A Connective Framework to Minimize the Anxiety of Collaborative Cyber-Physical System

Authors: Syed Osama bin Islam[1]†, Waqas Akbar Lughmani[1], Waqar S. Qureshi[2], Azfar Khalid[3]

1 Department of Mechanical Engineering, Capital University of Science and Technology (CUST), Islamabad Expressway, Zone 5, Islamabad, 45750, Pakistan

2 School of Computer Science, Technological University Dublin, Dublin Ireland

3 Digital Innovation Research Group, Department of Engineering, School of Science and Technology, Nottingham Trent University, NG11 8NS Nottingham, UK

†Corresponding Author Email: osama_bin@yahoo.com

***Abstract*—** The role of Cyber-Physical systems (CPS) is well recognized by researchers in the context of Industry 4.0, which consists of human operators working with machines/robots controlled by a computational layer. The interactions among them can be quite demanding in terms of cognitive resources. Existing systems do not yet consider the psychological aspects of safety in the smart manufacturing domain. This lack can lead to hazardous situations, thus compromising the performance of the working system. This work proposes a connective decision-making framework for a flexible CPS, which can quickly respond to dynamic changes and be resilient to emergent hazards. First, Anxiety is defined and categorized for expected/unforeseen situations that a CPS could encounter through historical data using the Ishikawa method. Second, visual cues are used to gather the CPS's current state (such as human pose and object identification). 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 Anxiety caused by historical knowledge, current state, and suggested optimization. The proposed method was tested on a realistic industrial scenario incorporating a collaborative CPS. The results demonstrated that the proposed method improves the decision-making of a CPS facing a complex scenario, ensures physical safety, and effectively enhances the human-machine team's productivity.

Keywords: Cyber-physical system; Smart factory; Social safety; Optimization; Artificial Intelligence; Human-robot collaboration.

1 Introduction

The basis of the fourth industrial revolution (Industry 4.0) is Cyber-Physical Systems (CPS). The concept involves decision-making through real-time data evaluation collected from interconnected sensors. It is an intelligent system that contains both physical and computational elements. These elements include four layers consisting of sensors, network, analysis, and execution (Rad et al. 2015). Monostori (2014) proposed complete automation of the layers for production systems interconnecting necessary physical elements such as machines, sensors, robots, and conveyors through computer science and termed it a Cyber-Physical Production System (CPPS). The decision-making is dependent on logic; however, these systems lack the flexibility to handle deviations from the predefined, and extension of the concept is necessitated from fixed to autonomous production systems using artificial intelligence (AI) and the internet of things (IoT). On the other hand, human involvement is necessary to supervise and cover the intelligence gap. An anthropocentric cyber-physical system was presented by (Pirvu, Zamfirescu, and Gorecky 2016), confirming humans' essential requirement in any CPS. Modern CPSs are now expected to handle social interaction issues between humans and machines. Information on social interaction is required to design such systems, along with data attained from physical sensors (Zhuge 2010).

The close interaction between humans and machines due to the necessity of human supervision poses several risks/hazards. Occupational safety, especially in industrial environments, has gained importance nowadays. In addition, ergonomics is found to have a great impact on the performance of a worker. Human factors like physical or cognitive stress, anxiety, consciousness, etc. play an important role in the system's productivity. Monitoring such activities during interaction is now essential to avoid accidents and discomfort. On the other hand, condition monitoring during the manufacturing processes is essential for accident avoidance and product quality enhancement. One such example to avoid tool breakage is given by (Beruvides et al. 2014), online monitoring is proposed for the run out of micro drilling tools. The industry should take a step forward to improve occupational safety, ergonomics, and condition monitoring using some monitoring mechanisms. Complex processes, unavoidable behaviors, and undesirable results yield uncontrolled situations. AI-based real-time monitoring promises better situational assessment for quality improvement. An intelligent monitoring system is proposed by (Castaño et al. 2020) that measures in-process product quality for the improvement of the finished product. Osama et al. (2019) proposed an assessment of social metrics for smart factories through the integration of AI and IoT.

On the same lines, the role of robots in modern production systems had also transformed from automation to collaboration. Collaborative robots (cobots) are now an essential component of modern CPPS (Colgate, Edward, and Peshkin 1996). Collaboration has roots in the social intelligence of humans and animals (Baraka, Alves, and Ribeiro 2020). The collaborative robot must possess the intelligence to act in an arising scenario. The concept of legibility emerged here that states that the actions performed by the human operator should be inferred by the cobot and vice versa (Dautenhahn 2007). Khan et al. (2016) presented an example of social interaction between robots and humans in the food industry. The challenge was to provide real-time evaluation of hazards and ensure safety accordingly.

The broad categories of safety in the social domain are physical and psychological safety. The earlier provides safety from physical hazards, whereas the latter from psychological discomforts such as close interaction of machines or monotonous operations. Different physical safety protocols for HRC-based CPS were presented by authors (Krüger et al. 2009; Lasota et al. 2015; Morato et al. 2014; Flacco et al. 2012), whose activation is dependent on proximity between the cobot and the human operator. Sharma et al. (2015) applied an object classification technique to identify objects and the human body for the safe operation of a robot. Khalid et al. (2016)

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 (Lasota et al. 2014). 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 (Dragan et al. 2015). As Industry 4.0 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 (D'Auria and Persia 2017). 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. Flexible CPPS in this regard is required to counter these changes by defining contingencies.

A flexible CPPS was proposed in the previous work (Islam et al. 2019) that ensures the social safety of the smart system while assessing psychological and physical threats. A novel concept, *Anxiety of a CPS*, was given to assess physical and psychological issues. Different situations, intended and unplanned, could be encountered by a CPS during its operation were listed. Indexing was done for the situations to prioritize handling high-impact ones: a qualitative management technique, Ishikawa analysis, was used for the indexing that relies on the knowledge of experts. The index estimated was termed as the *Anxiety* of that particular situation. A case study of a complex industrial scenario involving HRC under a socially constrained environment was considered. A set of assigned tasks were to be completed ideally by the CPPS. However, if some change appears astray from the intended situation, the system is flexible to adapt to a contingency. A logic-based framework was proposed to induce this flexibility. In addition, AI was applied to the information attained from visual cues and positions of objects/humans for real-time detection of situations. In this context, the state-of-the-art AI-based object detection algorithm YOLOv3 by (Redmon and Farhadi 2018) was trained to detect objects and humans in the workspace. Another algorithm, 'OpenPose' by (Cao et al. 2018), was used to detect the operator's pose while performing different jobs. The method proposed indexing that depends on historical knowledge, which is, however, broad and lacks a rationale for defining and indexing Anxiety generated in different situations. The CPPS was also accustomed to detecting multiple situations at a time. However, it can allot resources to handle situations one by one in terms of priority, whose priority is declared through the defined index. The system was, therefore, not optimized to utilize all the available resources at one time when multiple situations are being faced. Different optimization techniques are employed in flexible CPSs (Li et al. 2008; Lanza et al. 2015; Scholze et al. 2017; Lv et al. 2018) to achieve the desired goals.

In this paper, a layered framework is proposed for decision-making in a cyber-physical system (CPS), shown in Fig. 1. The method decides on the confronted situations to mitigate the Anxiety generated by them. The CPS, at the core, performs the desired operations through the interactions between its physical component (PC), computational component (CC), and human component (HC). A situational assessment layer is proposed over the core layer to assess the nature of braved situations. Real-time sensing is incorporated through Visual, IR cues, and other sensing methods for simultaneous detection of various situations. This layer uses the knowledge base of HC to assess the Anxiety generated by confronted situations. For this, indexing of Anxiety for expected situations is proposed, supported by Ishikawa analysis. The indexing is further aided by a categorization technique derived through a rationale based on similarities with medical terminologies. The CPS may have several resources to handle various situations; the calculation of matching scores through a mathematical model is proposed for each resource vs. situation, is termed it an anxiety factor. The third layer is the resource optimization layer, on top of the situational assessment layer. This layer optimizes the allocation of available resources through an optimization algorithm using the matching score evaluated in the preceding layer, the objective function, and the defined constraints. A Mixed-integer programming (MIP) technique is proposed to formulate an optimization model. 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. The logic remains specific for every particular case/example in which the CPS is employed. In this paper, the proposed framework is validated on a case study of an industrial scenario facing multiple situations.

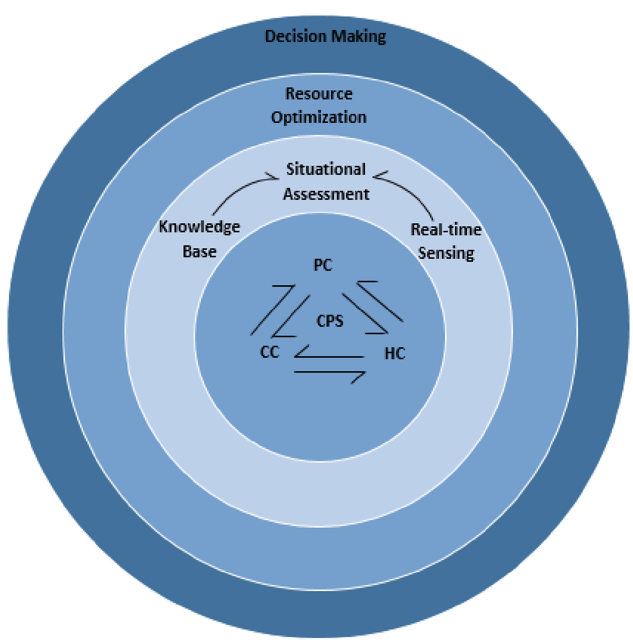


Fig. 1. Layered Framework; Decision-making for Anxiety Mitigation.

The paper is arranged as follows. Section 2 explains the proposed method; and first gives an overview of the concept of anxiety of a CPS and then calculate the anxiety factor through proposed variables. Then the optimization technique is presented in subsection 2.2 for resource allocation to emerging situations. Finally, subsection 2.3 presents an overview of the decision-making system for anxiety mitigation. Section 3 explains the proposed method's implementation and experimental validation using an industrial case study. The subsection 3.1 presents the situational awareness techniques and their results. Subsection 3.2 provides an anxiety assessment for the scenario. Subsection 3.3 provides resource optimization criteria for the case. Subsection 3.4 contains the decision-making logic for the considered case. Subsection 3.5 incorporates the results from the case study, a discussion of the outcome, and a comparison of the proposed method with contemporary systems. The last subsection contains recommendations for future work.

2 Methodology

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 of a process cycle. Both the pre-process and in-process steps concerning each layer are shown in Table 1.

Table 1
Stages of Decision-Making System

Ser	*Layer*	*Pre-Process*	*In-Process*
1	CPS	Preparation of Manufacturing/ Production plan	
2		Definition of expected situations	
3			Start of the process
4			Sensing of processes and human behaviour
5			Control
6			Execution of the process

7	Situational Assessment	Indexing of the defined situations' anxieties through Ishikawa method	
8		Categorization of situations into the type of Anxiety	
9		Assignment of weights to key variables for estimation of matching score	
10		Calculation of matching score (anxiety factor) with respect to resources	
11			Assessment of current situations
12			Anxiety assessment of emerged situations
13			Re-designation of anxiety category in case change is necessary
			Re-estimation of matching score in case category is changed
14	Resource Optimization	Defining the optimization criteria for allocation of resources; the objective function and the constraints	
15			In case of a single situation, input to process control through 4th layer
16			In case of multiple situations, resource allocation to high-impact situations through optimization technique, MIP in our Case
17	Decision Making	Defining and designing the logic for the case being handled along with anxiety mitigation strategy by experts	
18			Decision on task assignment to available resources based on suggested optimization and the calculated anxieties
19			Control
20			Implementation based on defined logic, actuation of PC and social signals to HC

An overview of the proposed framework's execution as explained in Table 1 is shown in Fig. 2.

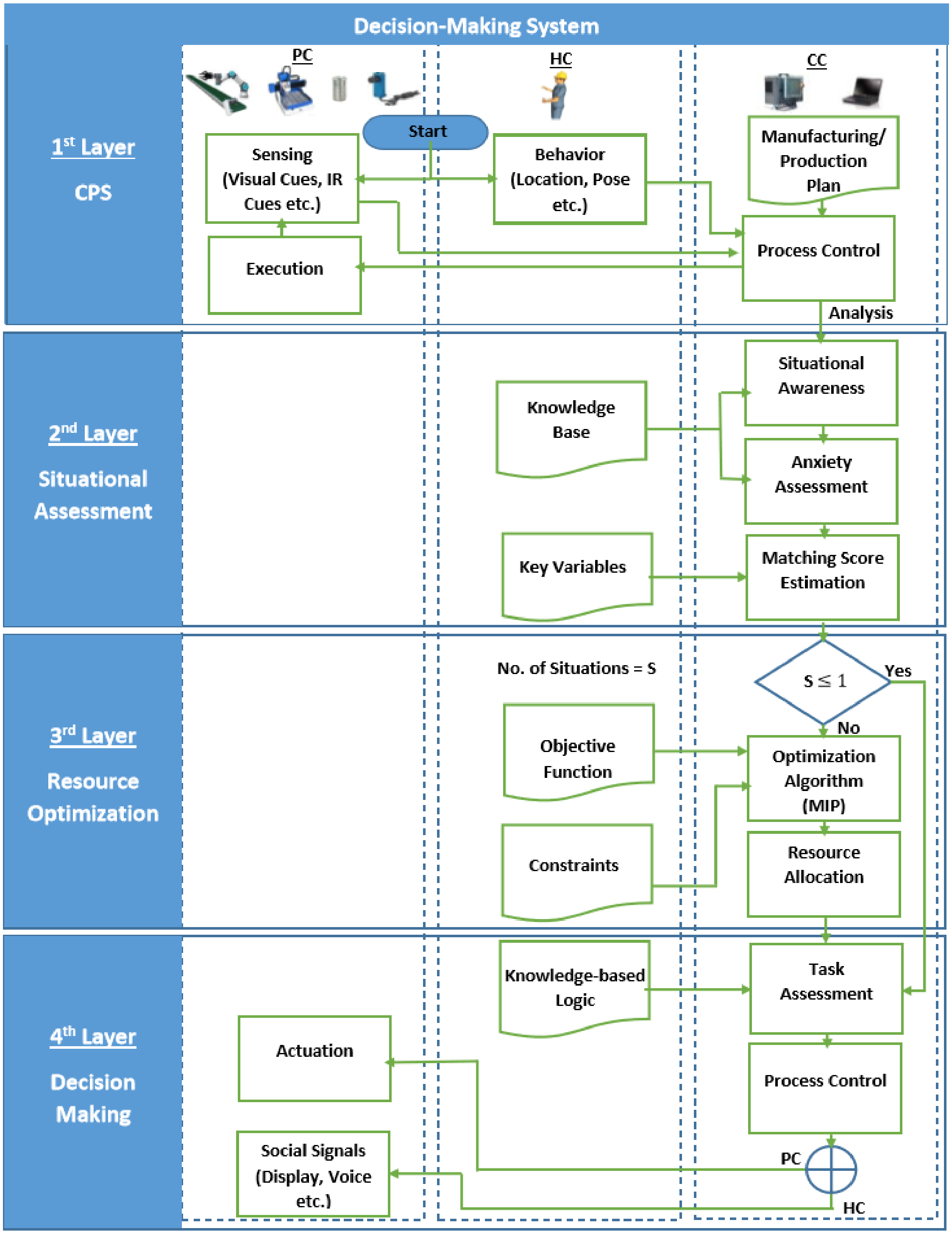


Fig. 2. Decision-making Framework Execution.

2.1 *Anxiety of Cyber-Physical Systems*

Anxiety is the unpleasant state when an expectation is not achieved due to any stressful, dangerous, or unfamiliar situation. It needs to be elaborated more and should not be confused with the risk. Risk is based on hazard whereas "anxiety can be defined as an urge to perform a particular job even to avoid a hazard or to do a righteous job." In this article, Anxiety is first defined and then categorized to make it scalable for CPSs. The anxiety module presented estimates the braved Anxiety due to the current situations at an instance. The module is initialized by the results of Ishikawa which assigns an index to each anticipated situation. After initial indexing is done, a novel and intelligent technique based on medical knowledge categorizes situations into different anxiety types. Each type relates to a particular level of severity. Anxiety factor i.e. the matching score is then calculated through a mathematical model dependent on the category and the variables related to tasks/resources. The procedure is repeated at each iteration and the situations faced are analyzed. Different types of anxiety orders from medical science 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 sudden. *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 which 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 knowledge. *Social Anxiety* is a communal problem not liked by humans and assessed through observations like cleanliness, cluttering of objects in the environment, etc. (Torpy et al. 2011). There is a need to differentiate between a scenario and a situation, a scenario is the amalgamation of different situations, whereas a situation is one condition faced by the system.

2.1.1 *Categorization of Anxiety*

The criterion for categorizing and indexing Anxiety in different situations faced by the CPS is defined in Table 2. 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 the severity and the category of a particular situation whenever it emerges. Anxiety for a situation is the sum of the lowest severity limit and the index *'I'* defined by Ishikawa. The value of *I* ranges from 0 to 100.

Table 2
Anxiety Categories

Level	***Name***	***Description***	***Severity***	***Equation***
1	Panic	Emergency	> 80 to 100	$P=80+ I \times 20/100$
2	Post traumatic	Trauma / Fear	> 60 to 80	$T= 60+ I \times 20/100$
3	Agora-phobia	Known Situation	> 20 to 60	$K= 20+ I \times 40/100$
4	General Anxiety	Intended Situation	20	$G= 20$
5	Social norms	Etiquettes	> 0 to 20	$N= 0+ I \times 20/100$
6	Obsession	False	0	$O = 0$

Ishikawa is a team brainstorming tool that analyses and provides a systematic way of looking at the effect and the causes that create or contribute to that effect. Because of the shape of the cause-and-effect diagram, it is referred to as a Fishbone diagram (Watson, 2004). The benefits of constructing a Fishbone diagram are that it helps determine the root causes of a problem using a structured approach, encourages group participation, and utilizes group knowledge of the process (Sokovic et al. 2009). 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. 3.

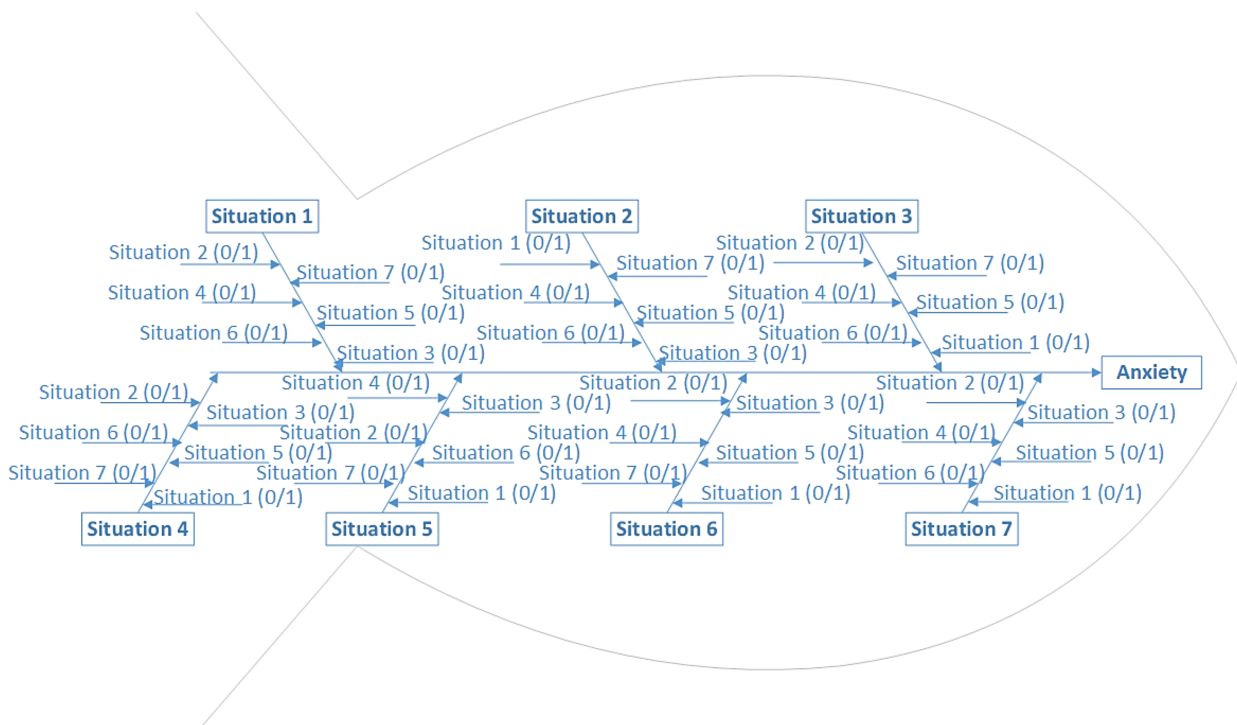


Fig. 3. Method for Calculating Index *I* of Situations.

A detailed description of each category is explained in the subsequent paragraph. The authors define *Panic* 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, 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 declaration of the situation as post-traumatic. In case post-traumatic is declared, the complete system must stop and observations be rectified by the operator. After certain repetitions without any damage, the same may be transferred to Specific-Phobia with the consent of the human supervisor. The 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 the 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 the 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 for 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, however, does not affect operations 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.

$$Total\ severity = G + P + O + T + K + N \tag{1}$$

2.1.2 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 2. If there are S number of situations, they can be related 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., if there are two resources then '0' for the prior resource and '1' for 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, there is a 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.

2.1.3 Anxiety Factor Calculation

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

$$a_{rs} = Q_{rs}\,[A_{rs} + (p_{rs} - t_{rs})] \quad (2)$$

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, the 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. If there are two resources, then *t*= 0, 1.

The value of *Q* will either be 0 or 1.

2.2 Resource Optimization

There is a need to identify the best resources that can handle the situations bearing major impacts. The value of the anxiety factor '*a'* for each situation can also be referred to as a matching score. The preference of assigning which resource to handle each situation is defined through the calculated matching score (anxiety factor), which is subsequently used in the optimizer model. For example, if there is a missing item in a workspace and there are two operational resources: a cobot and a human operator; only one resource can be assigned to handle this situation. The preference to handle a missing item must be assigned to the human and the cobot may move on to the next task. The 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." A model is required that minimizes the Anxiety by addressing situations in terms of priority while optimizing the resources. Since the problem incorporates both integers and variables thus making it complex, therefore, mixed-integer programming (MIP) is the best solution. The MIP can use both binary digits and whole numbers that greatly increase the scope of optimization problems while satisfying the constraints and objective function. The Gurobi Optimizer (Gurobi 2021) 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 optimizer identifies situations having maximum scores and subsequently assigns the resources to minimize the Anxiety. The overall technique addresses all the situations sequentially in terms of priority. This type of problem can be referred to as a Resource Assignment Problem.

2.2.1 Situation Constraints

These are the constraints associated with the situations. They ensure that each situation is handled by exactly one resource. This corresponds to the following:

$$r \in R \sum X_{rs} \leq 1 \tag{3}$$

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

2.2.2 Resource Constraints

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. This constraint can be written as follows:

$$s \in S \sum X_{rs} \leq 1 \tag{4}$$

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

2.2.3 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:

$$Maximize\ s \in S \sum r \in R \sum a_{rs} X_{rs} \tag{5}$$

2.3 Decision-Making for Anxiety Mitigation

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. A module-based software system is proposed, where different modules represent different layers of the proposed framework, and knowledge is transferred among them in an interoperable way. The data from all the layers must be stored in a central database. Four basic modules proposed to be incorporated in any CPS for anxiety mitigation 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 number of modules is not standard and may vary as per the requirement of a particular case. The general connectivity of the modules is shown in Fig. 4, however, the detailed representation for the particular case study is shown in the experimental validation section. The main module holds the intended scenario and looks for the changes at every instance of operation. It is connected to the other modules, and in case changes are faced, the matching score is ascertained for the situations through the anxiety module. Accordingly, the situations with the highest anxiety factor (matching score) are assigned the best possible resources through the optimization module. Here, the optimization module only sorts out the best feasible resources, whereas the decision-making module encompasses the logic to handle the braved situations. Therefore, the outputs of the Anxiety and the optimization modules are given to the decision-making module, which decides on the assignment of resources for task handling, based on the knowledge-dependent logic. Commands are given to the physical resources which could be a human operator, a cobot, a machine, etc. depending on the identified tasks. The human component is also given cautions through social signals on observation of social norms and obsessions.

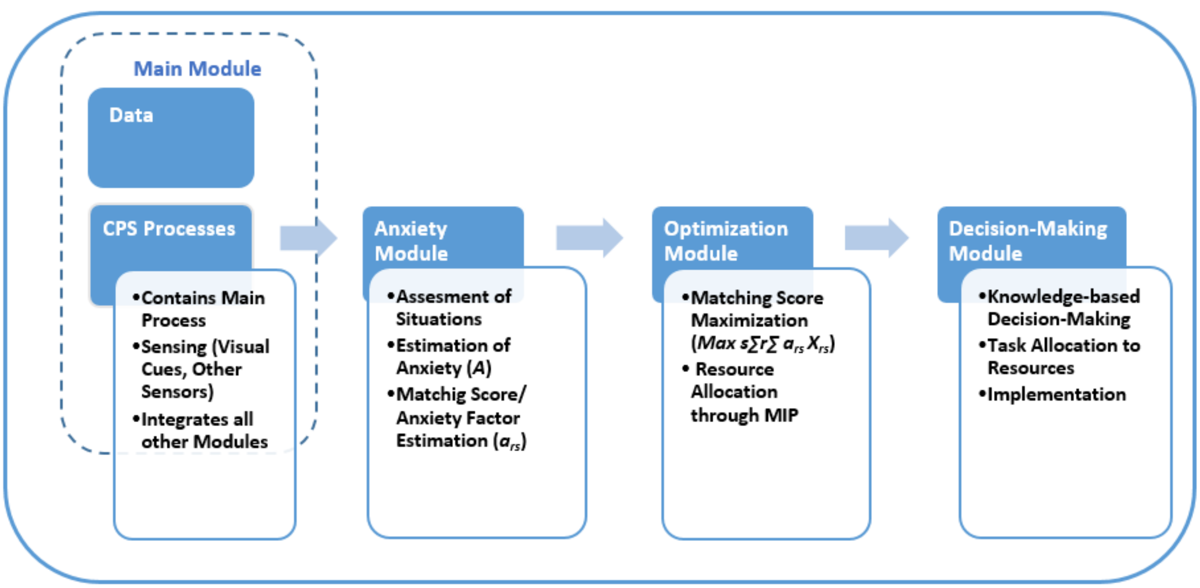
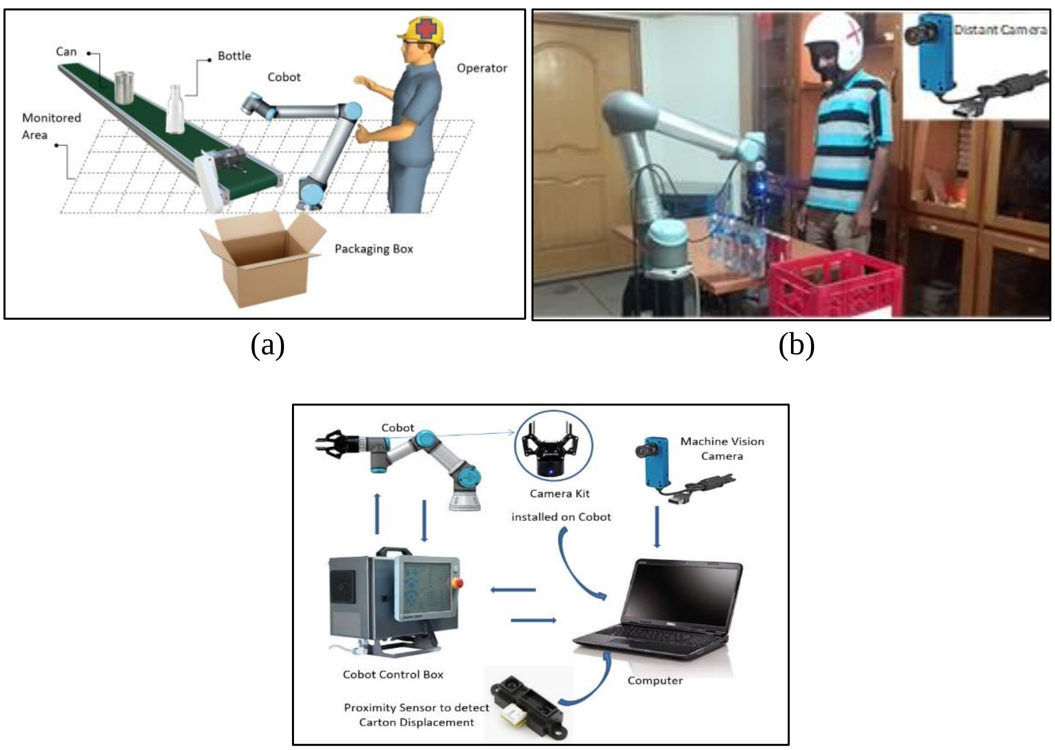


Fig. 4. Module-based Software Implementation for Decision-making.

3 Experimental Validation

An example of a beverages manufacturing industry is considered from the previous work (Islam et al. 2019), as shown in Fig. 5. 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 is monitoring operations and places crates. Despite replacing crates, the supervisor will also look for defective items like broken bottles or dented cans. It means he is in both collaborative and supervisory roles. After the package is complete, the operator removes the crate and fills the space with an empty one. A total of twelve items have to be packaged, that is six bottles and six cans.



(a) (b)

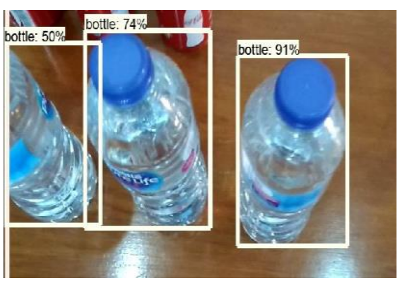
(c)

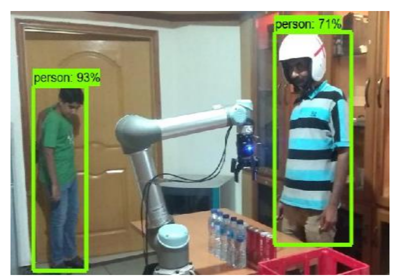
Fig. 5. (a): Scenario; (b): Setup of Considered Case; (c): Interfacing of CPS elements.

Two complete cycles i.e. packaging of two crates/24 items are considered for the study. There are two resources, a human and a cobot, and the CPS anticipates twelve situations.

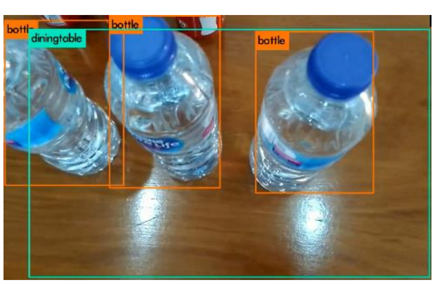
3.1 Situational Awareness

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. 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. Different new situations were considered and assessment of metrics are: ‘time delay’ is gauged through a clock measuring the cycle time, ‘threshold distance’ is assessed through the calculation of separation distance between the cobot and the object-detection-bounding-box covering the human supervisor, cobot collision through impact sensors on 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, later declared obsession since not an obstruction to the cobot’s motion. Detection of various situations through visual cues is shown in Fig. 6.





(a) (b) (c)



(d) (e)

Fig. 6. Detection of Situations through Visual Cues; (a): Right item; (b): Wrong item; (c): Unidentified person; (d): Table; (e): Human intervention.

3.2 Scenario's Anxiety

Different situations can emerge during this cycle that include both anticipated and unforeseen. The situations considered for the case and the estimate of Anxiety posed by them calculated through Ishikawa are shown in Table 3. Situations with serious nature of impact were considered to judge the unforeseen. Two new situations were added in the previous case to differentiate unforeseen from anticipated, which are 'power failure of the cobot' and 'collision of the cobot'. To include the social impact, the 'threshold distance' between the cobot & the human, and the 'time delay' in the work cycle were added.

Table 3
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 data set generated for the case study is shown in Table 4. The parameter *A* is calculated for the previous and new situations. The calculations are done under the specific category assessed for the particular situation. It can be observed from Table 4 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. The task priorities are defined through *t*; 0 is assigned to the prior resource and 1 is to the least prior in the table. The preferences of the situations are defined through *p*. The higher is the parameter *A*, the higher is the preference. Suitable resources for a particular situation are shown against *Q*, where ‘1’ describes the suitability of resources to tackle a particular situation.

Table 4
Data Set

Situation	***Category***	***Parameter (A)***	***Task Variable (t)***		***Preference Variable (p)***		***Resource Suitability Variable (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

3.3 Optimization Criterion for the case

For the optimization algorithm, the decision variables X_{rs} were defined which shows the relationship for assignment of available resources to the possible situations. As 12 situations are considered and 2 resources are available for this particular case, therefore 24 decision variables were defined which are to be used in equations (3), (4), and (5). For example, X_{21} is the decision variable associated with assigning the resource '2' to the situation '1' and X_{12} is the decision variable associated with assigning the resource '1' to the situation '2'. The situation constraints for this particular case were then defined. As equation (3) contains the summation of 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). Similarly, eleven other situations' constraints were formulated.

$$X_{11} + X_{21} \leq 1 \qquad (6)$$

In the same way the resource constraints were defined. The equation (4) 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 2 equations were formed for the 2 resources. The constraint for resource 1 (Human) can be written as (7) in which the first index of every decision variable represents the resource number and the second the situation number:

$$X_{11}+X_{12}+X_{13}+X_{14}+X_{15}+X_{16}+X_{17}+X_{18}+X_{19}+X_{110}+X_{111}+X_{112}\leq 1 \qquad (7)$$

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

$$X_{21}+X_{22}+X_{23}+X_{24}+X_{25}+X_{26}+X_{27}+X_{28}+X_{29}+X_{210}+X_{211}+X_{212}\leq 1 \qquad (8)$$

The objective function (5) 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 (9), where only one term in this summation will be nonzero. Similarly, other terms for each resource versus each situation were included in the objective function.

$$a_{11}\,X_{11} \;+\; a_{21}X_{21} \qquad (9)$$

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

3.4 Decision-Making Logic for 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 (Mayer et al. 1995). The five modules are the main module, item in place module, anxiety module, optimization module, and decision-making module. The main module Fig. 7, integrates all the other modules, it keeps count of the intended task (Right item) and looks for the situations identified in Table 3 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. The item in place module Fig. 8, 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 Fig. 9, otherwise, it works as per the intended situation. The contingencies to handle other situations are also looked after by the decision-making module. 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.

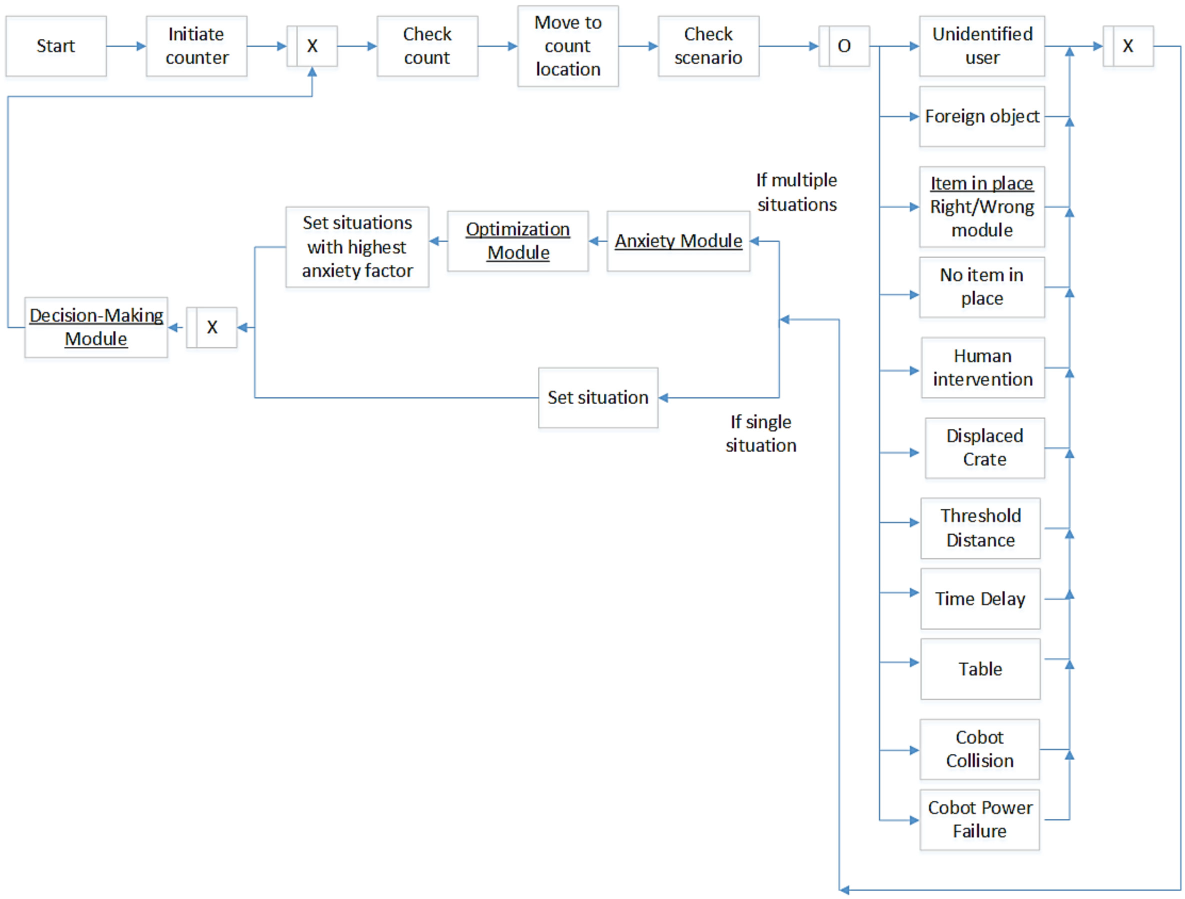
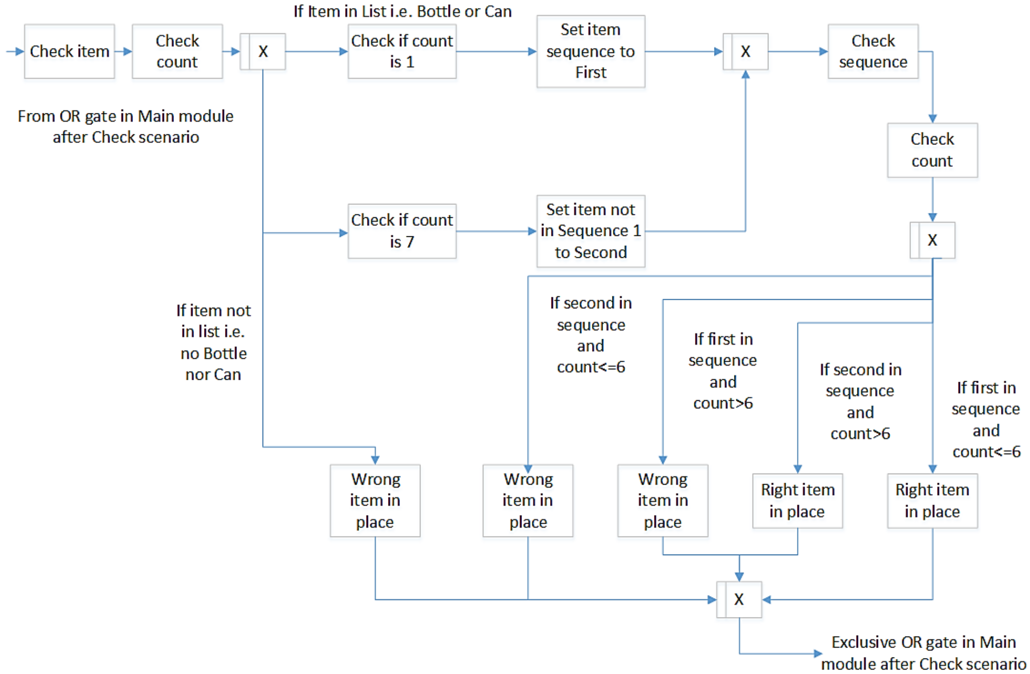


Fig. 7. Main Module.



496

497 Fig. 8. Item in Place Module.

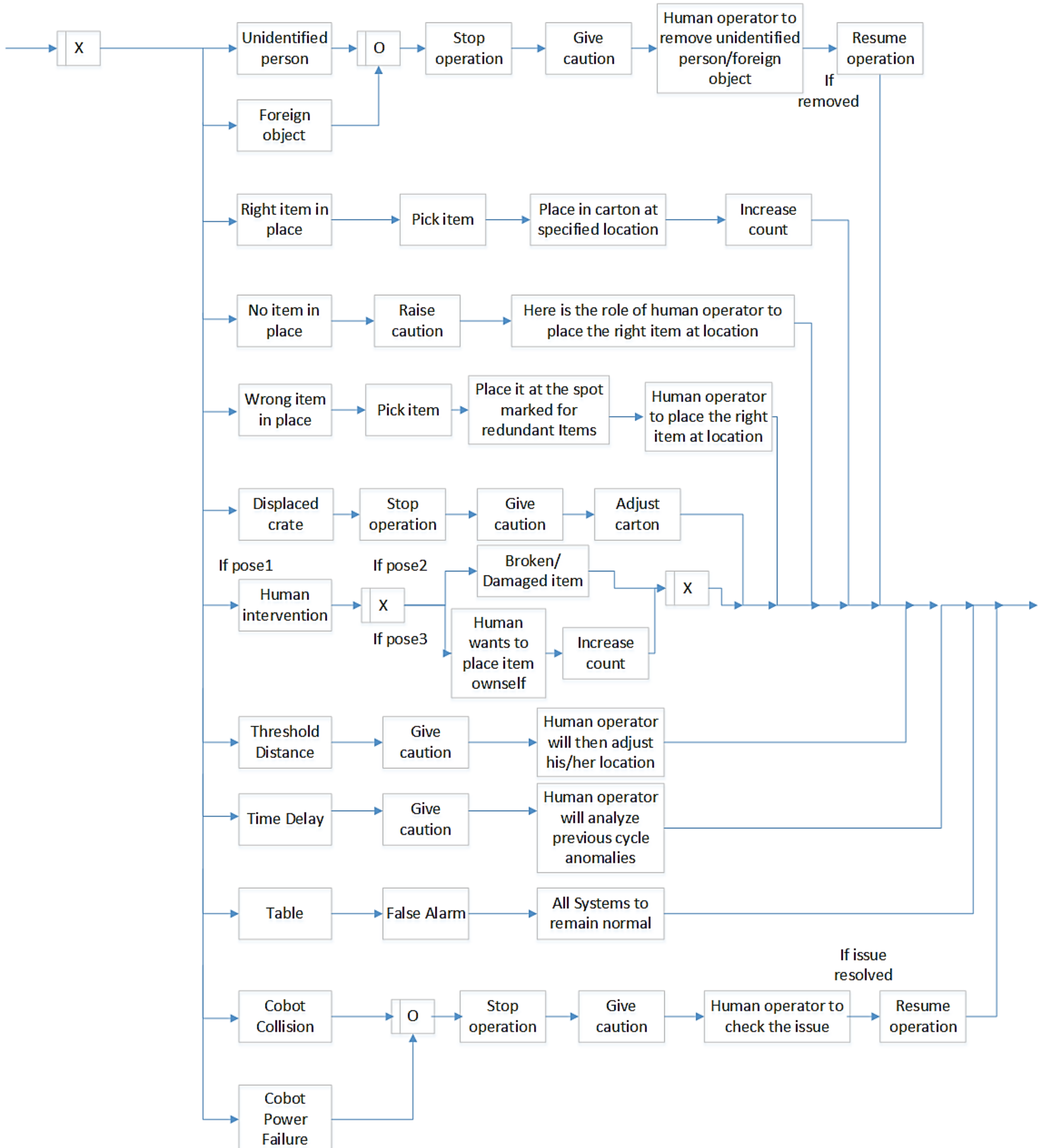


Fig. 9. Decision-Making Module.

3.5 Results

A detailed list of situations encountered at each iteration throughout the two cycles is shown in Table 5. Individual/total severity is calculated by the system, and resource assignments are shown accordingly.

Table 5
Situations vs. Resource Assignment

Iteration	*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

The important cases are discussed here. 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 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. 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 appeared at the 20th iteration that 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. At 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. 9). The Right item situation will then be activated on the ‘resume operation' command. Here the authors compare the current method with the previous approach (Islam et al. 2019). Only the most prior situation having maximum Anxiety was catered for in the previous method during a single iteration. Whereas 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; it can be seen 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, first situations with higher anxiety situations will be addressed, subsequently the remaining catered for sequentially. For example, if two situations are encountered i.e. 'Unidentified person' and 'Cobot Power Failure' then the resource 'Human' is the only suitable resource to handle both situations one by one in terms of Anxiety.

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 situational handling, the system provides. Details are given in Table 6.

Table 6
Comparison of Proposed Method with Contemporary Systems

Authors	***Technique***	***Safety Parameters***	***Situation Handling***
Flacco et al. 2012	Collision avoidance using depth space	Physical Safety for safe HRC	Caters single situation
Morato et al. 2014	Kinect and sphere-based simulation model for collision avoidance	Physical Safety for safe HRC	Caters single situation
Safeea and Pedro, 2019	Laser scanner and Inertial measurement unit (IMU) based model for collision avoidance	Physical Safety for safe HRC	Caters single situation
Sharkawy et al. 2020	Neural network and Torque-sensing for collision detection	Physical Safety for safe HRC	Caters single situation
Bekele et al. 2014	Physiological monitoring for adaptive HRI	Psychological safety	Caters single situation (difficulty level)
Lasota et al. 2014	Monitoring of separation distance for collision avoidance and speed adjustment	Physical and psychological safety for safe HRC	Caters single situation
Dragan et al. 2015	Intent awareness for fluent HRC	Psychological safety (Legibility)	Cater single Hybrid situation
Chadalavada et al. 2020	Bi-directional intent communication using spatial augmented reality (SAR)	Physical and psychological safety for safe HRC	Cater single situation
Islam et al. 2019	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

It can be seen from Table 6 that in the previous method, indexing of Anxiety was carried out through a more generic approach which lacks a rationale for establishing different levels of Anxiety. Although the current method is supported by the previous technique, however, a logical approach having a connection to different types of situations is presented. The technique makes it easy to differentiate and prioritize situations with varying anxiety levels based on knowledge acquired from the nature. It is also observed that legibility is ensured for both the robot and the operator through social cues. 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 emphasized here to observe the time taken by the setup in deciding on the braved situations. The maximum time taken for deciding on a scenario is shown in Fig. 10 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. 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 contribution of the works is that the CPS has been made more intelligent, safe, resilient and smart, and an increase in the overall productivity of the system has been observed. The amalgamation of four layers highlights the contribution of AI in the industry and a real manifestation of the computers' integration in industry 4.0, which is implemented in every layer of the proposed work i.e. the intended working of the CPS through software/algorithms, use of AI and algorithms for situational assessment, algorithms for optimization and logic-based decision-making/implementation, and integration of CPS elements. The method as a whole improves the decision-making of a CPS facing a complex scenario, and the proposed framework is accommodative to incorporate any industrial scenario may it be manufacturing, packaging, or any other production scenario.

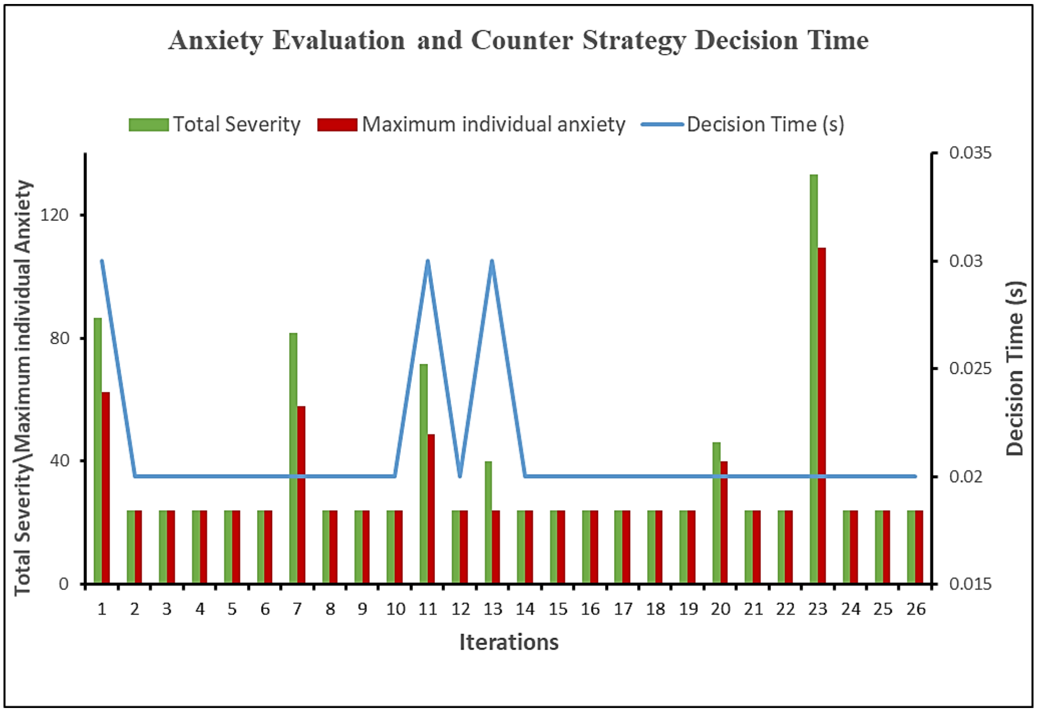


Fig. 10. Anxiety Evaluation and Counter Strategy Decision Time.

Future research should aim to improve the method with the support of machine learning techniques/AI-based knowledge systems, which may learn in real-time from the environment and will improve the knowledge base continuously. The existing system is dependent on predefined solutions, it is proposed for future work that the system may learn by observing the repetitive patterns and solutions provided to the situations, and may automatically resort to the same solutions. 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, though supervision by the human component is still recommended.

4 Conclusion

In this work, the authors propose a connective framework that intelligently safeguards a CPS's physical and psychological safety. The novel concept of Anxiety in CPS recently emerged, which can gauge both psychological and physical safety issues faced by the CPS in the social domain. The designed framework can optimally decide on continuous situations by evaluating the current state of Anxiety. The approach combines knowledge, human intelligence, and AI to improve the decision-making of the CPS encountering complex and dynamic situations. AI-based methods supported by visual and IR cues are employed to produce a flexible system in which the cooperating physical elements can detect and react well to better-conceived situations. Regardless of the specific case, the proposed method's effectiveness and applicability have been validated in a real-world industrial scenario. The technique has an edge in developing safe mechanisms for intelligent factories to safeguard costly physical assets and involve human workers to conserve and optimize the desired goal's efficiency and productivity. The developed methodology can be applied to various industrial scenarios. It will set a new direction for future research where Anxiety is perceived as the primary concern by all the collaborative parties and the decision-making elements of the CPS.

5 References

Baraka, K, P Alves-Oliveira, T Ribeiro - Human-Robot Interaction, 2020. "An Extended Framework for Characterizing Social Robots." *Springer*.

Beruvides, G, R Quiza, M Rivas, … F Castaño - … International Journal of, and undefined 2014. 2014. "Online Detection of Run out in Microdrilling of Tungsten and Titanium Alloys." *Springer* 74 (9–12): 1567–75. https://doi.org/10.1007/s00170-014-6091-1.

Cao, Z, G Hidalgo, T Simon, … SE Wei - IEEE transactions on, 2019. "OpenPose: Realtime Multi-Person 2D Pose Estimation Using Part Affinity Fields." *Ieeexplore.Ieee.Org*.

Castaño, Fernando, Rodolfo E. Haber, Wael M. Mohammed, Miroslaw Nejman, Alberto Villalonga, and Jose L. Martinez Lastra. 2020. "Quality Monitoring of Complex Manufacturing Systems on the Basis of Model Driven Approach." *Smart Structures and Systems* 26 (4): 495–506.

Chadalavada, RT, H Andreasson, … M Schindler - Robotics and Computer, 2020. "Bi-Directional Navigation Intent Communication Using Spatial Augmented Reality and Eye-Tracking Glasses for Improved Safety in Human–Robot Interaction." *Elsevier*.

Colgate, JE, J Edward, and MA Peshkin. 1996. "Cobots: Robots for Collaboration with Human Operators."

D'Auria, D, … F Persia - on Information Reuse and Integration (IRI), 2017 "A Collaborative Robotic Cyber Physical System for Surgery Applications." *Ieeexplore.Ieee.Org*.

Dautenhahn, Kerstin. 2007. "Socially Intelligent Robots: Dimensions of Human-Robot Interaction." *Philosophical Transactions of the Royal Society B: Biological Sciences* 362 (1480): 679–704.

Dragan, AD, S Bauman, … J Forlizzi - 2015 10th ACM/IEEE, 2015. "Effects of Robot Motion on Human-Robot Collaboration." *Ieeexplore.Ieee.Org*.

Flacco, F, T Kröger, … A De Luca - 2012 IEEE international, 2012. "A Depth Space Approach to Human-Robot Collision Avoidance." *Ieeexplore.Ieee.Org*.

Gurobi Optimization Inc. 2021. "Gurobi." 2021. gurobi.com.

Islam, Syed Osama Bin, Waqas Akbar Lughmani, Waqar Shahid Qureshi, Azfar Khalid, Miguel Angel Mariscal, and Susana Garcia-Herrero. 2019. "Exploiting Visual Cues for Safe and Flexible Cyber-Physical Production Systems." *Advances in Mechanical Engineering* 11 (12).

Khalid, Azfar, Pierre Kirisci, Zied Ghrairi, Klaus Dieter Thoben, and Jürgen Pannek. 2016. "A Methodology to Develop Collaborative Robotic Cyber Physical Systems for Production Environments." *Logistics Research* 9 (1).

Khan, ZH, A Khalid, J Iqbal - Innovative food science & emerging, 2016. "Towards Realizing Robotic Potential in Future Intelligent Food Manufacturing Systems." *Elsevier*.

Krüger, J, TK Lien, A Verl - CIRP annals, 2009. "Cooperation of Human and Machines in Assembly Lines." *Elsevier*. Accessed October 2,

Lanza, G, B Haefner, A Kraemer - CIRP Annals, 2015. "Optimization of Selective Assembly and Adaptive Manufacturing by Means of Cyber-Physical System Based Matching." *Elsevier*.

Lasota, PA, JA Shah - Human factors, and undefined 2015. 2015. “Analyzing the Effects of Human-Aware Motion Planning on Close-Proximity Human–Robot Collaboration.” *Journals.Sagepub.Com*

Lasota, PA, GF Rossano, JA Shah - 2014 IEEE International, 2014. “Toward Safe Close-Proximity Human-Robot Interaction with Standard Industrial Robots.” *Ieeexplore.Ieee.Org*, 339–44.

Li, Zukui, and Marianthi G. Ierapetritou. 2008. “Robust Optimization for Process Scheduling under Uncertainty.” *Industrial and Engineering Chemistry Research* 47 (12): 4148–57.

Lv, C, X Hu, … A Sangiovanni-Vincentelli - IEEE Transactions, 2018. “Driving-Style-Based Codesign Optimization of an Automated Electric Vehicle: A Cyber-Physical System Approach.” *Ieeexplore.Ieee.Org* 66 (4): 2965–75.

Mayer, RJ, CP Menzel, MK Painter, PS Dewitte, and T Blinn. 1995. “Information Integration for Concurrent Engineering (IICE) IDEF3 Process Description Capture Method Report.”

Monostori - Procedia, CIRP, 2014. “Cyber-Physical Production Systems: Roots, Expectations and R&D Challenges.” *Elsevier*.

Morato, C, KN Kaipa, … B Zhao - … of Computing and, 2014. “Toward Safe Human Robot Collaboration by Using Multiple Kinects Based Real-Time Human Tracking.” *Asmedigitalcollection.Asme.Org*.

Osama Bin Islam, Syed, Ali Khan, Azfar Khalid, and Waqas Akbar Lughmani, 2019. “A Smart Microfactory Design: An Integrated Approach.” *Taylorfrancis.Com*.

Pirvu, BC, CB Zamfirescu, D Gorecky - Mechatronics, 2016. “Engineering Insights from an Anthropocentric Cyber-Physical System: A Case Study for an Assembly Station.” *Elsevier*.

Watson, G - Quality progress, 2004. “The Legacy of Ishikawa.” *Search.Proquest.Com*.

Rad, CR, O Hancu, IA Takacs, G Olteanu - Agriculture and Agricultural, 2015. “Smart Monitoring of Potato Crop: A Cyber-Physical System Architecture Model in the Field of Precision Agriculture.” *Elsevier*.

Redmon, Joseph, and Ali Farhadi. 2018. “YOLOv3: An Incremental Improvement,” April.

Safeea, M, P Neto - Robotics and Computer-Integrated Manufacturing, 2019. “Minimum Distance Calculation Using Laser Scanner and IMUs for Safe Human-Robot Interaction.” *Elsevier*.

Scholze, S, J Barata, D Stokic - Sensors, 2017. “Holistic Context-Sensitivity for Run-Time Optimization of Flexible Manufacturing Systems.” *Mdpi.Com*.

Sharkawy, Abdel-Nasser, Panagiotis Koustoumpardis, Nikos A Aspragathos, Panagiotis N Koustoumpardis, and Nikos Aspragathos. 2020. “Human–Robot Collisions Detection for Safe Human–Robot Interaction Using One Multi-Input–Output Neural Network.” *Springer* 24 (9): 6687–6719.

Sharma, V, … F Dittrich - Machine Learning, 2015. “Efficient Real-Time Pixelwise Object Class Labeling for Safe Human-Robot Collaboration in Industrial Domain.” *Proceedings.Mlr.Press* 40.

Sokovic, Mirko, Jelena Šaković Jovanović, Zdravko Krivokapic, and Aleksandar Vujovic. 2009. “Basic Quality Tools in Continuous Improvement Process.” *Researchgate.Net*.

Torpy, JM, AE Burke, RM Golub - Jama, 2011. “Generalized Anxiety Disorder.” *Jamanetwork.Com*.

Zhuge, H - Artificial Intelligence, 2010. “Interactive Semantics.” *Elsevier*.