defected item, he may drop the item at the drop point or the wrong item spot, the count will then be incorporated by checking the human pose when doing action; in case of displaced case, the robot adjusts it by pushing it to the fixed enclosure and if the robot is not available then the human performs it; in case unidentified person enters the workspace, the human has to remove it from the area, a caution is displayed on the screen for the human to perform this action; similarly if a foreign object appears in the workspace, a caution is raised to the human to remove the object from the workspace, in both the last two cases the robot stops action until the human presses the button for resume operation; in case of obsession, none of the resources perform any action and perform the task as intended; in case of time delay and threshold distance is breached, a caution is given to the human operator to analyse and adjust accordingly; in case of cobot power failure, the human checks the reason, rectify it and resume the operation, however, the whole system is to remain at stand still; similarly in case of cobot collision, the whole system comes to stop and the human checks, resolve the issue, and then resume the operation.

If we may analyze, we see that all the actions are interlinked with the variables assigned in Table 7.2. The experts decide the variables' values based on experience and consultation.

The five formulated modules are similar to the previous case: the main module, item in place module, anxiety module, optimization module, and decision-making module. The anxiety and optimization modules comprise codes for calculating anxiety, anxiety factors, and optimization algorithms. The main module, item-in-place module, and decision-making module contains the logic for decision making. The decision-making diagrams shows the contingencies to be performed when a situation emerges. The resources to handle the contingencies are decided on the recommendation of the optimization module. The actions are then performed by either the cobot or the human supervisor as discussed above.

Logic diagrams for the main module and item-in-place module, are shown in Fig. 7.2 and Fig. 7.3 respectively.

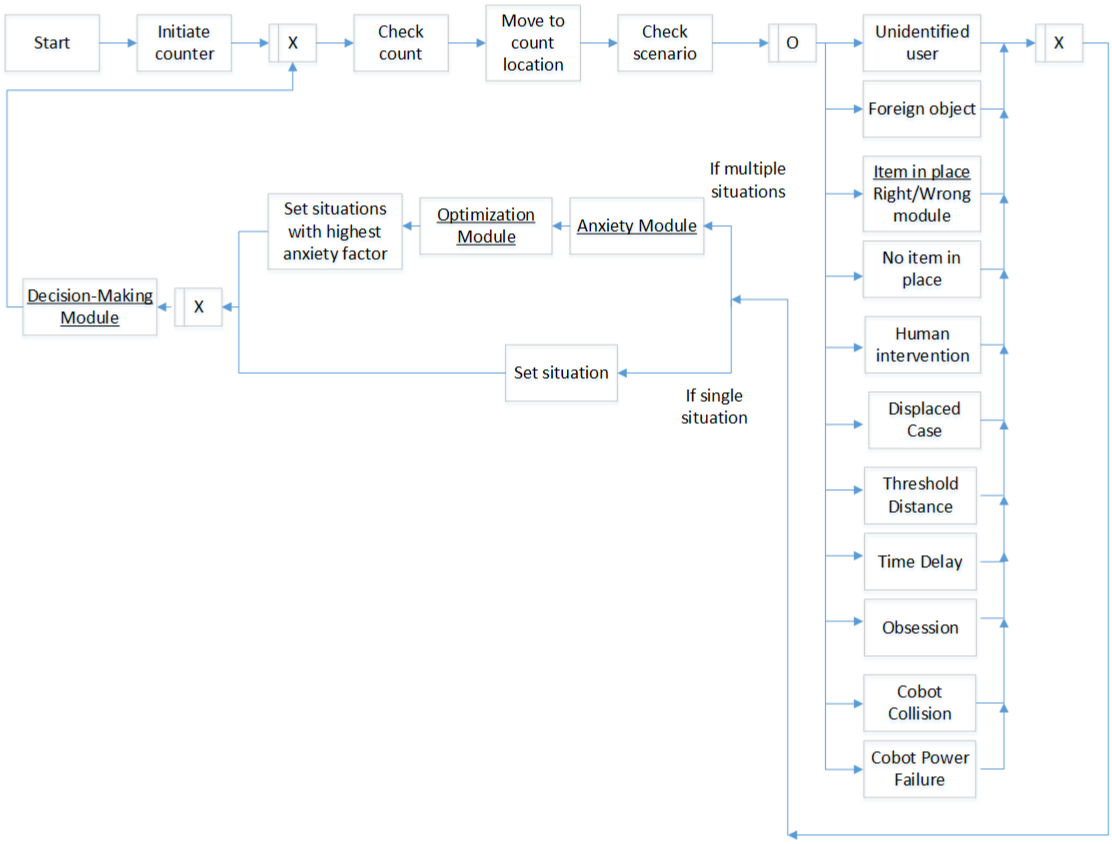


FIGURE 7.2: Case Study 2: Main Module.

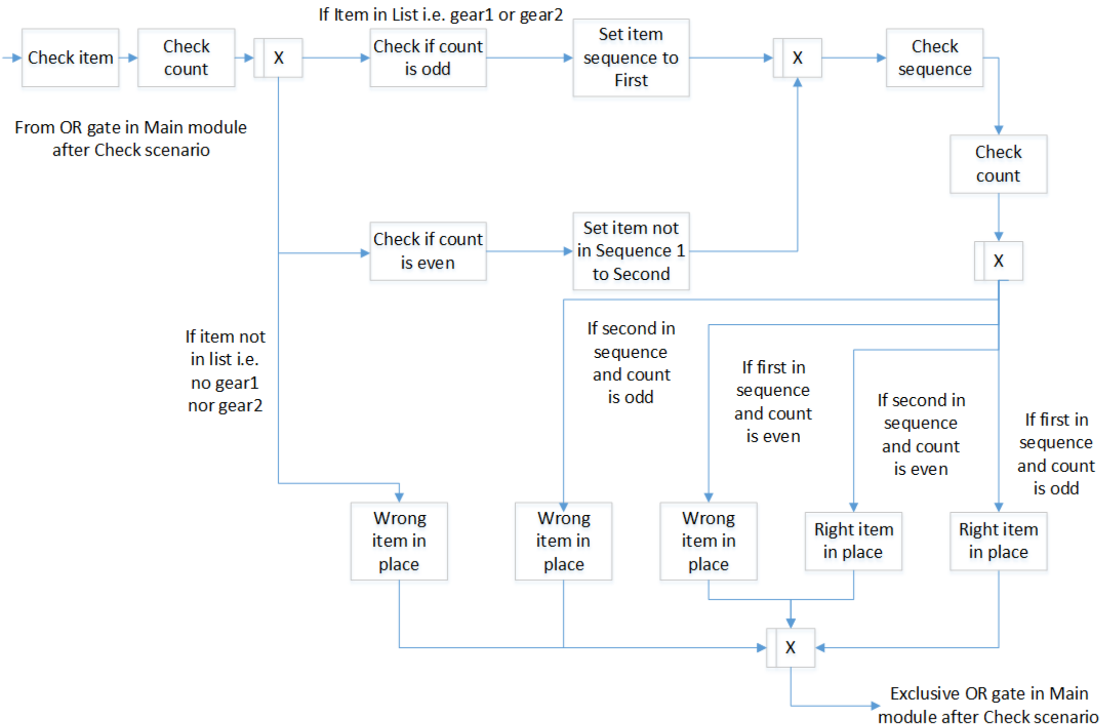


FIGURE 7.3: Item in Place Module for Case 2.

Logic diagrams for the decision-making module is shown in Fig. 7.4.

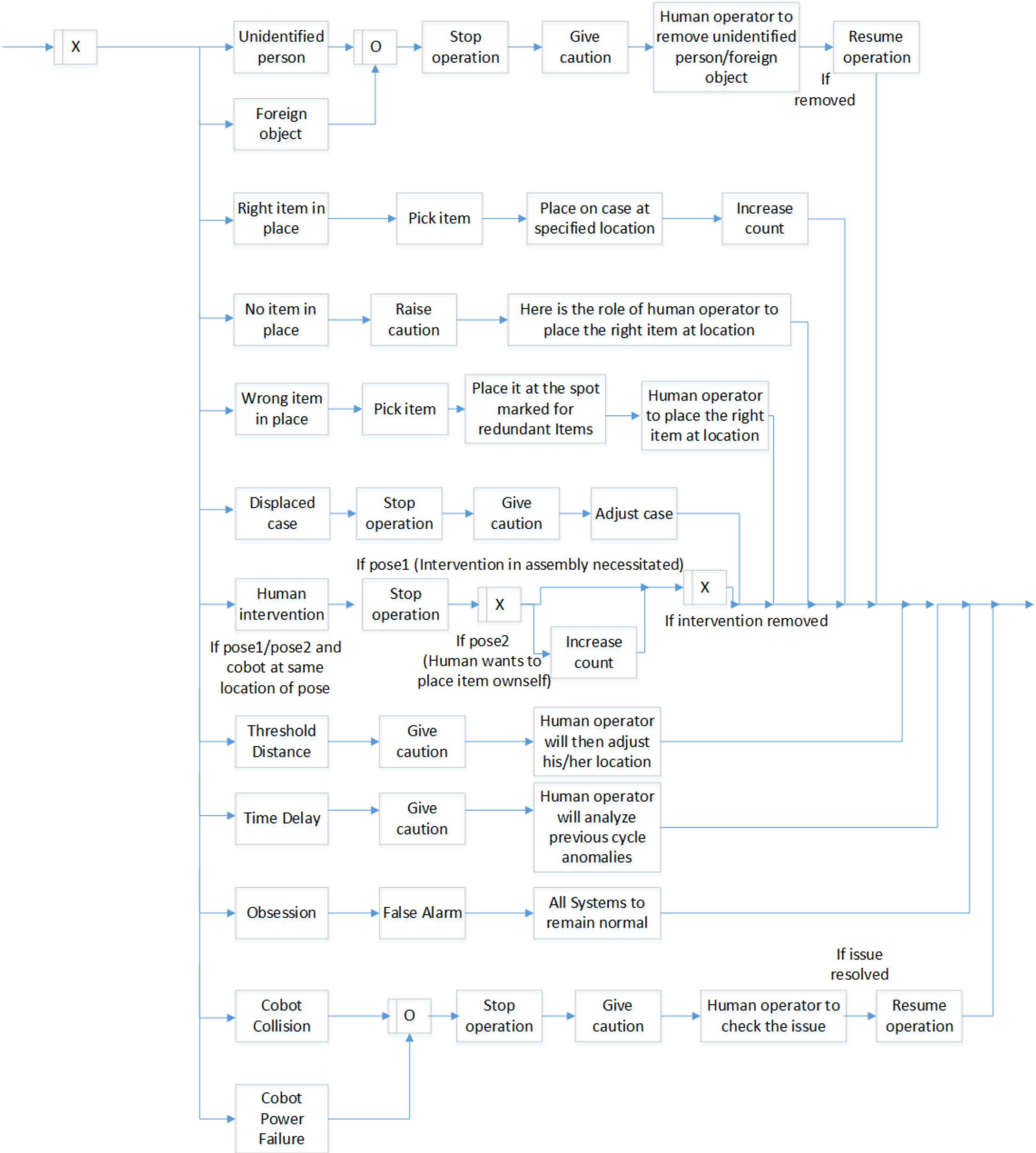


FIGURE 7.4: Decision-Making Module for Case 2.

7.5 Survey

A survey that consisted of participants pooled from university students and faculty was carried out. The ages of the participants range from 19 to 40 years (M = 28.7, SD = 7.73).

The participants were informed before the experiment to continuously monitor the screen for instructions during the operation. Previous research has shown that similar surveys were carried out keeping in consideration metrics proposed by Hoffman and Breazeal [170]. The surveys were based on individual execution times, concurrent time of human-robot motion, and robot and idle human times. These metrics are not valid for this experiment as one stereotype motion is not considered for the completion of the task; rather, uncertainties are catered to that depict the sequence of tasks may be different in every cycle. Therefore relevant metrics are devised which are similar to the work in [15]. The subjects had nominal knowledge of the specifics of the system and were briefed on the assigned task only. A total of 20 subjects participated, the repeated-measure design was considered for the experiment, and the subjects were divided into two randomly selected groups. Two types of conditions were assigned, the first group includes those who first worked with the decision-making design (n = 11), and the second group includes those who worked with the standard design without a decision-making system (n = 9). Before the experiment, the subjects were not informed what condition was assigned and what metrics were being measured. Both quantitative and subjective measures were ascertained. The quantitative measures include the decision time taken to decide on each situation and the accuracy of the process. Based on the questionnaire responses, the subjective measures include perceived safety, comfort, and legibility.

First, both groups executed a training round, during which the participants performed the complete experiment by themselves, without an assistant and the robot, to familiarize themselves with the task. Next, all participants were provided with a human assistant to perform the task collaboratively as would be required to perform with a robot in the subsequent phase, i.e., the 3rd phase. Finally, two task executions were conducted firstly in one condition and later in a switched mode; however, the sequence was different for both groups. A questionnaire is given to participants after each task execution, as shown in Table 7.3. Each participant performed two training sessions with the robot before each task execution to build mental compatibility. To prevent any involuntary bias from the participants, the first task execution was conducted in a way that the participant was unaware of which out of two conditions each participant had been assigned to. Before the conduct of the alternate mode, participants were educated that the system would behave differently during the second phase. The participants were briefed; the robot may take some automated measures, and they are required to monitor instructions on the screen.

Table 7.3: Questionnaires

	Fluency with the Collaborative Robot
1	I trusted the robot to do the right thing at the right time.
2	The robot did not understand how I desired the task to be executed.
3	The robot kept disturbing me during the task.
4	The robot and I worked together for better task performance.
	Perceived safety, comfort, and legibility
5	I felt safe while working with the robot.
6	I trusted the robot would not harm me.
7	The robot moved too drastically for my comfort.
8	The robot endangered the safety of unknown persons in the workspace.
9	I understand what the robot will be doing ahead.

The questions, shown in Table 7.3, were intended to determine each participant's satisfaction with the robot as a teammate as well as his/her perceived safety, comfort, and legibility. A 5-point Likert scale was used for the two questionnaires on which the participants had to respond, strongly disagree to strongly agree for the first questionnaire and much less to much more for the second questionnaire. Based on the dependent measures, the two main hypotheses in this experiment were as follows:

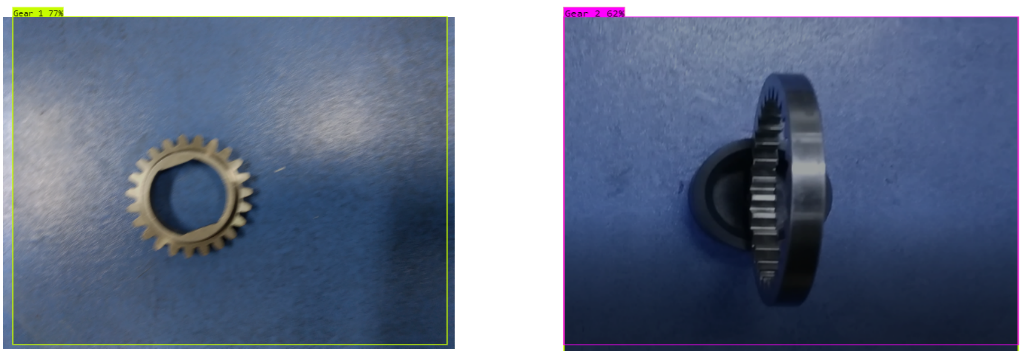
Hypothesis 1: Using a decision-making framework for anxiety will lead to more fluent human-robot collaboration based on timely automated decisions and the accuracy of the approach.

Hypothesis 2: Participants will be more satisfied with the decision-making framework performance while collaborating with the robot and feel more comfortable, safe, and legible compared to a CPPS that uses standard task planning.

The automated decision time cannot be calculated for both conditions as the standard approach does not cater to unprecedented situations; rather, the operator has to stop the system and apply countermeasures. The accuracy of the approach is defined as the number of errors (situations that could not be handled automatically) observed during one cycle divided by the total number of iterations. At least two situations were intentionally generated in each trial to check the system response.

7.6 Results

As stated before, two types of gears were trained to be detected by the system and subsequently to be picked and placed by the cobot for the assembly operation. The detection of gears through the object detection technique is shown in Fig. 7.5.



(a) (b)

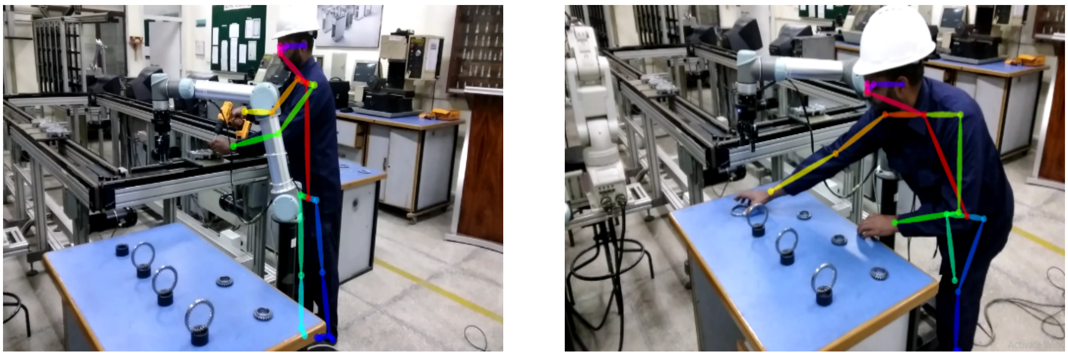
FIGURE 7.5: Recognition of Gears, (a): Detection of Gear 1; (b): Detection of Gear 2.

Similarly, human detection is also carried out through the object detection technique. Results for the detection of an authorized operator and an unidentified person are shown in Fig. 7.6. The identification of the authorized operator within the workspace through object detection is complemented by the RFID sensor in the helmet.

(a) (b)

FIGURE 7.6: Recognition of Humans in Workspace, (a): Detection of Operator in Blue; (b): Detection of Unidentified Person in Red.

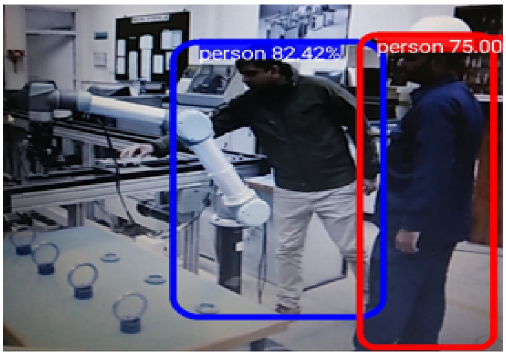
Detection of two specific poses of the operator is shown in Fig. 7.7, the first is the pose of the operator when interfering in assembly, and the second is the pose of the operator while placing one of the gears himself. It is pertinent to mention here that the contingencies were adopted only when a particular pose detected is complemented by the position of the robot at the same location. This is because, while doing parallel operations, the same pose could be detected while the cobot may be operating at some other place.



(a) (b)

FIGURE 7.7: Detection of Human Interventions, (a): Detection of intervention 1; (b): Detection of intervention 2.

Our approach is capable of detecting multiple situations and their disposal at once. For example, two individual situations are considered at a time: a displaced case and an unidentified person. An inspector entered the workspace and displaced the outer case during inspection (see Fig. 7.8).



(a)

(b)

FIGURE 7.8: Detection and Action on Multiple Situations, (a) Detection of unidentified person and displaced case; (b) Picture showing the case being aligned by the cobot.

The 'unidentified person' situation is detected by object detection, whereas the 'displaced case' is detected by the proximity sensor. As the two situations were detected, the anxiety factors were calculated for both, and the optimization algorithm decided the resource 'human' for the unidentified person and the resource 'cobot' for the displaced case. Based on the decision given by the decision-making module, the algorithm chooses the action for an unidentified person scenario, and the cobot stops working initially. Until the operator removed the unidentified person from the workspace, the cobot did not resume its operation. The signal was then given to the cobot's software for the displaced case situation; the cobot then resumed operation and moved the case to its original location by pushing it to a fixed enclosure. The table on which gears were placed was initially detected as a foreign object; however, it later declared obsession as not an obstruction to the cobot's motion, as shown in Fig. 7.9.

An example case is presented and a few situations are incorporated for understanding. Only the variant situations are discussed in this paragraph. A list of situations encountered at single iterations throughout the cycle is shown in Table 7.4. Individual and total severity is calculated for each iteration, and resources are assigned accordingly.

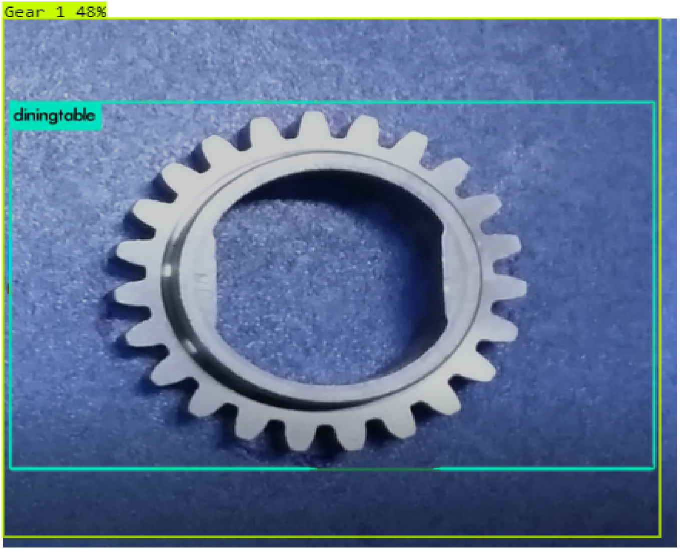


Figure 7.9: Detection of Dining Table as Obsession.

At the 1st iteration, a foreign object situation along with the right item situation emerged. As the object detection algorithm is trained to detect day-to-day items, the table is detected as a foreign object. The human supervisor assessed that the table was not creating a disturbance in the process and declared it an obsession. Thereafter in subsequent iterations, the table reappeared as an obsession. In the 6th iteration, the right item situation was encountered along with the obsession; however, an inspector came into the work area to inspect the process. The inspector was detected as an unidentified person who had entered the workspace. The inspector had displaced the case while inspecting it, and another situation, i.e., the displaced case, emerged. The right item situation diminishes as the item is already placed. The system decided the human for the unidentified person and the cobot for the displaced case.

At the 9th iteration, the right item situation appeared with obsession. While the cobot was on the move, the human operator interfered at the assembly station as he observed something there. This is the human intervention situation 1; the system decided the cobot for the interference, which stopped at its location, and the human operator decided on the right item situation. As the cobot was on its move, the operator left the item in the cobot's grip and continued working at the assembly station. On termination of the human intervention, the right item situation is left, and the system then decides on the cobot to handle it, which resumes the motion to the dedicated location for gear placement.

Table 7.4: Situations vs. Resource Assignment

Iter.	***Situations***	***Individual Severities (a)***	***Resource Assignment***	***Total Severity***	***Decision Time (s)***
1	Foreign Object, Right item	62.4, 24	Human, Cobot	86.4	0.03
2	Obsession, Right item	0, 24	Cobot	24	0.02
3	Obsession, Right item	0, 24	Cobot	24	0.02
4	Obsession, Right item	0, 24	Cobot	24	0.02
5	Obsession, Right item	0, 24	Cobot	24	0.02
6	Obsession, Right item	0, 24	Cobot	24	0.02
6	Unidentified Person, Displaced Case	57.8, 48.6	Human, Cobot	106.4	0.02
7	Obsession, Right item	0, 24	Cobot	24	0.02
8	Obsession, Right item	0, 24	Cobot	24	0.02
9	Obsession, Right item	0, 24	Cobot	24	0.02
9	Human intervention1, Right item	53.2, 23	Cobot, Human	76.2	0.03
9	Right item	24	Cobot	24	0.02
10	Obsession, Right item	0, 24	Cobot	24	0.03
10	Human intervention2, Right item	53.2, 23	Cobot, Human	76.2	0.02
11	Obsession, Right item	0, 24	Cobot	24	0.02
12	Obsession, Right item	0, 24	Cobot	24	0.02
13	Obsession, Wrong item	0, 40	Cobot	40	0.02
14	Obsession, Right item	0, 24	Cobot	24	0.02
15	Obsession, Right item	0, 24	Cobot	24	0.02
16	Obsession, Right item	0, 24	Cobot	24	0.02

Then at the 10th iteration, the situation was normal in the beginning; however, the operator observed that the gear that was to be picked by the cobot was not properly placed. The operator then decided to pick the gear on its own; here, the human intervention situation emerged again. However, this time the count for the item was incremented as the pose estimation detected pose 2. At this stage, there were two situations; human intervention 2 and the right item. The system decided the cobot for the human intervention and the human for the right item situation. The cobot performed a stop operation while the operator placed the item in its defined location. The time taken for decision for handling situations for the example case is shown in Fig. 7.10. Anxieties, total anxiety, and the maximum anxiety situation for each iteration are shown. The maximum time taken to decide on a scenario was noted as 0.03s.

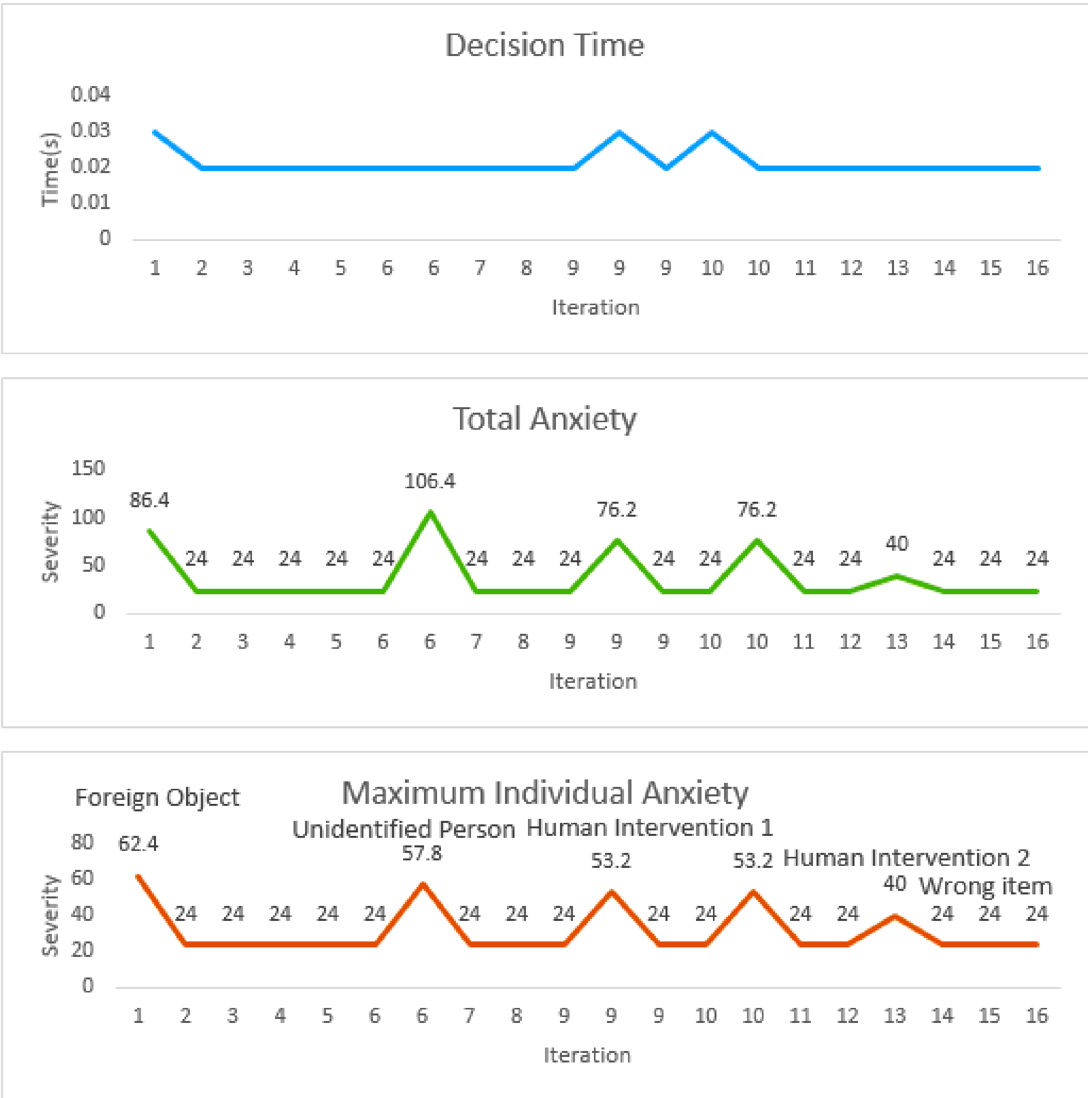


FIGURE 7.10: Anxiety Evaluation and Counter Strategy Decision Time.

The quantitative analysis from the survey was carried out; the overall mean automated decision-time (MADT) for the proposed method and accuracy of both approaches were calculated with a minimum of two situations in each cycle.

It was revealed that the mean automated decision time for a contingency is 0.21s, as can be seen in Table 7.5. The decision-making system (accuracy of 89.98 %) was found to be 16.85 % more accurate than the standard system (accuracy of 73.125 %).

The t-test for the significance of the results was conducted with a confidence level set to $p < 0.05$ (95% confidence level), and the p-value for the test was found to be $p < 0.05$. The Standard error mean (SEM) for the MADT was 9.36E-5, the upper limit was 0.0211s, and the lower limit was 0.0208s.

Significant differences (at $p < .05$) were found for the questions of fluency with the collaborative robot; the participants exposed to the decision-making system agreed more strongly with “I trusted the robot to do the right thing at the right time” (p = 5.99E -11) and “The robot and I worked together for better task performance” (p = 7.43E -09) and disagreed more strongly with “The robot did not understand how I desired the task to be executed” (p = 4.42E -11), and “The robot kept disturbing during the task” (p = 7.94E -09). Similarly (at confidence level $p < .05$), significant differences were found for the questions of perceived safety, comfort, and legibility; the participants exposed to the decision-making system agreed much more with “I felt safe while working with the robot” (p = 2.7E -14), “I trusted the robot would not harm me” (p = 9.58E -16) and “I understand what robot will be doing ahead” (p = 2.58E -10), and agreed much less with “The robot moved too drastic for my comfort” (p = 1.79E -12), and “The robot endangered safety of unknown persons in workspace” (p = 1.91E -14).

The results support both the hypothesis in favor of the decision-making system; they indicate that the proposed approach leads to more fluent HRC (Hypothesis 1) and also highlight that the method extends safety, comfort, and legibility (Hypothesis 2).

Table 7.5: Accuracy of Two Methods, Mean Automated Decision-Time and the SEM

Subj.	***Standard Method***			***Decision-Making Method***				***Remarks***
	Iter.	***Err.***	***Acc.***	***Iter.***	***Err.***	***Acc.***	***MADT***	
1	8	2	75	16	1	93.75	0.0206	
2	8	2	75	15	1	93.33	0.0206	
3	8	2	75	14	1	92.85	0.0207	
4	8	2	75	17	2	88.23	0.0211	
5	8	2	75	16	1	93.75	0.0206	Subj. = Subject
6	8	2	75	13	2	84.61	0.0215	Iter. = Iteration
7	8	2	75	12	1	91.66	0.0208	Err. = Error
8	8	3	62.5	14	2	85.71	0.0214	Acc. = Accuracy
9	8	2	75	10	2	80	0.022	Average Accuracy
10	8	3	62.5	11	1	90.90	0.0209	(Standard) = 73.12 %
11	8	2	75	12	1	91.66	0.0208	SEM=1.02
12	8	2	75	10	1	90	0.021	Average Accuracy
13	8	2	75	15	3	80	0.022	(Decision-Making Method)
14	8	3	62.5	14	1	92.85	0.0207	= 89.98 %
15	8	2	75	11	1	90.90	0.0209	SEM =0.94
16	8	2	75	12	1	91.66	0.0208	MADT=0.021s
17	8	2	75	12	1	91.66	0.0208	SEM = 9.36E-5
18	8	2	75	11	1	90.90	0.0209	p = 1.83E-10
19	8	2	75	13	1	92.30	0.0207	
20	8	2	75	14	1	92.85	0.0207	

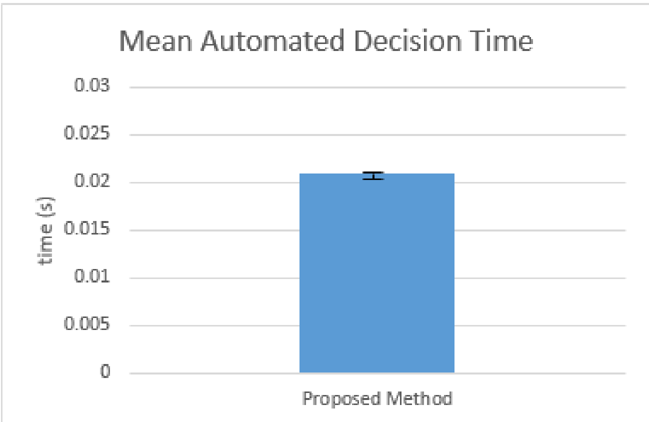


Figure 7.11: Mean Decision Time with Standard Error Mean (SEM) at 95% Confidence.

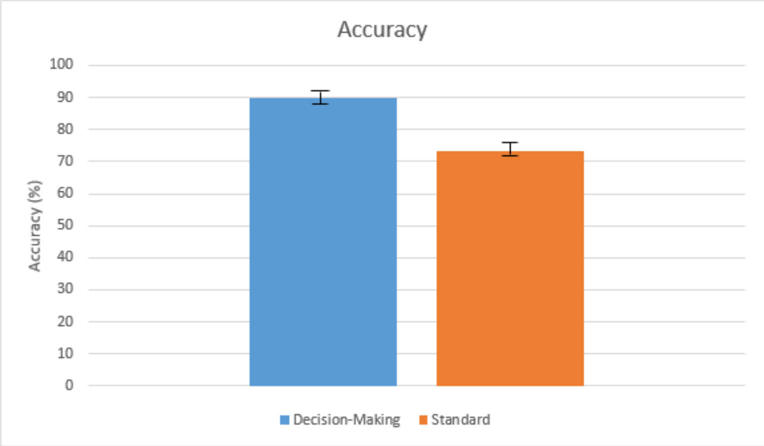


FIGURE 7.12: Accuracy of Conditions with Standard Error Mean (SEM) at 95% Confidence.

Chapter 8

Conclusion and Future Work

8.1 Conclusion

Exponentially growing technologies, such as intelligent robots in the context of Industry 4.0, are radically changing traditional manufacturing to intelligent manufacturing with increased productivity and flexibility. Workspaces are transformed into fully shared spaces for performing tasks during human-robot collaboration (HRC), increasing the possibility of accidents as compared to fully restricted and partially shared workspaces. The interactions among them can be quite demanding in terms of safety, employing both cognitive and physical resources. In this work, a four-layered connective framework is proposed that can quickly respond to changing physical and psychological safety situations. First, a scalable factor, 'anxiety,' to represent the gravity of expected/unforeseen situations a CPS could encounter is defined and categorized through historical data using the Ishikawa method. Second, current situational awareness of the CPS is ascertained through visual cues (such as human pose, object identification, etc.). Third, a mathematical model is developed using Mixed-integer programming (MIP) to allocate optimal resources, to tackle high-impact situations generating anxiety. Last, logic is designed for an effective counter-mechanism to mitigate the generated anxiety based on historical knowledge, current state, and suggested optimization. The proposed method was tested on real-world manufacturing scenarios involving HRC.

The research shows that the previous works address limited situations and solely focus on a single aspect, e.g., collision avoidance, motion planning, or psychological safety. The proposed method collectively addresses all the issues earmarked by the experts that a CPPS may face. Here, the current method must be compared with the previous work [168]. Only the most prior situation with maximum anxiety can be handled using the previous method. Whereas the current approach is optimized, that employs all available resources to relieve the current state of anxiety. The method is feasible to include any number of resources by modifying the equations in the anxiety and optimization algorithm. At times when limited resources are available, situations with higher anxiety are addressed first, followed by lower ones. The indexing of anxiety was carried out through a more generic approach in the previous method that lacked rationale for scaling different levels. The current method, though, partially uses the previous technique; however, a logical approach with a biomimetic connection is presented, making it easy to differentiate and prioritize situations. The limitation of this work is that the proposed approach is validated for two resources only that were the human and the robot, using equation (4.2), and can be applied to multiple resources using equation (4.3).

The results from the experimental validations demonstrated that the proposed method improves the decision-making of a Cyber-physical production system (CPPS) facing complex situations, ensures physical safety, and effectively enhances the productivity of the human-robot team by leveraging psychological comfort. The proposed framework is accommodative to incorporate any industrial scenario, whether manufacturing, packaging or any other production scenario. The method combines human knowledge and intelligence with AI techniques to minimize the decision time; the maximum time recorded to decide on a scenario is 0.03s, which shows that the method is not time-intensive.

The contribution of the work is that a framework is presented to address the combined physical and psychological safety issues. While not only ensuring the human well being, the human-machine teamwork in a CPPS has been augmented through meaningful and manageable task allocation thus improving productivity. The CPPS has been made more intelligent, aware, safe, resilient, and smart, thereby alleviating the physical and mental tasks of humans. While considering the worker role and associated skill requirement, an environment has been created where the human operator feels more integrated into the loop and actively contributes to the overall process. The decision-making of the production system is improved, which provides it the flexibility to tackle multiple situations at once in an optimal manner and can fit in any industrial scenario; manufacturing, assembly, packaging, etc. As the proposed work allows a safe and comfortable working environment, optimized processing, and enhanced productivity by merely employing low-cost sensing and interfacing technologies, thus ensuring social and economic sustainability. The work exhibits the integration of computers in industry, which is implemented in every layer of the proposed work, i.e., the functioning of the CPS, situational assessment, optimization, and decision-making through software, algorithms, AI, and interface. The amalgamation of four layers demonstrates the contribution of AI in the industry, resulting in improved overall system productivity. Therefore, the work is a real manifestation of the concept of Industry 5.0 that allows the creation of a human-centric, resilient, and sustainable working environment for the industry while increasing the efficiency and productivity of a CPPS.

8.2 Future Work

In the following, a list of possible future works related to this dissertation is proposed:

- The existing system is dependent on predefined solutions, as the current approach is initiated by a brainstorming tool to ascertain priority and solutions to situations. The approach can further be improved by employing machine learning techniques/AI-based knowledge systems, which will make it more intelligent; it is proposed that the system may learn through repetitive patterns and solutions provided to the previously confronted situations and automatically resort to the same solutions. That is to say, the CPPS may learn in real time from the environment and will improve the knowledge base continuously.

- Cloud base and semantic systems are emerging trends that may be incorporated to further enhance the capability and customization of these systems. In this way, multiple situations can be updated and omitted automatically in the system through distant central servers that many users can access. However, it is still recommended that on-ground supervision be carried out by the human component.

- Pragmatics and Ontology provide a solution to formalizing smart manufacturing knowledge in an interoperable way. As industry 4.0 recommends the use of a coherent approach for semantic communication between multiple agents, ontology and pragmatic-based systems can be incorporated to enhance the connectivity of these systems.

- Machine-learning-based image processing techniques were used as a tool, which are known for uncertainties due to the statistical methods and probability distributions used in them. The probabilistic nature of these models is prone to errors that cannot be ignored. In the future, the confidence level of detection may be included in the calculation of the anxiety factor. The method's accuracy may either be increased by selecting a threshold level of detection or adding a variable incorporating the detection level that will affect the anxiety factor of the confronted situation.

- The utilization of digital twin technology in the industry is on the rise, particularly in conjunction with CPS. This entails generating a virtual depiction of the CPS environment, integrating real-time data from various systems, and employing sophisticated algorithms to allocate tasks efficiently and coordinate operations. It is advisable to integrate a digital twin framework into CRCPS, enabling the examination of situations related to ergonomic factors, potential hazards, and the optimization of collaborative workflows to ensure the safety and well-being of human operators working alongside robots.

The proposed model can be applied to any CPS confronting anxiety in various situations. For the future, the motivation exists to apply the model to other industrial problems and processes involving CPS, like business processes, supply chain models, etc. The proposed model must be applied to various sectors of existing industries to ensure human workers' well-being and provide a collaborative environment in consensus with all stakeholders. It can be applied to the manufacturing industry to foster better collaboration between human workers and advanced technologies, improving the system's productivity. It can be applied to the healthcare industry by integrating the combination of AI, IoT, and cobots. This may enable accurate diagnostics, personalized treatment, and efficient monitoring. The model can be applied to real-time incoming/outgoing supplies in the supply chain using AI-driven analysis and collaborative decision-making between humans, robots, and machines. This may lead to better inventory management and increased efficiency of the system. The proposed work can be employed in space programs requiring deliberate and tedious collaboration between humans and robots. And lastly, it may be applied to service industries like food services or especially where robots have to look after disabled and old people. This may be done considering the ergonomic factors, which may provide relief and comfort to these people.

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Appendix A

Appendix

A.1 Visual Cue

A cue defines the measurement that can be taken out from a sensor's output. The measurement could be statistical data or a signal in the user's interest. It is a systematic arrangement of data extracted from the signal that can be used for further analysis. A visual cue is a cue related to vision in human beings, which is the signal received from the eye and forwarded to the brain. The eye processes the light from the surroundings and extracts data from it as per the brain's requirement. The visual cue is one of the main sources of information in human beings and other living beings, despite other sensory cues. Therefore, it is considered an overriding authority for other sensory systems. It can be related to a proverb, " Seeing is believing."

Similarly, machine vision techniques are commonly used in machines to extract various types of data related to surrounding and processes. The concept holds good for the machines which are a part of CPPS. The visual cues used in this dissertation are:

A.1.1 Object Detection

Object detection and identification are essential tasks in computer vision that involve locating and classifying objects within images or video streams. Over the years, several approaches have been developed to address these challenges. The Object Detection API is an open source available online which provides an opportunity to detect objects. TensorFlow and YOLO are object detection programming interfaces that can be trained and deployed to detect common or special items. Here is an overview of different object detection and identification techniques:

- Traditional Computer Vision Techniques: Before the emergence of deep learning, traditional computer vision techniques were commonly used for object detection. These methods involved handcrafted features like Haar-like features or Histogram of Oriented Gradients (HOG), coupled with machine learning classifiers such as support vector machines (SVM) or AdaBoost.

- Deep Learning-based Approaches: Deep learning has revolutionized object detection and identification. Convolutional Neural Networks (CNNs) have played a crucial role in enabling end-to-end learning. There are two popular deep learning approaches for object detection.

  Two-stage detectors, exemplified by the Region-based Convolutional Neural Network (R-CNN) family, follow a two-step process. First, they generate region proposals using algorithms like Selective Search or EdgeBoxes. Then, these regions are classified using a CNN. Examples include Faster R-CNN and Mask R-CNN.

  One-stage detectors, such as You Only Look Once (YOLO) and Single Shot MultiBox Detector (SSD), perform object detection in a single pass. These models divide the image into a grid and predict bounding boxes and class probabilities directly. They are generally faster but may sacrifice some accuracy compared to two-stage detectors.

- Anchor-based and Anchor-free Approaches: In recent years, there has been a shift from anchor-based methods (e.g., Faster R-CNN) to anchor-free approaches. Anchor-free detectors, like CenterNet or EfficientDet, eliminate the need for predefined anchor boxes. They directly predict object centers or keypoints, resulting in simpler architectures and improved accuracy in some cases.

- Transformer-based Approaches: Transformers, originally designed for natural language processing, have also demonstrated success in computer vision tasks. Models like DETR (DEtection TRansformer) leverage transformer architectures for end-to-end object detection. Instead of relying on anchor boxes, they formulate object detection as a set prediction problem, achieving competitive performance.

- Efficient Object Detection: Addressing the computational and memory constraints of object detection models has been a focus of research. Techniques such as model compression, quantization, network architecture design, knowledge distillation, and hardware acceleration (e.g., GPUs and TPUs) have been developed to overcome these challenges.

These APIs can extract data from the environment in real-time. They are now being used in the industry to detect material, jobs, workpieces, products, etc., after requisite training.

These models wrecked the problems confronted by vision software programmers of identifying and localizing numerous objects in a scene in real-time. It's important to note that the field of object detection and identification is continuously evolving, with new approaches emerging regularly. The choice of approach depends on specific requirements, available computational resources, and the trade-off between accuracy and speed.

A demonstration of this is shown in the subsequent paragraph while applying the technique to a live stream of objects that can be seen in Fig. A.1 and Fig. A.2.

Figure A.1: First Image for Object Detection Test.

Figure A.2: Second Image for Object Detection Test.

The algorithm successfully detected the objects in the surrounding. The bottles and chairs detected are shown in Fig. A.3 and Fig. A.4.

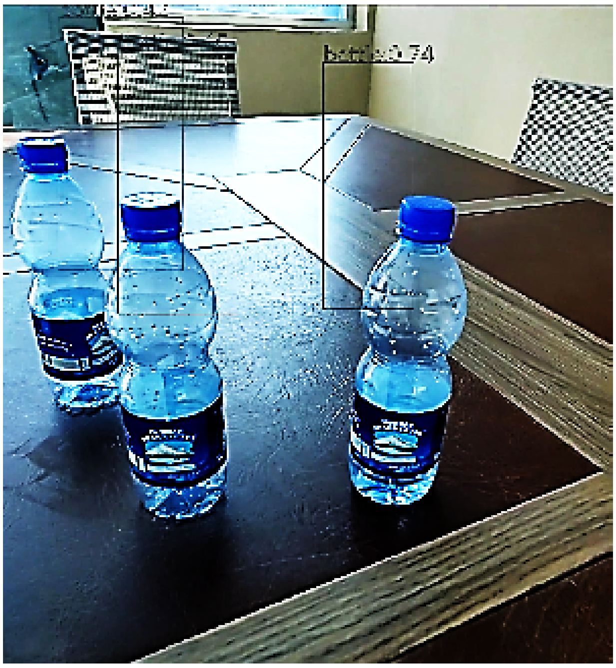

FIGURE A.3: Result of First Image showing Bottle with 74% Accuracy.

FIGURE A.4: Result of Second Image showing Chair with 84% Accuracy.

YOLO is a state-of-the-art object detection algorithm [171] that uses a neural network to detect objects. It can detect daily items by employing a pre-trained classifier network with its inbuilt data sets or can be trained to detect specific objects. It is famous for its fast detection ability with reasonable detection accuracy. The accuracy of the algorithm can be improved by training through available data can be trained to detect custom objects using the procedure explained in [166]. The latest version of the algorithm, YOLOv3 [166], was applied to two live streams, and the results are shown in Fig. A.5.

(a)

(b)

FIGURE A.5: Object Detection, (a) Picture showing detection of bottles, (b) Picture showing detection of a person.

A.1.2 Pose Estimation

Pose estimation is an estimation method that detects human pose in different orientations. Open Pose [167] is an algorithm designed to simultaneously detect the orientation of the human body, limbs, face, etc., which defines the pose of the human body in a 2D image. Neural networks are utilized in the algorithm to detect various body portions and their orientation with each other.

The complete linkage of parts is called a full-body pose. The orientation of parts is taken as 2D vectors, and the set of these vectors encompassing all parts represents a specific pose. The information from the pose estimation makes it feasible for machines to consider different operator poses that depict different tasks. The interference of a human operator in a machine's job is one scenario that can be ascertained through the pose estimation of the operator. It can be ascertained that the pose is in line or otherwise with the job. A depiction of this can be seen in Fig. A.6, where a person is detected in a standing pose and in second picture while picking an object.

(a) (b)

FIGURE A.6: Pose Detection, (a) Picture showing pose of a standing person, (b) Picture showing pose of person picking a bottle.

Moreover, sequential detection of different poses can relate to different tasks/situations; e.g., the number of poses in a sequence can depict a certain task or an anomaly. A pose related to picking an item followed by a pose of its disposal may depict its normal or abnormal situation. This can be done by detecting poses at both locations, i.e., picking and disposal.

A.2 UR-5 Polyscope

UR-5 is a lightweight collaborative robot that can tackle medium-duty applications, i.e., its payload capacity is 5 kg [172]. The arm of the UR-5 cobot comprises linkages and joints; at one end, the robot is mounted called the base, and at the other end of the manipulator, the tool can be attached. The motion of the robot's joints, linkages, and tools can be programmed through a user interface software, Polyscope. However, the motion is restricted to the area directly above and below the base.

The programming in the PolyScope can be done through a graphical user interface (GUI), or the software can be installed on a computer. A touch panel is provided with the cobot installed with the GUI making it easy for the users to program without typing commands. Therefore, users with little programming knowledge can use the robot. The system also has a control box that has ports for interfacing with the robot, sensors, computer, and touch panel. The program in either system comprises a list of commands for the robot's action; however, it also contains programming commands like 'if', 'then', and ' while loop' etc. For most of the tasks, programming can be done entirely using the touch panel, giving points for the motion. These points in PolyScope's language are called waypoints. As the motion of the end effector is crucial for performing required tasks, the robot is given an exact transformation for each link. However, where accuracy is not essential, a series of waypoints can be given by manually taking the robot to that point and registering it. For manual movement of the robot, an option for the free drive is available in the software. The user can simply hold the robot and position it in the location where he wants it by pressing the free drive button at the back side of the touch panel. In addition to giving commands to the robot, the program can direct signals to other devices while the robot is operating in parallel. Similarly, the interface can also give input to other programs [173].

A.3 Mixed Integer Programming

Optimization problems are often solved by Linear Programming (LP). The programming described does not relate to writing a program in a computer language. The linear relations between variables define objective functions and conditions. The optimization problems vary from situation to situation and category of problem, making them complex. Here computer algorithms are used to solve these problems known as solvers. The issue is to find the best algorithm for the confronted problem. Solvers are mathematical techniques that use a number of equations to solve an optimization problem. In LP, the solution is only viable for linear equalities and inequalities where equations only involve real numbers. The basis of the optimization calculation is the objective function. This function is represented by an equation that will either be maximized or minimized to find the solution. The second basis is dependent on the constraints defined by certain other equations. While maximizing or minimizing the solution (highest or minimum value) is found using various assignments of variables used in equations.

The problem becomes more complex when there is a requirement to include variables comprising binary digits or whole numbers, i.e., mixed integers (MI). In this case, when integers are incorporated into calculations, LP is not viable. Here comes the role of Mixed Integer Programming (MIP); however, it is comparatively difficult to do calculations through MIP. LP calculations are done multiple times in MIP in comparison to LP. Different techniques are in use for MIP, like Branch And Bound (B&B) or Branch and Cut (B&C). In these techniques, the solver de-integrates the area bounded by the equations. This is also termed as relaxation of LP problems. The LP for each bound is then solved with the method explained above. The integers will then be assigned real numbers. Then B&B or B&C program will run, and on the next bounds, LP is again calculated. The process is repeated till the optimal answer is found, and all variables are integers. This does not mean that the process starts from scratch; rather, the equations are re-evaluated after the impact of the previous ones.

A.3.1 Gurobi Optimizer

The Gurobi Optimizer [164] is one of the state-of-the-art solvers for optimization problems. It allows the development of a mathematical model of an optimization problem and automatically provides an optimal solution. It also allows adding complexity to the model and still solving in an acceptable time. It provides interfaces with multiple programming languages. The python API further makes it easier to build models and solve them. One of the advantages of the Gurobi solver is the decision-making that doesn't rely on past data compared to machine learning, where patterns from the past are used to make predictions. If something changes in real-time, it can be adjusted on the way, and the solver finds the best solution accordingly.

A.3.2 Gurobi Optimization Algorithm

The algorithm used for the optimization layer is stated below:

```
import gurobipy as gp
from gurobipy import GRB
# Resource and situations sets
R = ['Human', 'Cobot']
J = ['RightItem', 'WrongItem', 'NoItem', 'HumanInterference',
     'DisplacedCase', 'UnidentifiedUser', 'ForeignObject',
     'Obsession', 'TimeDelay', 'ThresholdDistance',
     'CobotFailure', 'CobotCollision']
a11=39
a12=40
a13=0
a14=0
a15=0
a16=0
a17=0
a18=0
```

```
a19=0
a110=6.3
a111=0
a112=0
a21=0
a22=0
a23=0
a24=0
a25=0
a26=0
a27=0
a28=0
a29=0
a210=0
a211=0
a212=0
# Matching anxiety data
combinations, anxiety = gp.multidict({
        ('Human', 'RightItem'): a11,
        ('Human', 'WrongItem'): a12,
        ('Human', 'NoItem'): a13,
        ('Human', 'HumanInterference'): a14,
        ('Human', 'DisplacedCase'): a15,
        ('Human', 'UnidentifiedUser'): a16,
        ('Human', 'ForeignObject'): a17,
        ('Human', 'Obsession'): a18,
        ('Human', 'TimeDelay'): a19,
        ('Human', 'ThresholdDistance'): a110,
        ('Human', 'CobotFailure'): a111,
        ('Human', 'CobotCollision'): a112,
        ('Cobot', 'RightItem'): a21,
        ('Cobot', 'WrongItem'): a22,
        ('Cobot', 'NoItem'): a23,
        ('Cobot', 'HumanInterference'): a24,
        ('Cobot', 'DisplacedCase'): a25,
        ('Cobot', 'UnidentifiedUser'): a26,
        ('Cobot', 'ForeignObject'): a27,
        ('Cobot', 'Obsession'): a28,
```

```
        ('Cobot', 'TimeDelay'): a29,
        ('Cobot', 'ThresholdDistance'): a210,
        ('Cobot', 'CobotFailure'): a211,
        ('Cobot', 'CobotCollision'): a212
})
# Declare and initialize model
m = gp.Model('RAP')

# Create decision variables for the RAP model
x = m.addVars(combinations, name="assign")

# Create situation constraints
situations = m.addConstrs((x.sum('*',j) <= 1 for j in J),
 name='situation')
# Create resource constraints
resources = m.addConstrs((x.sum(r,'*') <= 1 for r in R),
 name='resource')

# Objective: maximize total matching score of all assignments
m.setObjective(x.prod(anxiety), GRB.MAXIMIZE)

# Save model for inspection
m.write('RAP.lp')

# Run optimization engine
m.optimize()

# Display optimal values of decision variables
for v in m.getVars():
if v.x > 1e-6:
print(v.varName, v.x)

# Display optimal total matching anxiety
print('Total matching anxiety: ', m.objVal)
```

A.4 Ishikawa Diagram

The tool is named after Kaoru Ishikawa, who pioneered this idea in the 1960s [174]. His origin was from Japan, and he was a famous statistician known for quality control problems. The Ishikawa diagram is also called the Fishbone diagram, which is used to lay out a problem in hand and its causes. The layout is the process's dispersion, whose shape is similar to a fish skeleton [175]. Then the root cause is established through continuous brainstorming by experts. The sub-causes are laid under the main causes, and a cumulative effect is found for each main cause to establish which cause has a major impact. Therefore it offers an organized way of looking at an issue and the cause that contributes to it. Due to this property, some mention it as a cause-and-effect analysis [158]. The advantages that can accrue from the analysis are a systematic methodology, deliberation and use of knowledge by experts, and consolidation of a point of view. The study will also identify the areas for further deliberation [159]. The issue that is to be analyzed is placed at the skeleton head, and the causes are placed at the tentacles of the skeleton. Each tentacle of the skeleton is classified as a particular main cause. The sub-causes are distributed over the main cause tentacle. A typical Ishikawa diagram is shown in Fig. A.7.

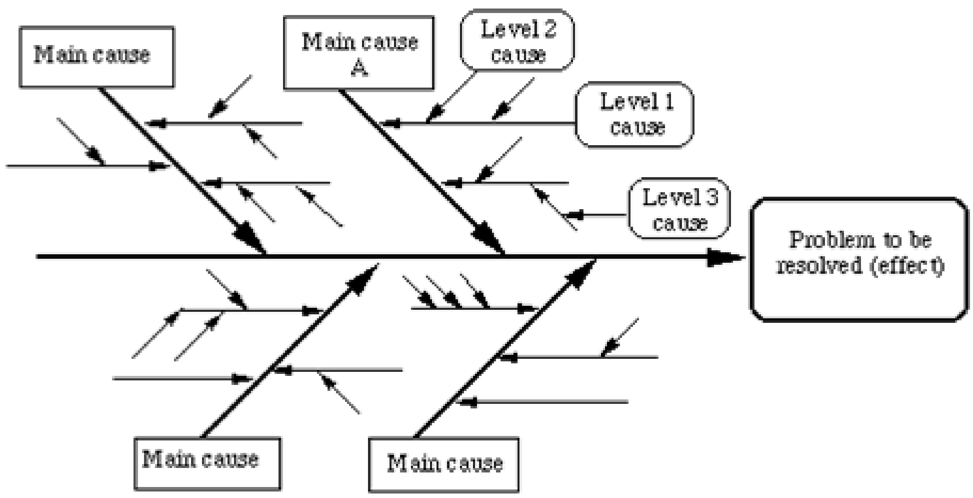

FIGURE A.7: Structure of Fish Bone Diagram.

The purpose of drawing an Ishikawa diagram is:

- To determine the root causes of an issue.
- To concentrate on a specific issue without going into irrelevant considerations.
- Identifying areas where a lack of data requires further deliberations.

A.4.1 Categorization Methods

The usual methods used for categorization are [176]:

- 8Ps: used for production, includes the product, people, place, price, process, proof, performance, and promotion.
- 6M: used for manufacturing, includes the manpower, machines, material, methods, mother nature (environment), and measurement.
- 5S: used for services, includes surroundings, suppliers, systems, skill, and safety.

A.4.2 Steps [177]

Ishikawa analysis includes the following steps:

A.4.2.1 Step 1 – Identification of effect and required analysis

First of all, the problem must be framed and written in the box at the head. All participants must be clear on the peculiarity of the issue under consideration. If there is any doubt, the session may not be helpful. The following rules must be applied:

- While deciding on the effect, it must be differentiated as a quality issue, work problem, planning issue, etc.

- It is recommended to use operational descriptions of the effect.

- The effect must be identified as objective (positive) or issue (negative).

- The positive effect tends to foster pride and ownership. This encourages participation and healthy discussion to achieve success. It is recommended to express the effect in positive words if possible.

- Negative effects tend to sidetrack the team justifying why the problem occurred and placing blame. Sometimes it is easier to focus on what causes the problem. At the same time, we should be careful not to fall out for false.

A.4.2.2 Step 2 – Drawing of central line and effect box

- An arrow must be horizontally placed pointing to the effect.

- A brief narrative of the effect must be written.

- The effect must be written in a box.

A.4.2.3 Step 3 – Identification of main causes

The main causes can also be termed categories. They are the labels under which sub-causes are listed. The diagram now will hae a central arrow and branches for major causes and sub-causes as shown in Fig A.8.

- The major causes leading to the effect be listed. Labels for categories be defined.

- The major causes decided after deliberation be written on the left side. Some of them may be above the central arrow, and some below.

- Arrow may emanate diagonally from each cause to the central arrow. Similarly, for sub-causes arrows may emanate from them leading to the diagonal arrow of main cause.

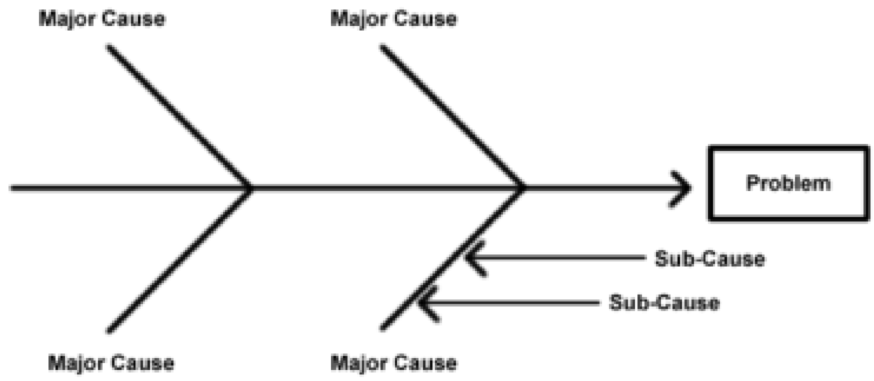

FIGURE A.8: Major and Sub Causes in Fishbone Diagram.

A.4.2.4 Step 4 – Identification of specific factors

- The specific factors (sub-causes) as many, leading to the main cause, be identified. They must be attached to the main branches, as explained in the previous step.
- A description of each sub-cause may be filled.
- If a specific factor is applicable to more than one major cause, write it under all relevant major causes.

A.4.2.5 Step 5 – Organization of Diagram

- Identify the detailed levels of causes. A series of questions would suffice.
- Organize the diagram.
- If there is too much cluttering, there may be a need to break the diagram into smaller diagrams. In this case, any major cause will then be made an effect for the sub-diagram.

A.4.2.6 Step 6 – Analysis of the diagram

The analysis may identify the portions where further investigation is needed. Pareto Chart may be used to focus on specific portions.

- The comparison may be drawn for all major categories. This is also called "balance" of the diagram.
- Look for thick clusters. They represent the areas warranting more focus.
- A major category under which only a few sub-causes may warrant more deliberation for further identification.
- The major categories having very few sub-branches may be combined if possible.
- The specific factors that appear repeatedly be deliberated; they may be the root cause.
- Deliberate on how to quantify each cause so as to measure the impact on the effect.

A.4.2.7 Final Step – Weightage to Causes

A survey or board meeting may be arranged to give weightage to causes based on voting, and accordingly, the main cause leading to the problem be identified. For this Pareto chart can be a helpful tool.

The complete process explained above is represented in Fig. A.9.

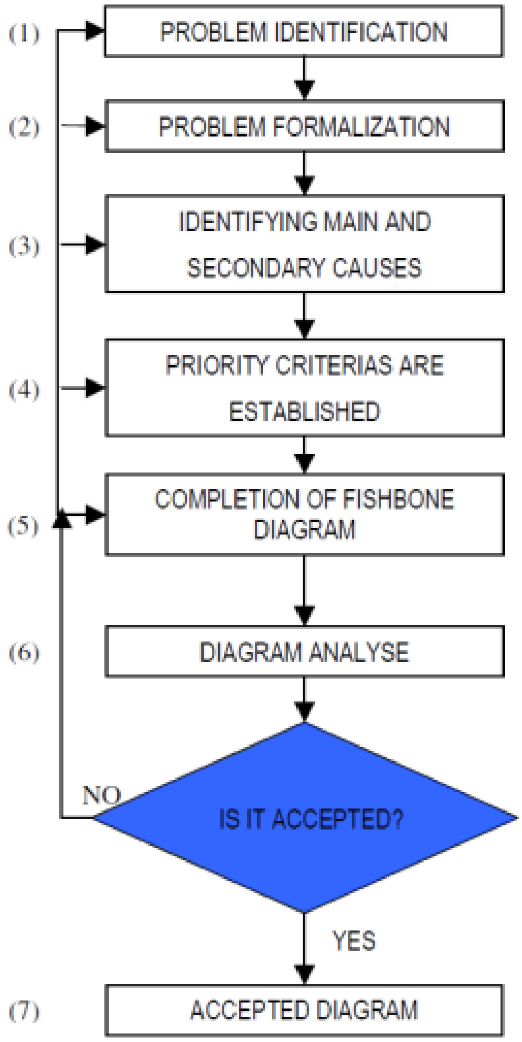

FIGURE A.9: Steps for Fish Bone Diagram [178].