# Human-Robot Interaction Review: Challenges and Solutions for Modern Industrial Environments

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**ABSTRACT** The demand for collaborative robots is growing in industrial environments due to their versatility and low prices. Thus, more collaborative solutions are emerging for industrial scenarios. However, implementing scenarios where robots work autonomously while synchronizing their operations in a safe industrial environment with shopfloor workers is not easy. To fill the gap existing in the safe implementation of industrial collaborative scenarios, this manuscript presents a review based on five identified challenges that gathers the primary vital aspects to bear in mind while developing applications for them. Thus, a four-level classification is proposed, which collects the identified challenges and the previous developments in the field of human-robot interaction. The five identified challenges pretends to be the missing enabling key for implementing industrial collaborative scenarios in modern industrial plants. Lastly, a discussion and conclusion are exposed to analyze the degree of development in the field and its potential growth.

**INDEX TERMS** Cobots, human-robot interaction, HRI challenges, industrial collaborative scenarios, industrial safety, review.

## I. INTRODUCTION

With the expansion of Industry 4.0 (or Connected Industry), industrial innovation requires more autonomous, adaptive, and flexible production systems [1], [2]. Autonomous and adaptive industrial production systems can be achieved through enabling technologies such as Digital Twins, IIoT (Industrial Internet of Things), or the CPS (Cyber-Physical Systems) [3], among others. However, the limited adaptability to unknown events or faults during production points out the lack of manufacturing flexibility [4]. To overcome this issue, the combination of robots and shopfloor workers in production lines is proposed as a suitable solution for flexible production in industrial environments [5].

In this scenario where human and robot coexists, technologies such as collaborative robots (cobots) grow on its importance to guarantee on-floor workers safety [6]. Thanks to the safe design, versatility, and lower prices of the cobots, industrial factories perceive economic, spatial and productivity benefits [7], [8]. These benefits are perceived in industrial processes through the lack of spatial reconfiguration or safety fences when installing one or several cobots [6].

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In these shared environments, it is relevant to install cobots instead of regular industrial robots for preserving the safety of operators at any time, as the main key factor for collaborative scenarios [9]. Thus, a protection fence-free space can be implemented entirely, allowing collaborative working modes between the shopfloor operators and the cobots [6]. This scenario is where human-robot interaction (HRI) makes all the sense to establish a proper way to ease and enable the safe interaction between humans and robots. In this manner, the HRI can also be considered as the tool to allow the completion of tasks that require the combination of human and robot skills in industrial environments [10].

However, implementing an industrial collaborative scenario takes more than a protection fence-free space or safe interaction modes. It requires the whole application to be harm-proof to guarantee shopfloor safety in any situation [11]. Therefore, real industrial collaborative scenarios must watch out for any risk source such as tool morphology or load characteristics. The literature shows that assuring shopfloor safety on a protection fence-free area in industrial environments is a growing concern [1], [12]–[14] for an adequate implementation of a collaborative application.

Even when the industrial panorama is evolving into a safer environment where the machines and robots can operate
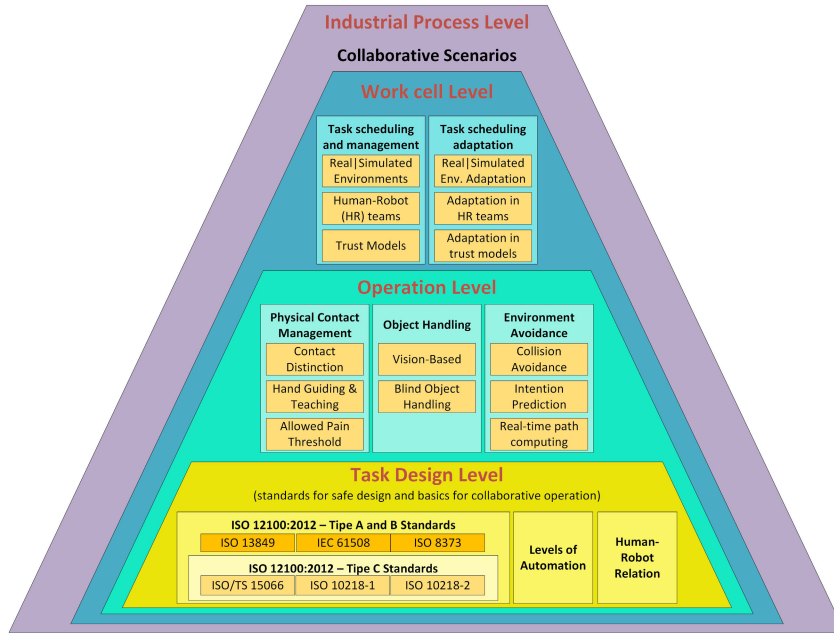
**FIGURE 1.** Collaborative scenarios: integration levels and challenges.

autonomously and collaboratively surrounded by operators, industrial collaborative scenarios are still far to be reached on current shopfloor layouts. The main reason why this happens is because of the lack of guarantee in safety while implementing advanced human-robot interactive capabilities in these environments. In order to assure the required levels of safety during collaborative modes of operation, this manuscript identifies five challenges to bear in mind while developing collaborative scenario applications. Since the basics of this kind of interaction are considered enough developed by the scientific community ([1], [12]–[14], among other possible references), this new complementary classification exposed in this work pretends to settle the requirements collaborative scenarios need to allow fluid and intuitive industrial collaboration. Therefore, their goal is to highlight the critical facts for enabling high-level safe interaction on industrial scenarios between the robots and the workers. Also, this work aims to gather solutions to beat this challenge sustainably, being aligned with levels 8 and 9 of SDGs (Sustainable Development Goals) [15], in the evolution to an autonomous and collaborative industry.

The remainder of this paper is distributed as follows. In section II, a brief description of the five identified challenges is exposed. Section III details every key aspect of each challenge by reviewing the solutions of the literature. Section IV shows a brief discussion of the main facts to consider while developing collaborative scenarios. Lastly, section V contains the conclusion and highlights a scope of the most promising research fields.

## II. MODERN COLLABORATIVE SCENARIOS CHALLENGES

Safety is the most leading criteria to guarantee in a human-shared industrial environment. By assuring that, collaborative applications can be deployed combining skills of shopfloor operators and robotics systems. In such a panorama, HRI appears to be a suitable tool to achieve safety through continuous communication and operation between the robot and the on-floor operator. However, HRI application is not a simple task due to the unpredictable behavior of shopfloor workers, which might cause collisions and dangerous or harmful situations around the robot [16]. Thus, HRI is a topic that has attracted more attention in the latest year by the scientific community, who has gathered several examples and approaches of diverse classifications about the different ways they consider this interaction should happen in industrial environments [1], [12], [13], [17]–[19].

The interaction at this essential level, as these sorting proposed, is necessary but not enough to enable implementation in real industrial environments of collaborative work cells. These scenarios require reactive methods to respond to uncertainties and unexpected behaviors to achieve fluid communication and workflow between operators and robots. Therefore, section II introduces a novel classification divided into four levels which are the task design, operation, work cell, and industrial process levels as shown in FIGURE 1. The lower level (task design) is the closest to direct human-robot interaction. This level is responsible for collecting the required safety aspects and level of automation, and essential human-robot interaction relations. It also defines a task as the elemental piece of action that a robot can execute. The immediate upper level, the operation level, gathers all actions the robot can handle, which are an association of several tasks. It focuses on handling aspects of direct interaction to achieve fluid workflow between humans and robots, such as the physical interaction or the collision avoidance during operation. Stepping up a level, the work cell level

encapsulates the management and coordination of several groups of operations (from both robots and operators) to describe an industrial subprocess. This level is responsible for the proper distribution of operations among robots and operators to optimize the workflow of the successive industrial subprocesses to reduce bottlenecks due to non-productive times and minimize the potential risky situations. The last level that handles the management of different subprocesses is the industrial process level. Its mission relies on coordinating the several autonomous and collaborative subprocesses to accomplish a satisfactory production. This classification responds to the five identified challenges: physical contact management, object handling, environment avoidance, task scheduling and management, and task scheduling adaptation challenges, also pictured in FIGURE 1. The first three challenges belong to the operation level, while the last two suit the work cell level. These challenges, detailed in section III, pretend to complement this classification, unraveling the current needs to develop industrial collaborative scenarios.

Therefore, the subsection below describes the different levels in detail and briefly illustrates the challenges and why they are only classified in two of the four levels. Thus, an overall idea of the proposed classification can be obtained.

## A. INTEGRATION LEVELS FOR COLLABORATIVE SCENARIOS

From all the levels developed below, the one that the literature extends the most is the task design level. For that reason, it will be the one more explained in the current section, while the others that address the challenges will be more detailed in section III of the paper.

### 1) TASK DESIGN LEVEL

The first level represented in FIGURE 1 corresponds to task design aspects for collaborative robots. In this work, a task is considered the minor action where a robotic system operation can be split to achieve a goal. Therefore, a task can be as simple as moving the robot between two positions, giving a command to the tool, or planning an obstacle-free trajectory path. They represent the minimum expression to bear in mind while designing robotic applications.

In a collaborative scenario, these tasks must be safe-oriented and do not only involve the robotic system. A shared task requires the distribution among shopfloor workers and cobot tasks, minding that safety must prevail in every action each executes. Thus, this low level of integration leans on various safety standards as the basics where the proposed classification starts. This classification relies on the sorting made by ISO 12100:2010 [20], where the various safety standards are divided into Type A, B, or C, from general ones to collaborative robotics-specific ones [5], [14], [21]. Supporting the general-purpose safety standards such as ISO 13849 [22], IEC 61508 [17], or ISO 8373:2012 [23], which are also backed up by the literature [3], [12], [24], [25], this level focuses on particular aspects for assuring safety in collaborative robotics.
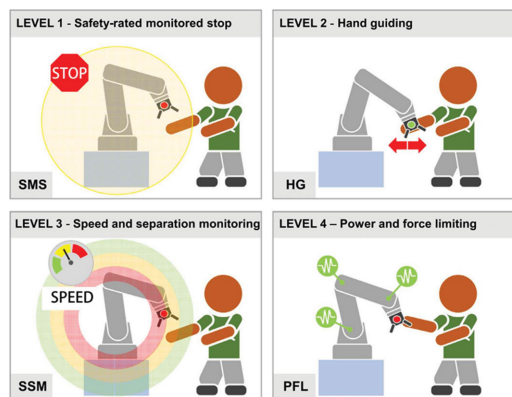


**FIGURE 2.** Collaborative working modes based on ISO 15066 standard [14], [28].

ISO 10218-1:2011 [26] and ISO 10218-2:2011 [27] standards detail cobots safe design characteristics to assure not harming the operator, while ISO 15066:2016 [28] defines collaborative aspects to bear in mind while designing shared tasks, such as the collaborative working modes. The last standard proposes the following four modes depicted in FIGURE 2: SMS (Separation Monitoring Stop), HG (Hand Guiding), SSM (Speed and Separation Monitoring), and PFL (Power and Force Limiting) [12], [21], [25], [29].

FIGURE 1 shows another goal this level targets based on whether the tasks are more oriented for an autonomous operation than for a collaborative model. In this sense, the literature proposes the levels of automation as an approach to define the task's autonomy degree. Compared to classical approaches that only include levels between automated and autonomous [12], [30] to fulfill their mission deliberately [31]–[34], this topic considers the chance of an operator to intervene during autonomous operation. Thus, the levels of automation gather the latest tendencies that fade between autonomy, cooperation, and handling [35]. This way, the traditional levels are evolving to Levels of Robot Autonomy (LORA) [4] which adds the automation to a specific framework for developing HRI applications.

On the other hand, FIGURE 1 also defends the importance of proper management of human-robot relations. This fact highlights that working modes for safe interaction are supported by synchronization among various tasks to ensure shopfloor safety [36]–[38]. This last topic refers to the different ways humans and robots can share both the workspace and the task operations [25], [39]. The literature exposes different classifications that differ in the number of proposed levels between three [29], [40]–[42], four [13], [39], [43], or five [18], [44] levels as the most accepted approaches.

The three-level classification divides de HRI into human-robot coexistence (HRCx), human-robot cooperation (HRCp), and human-robot collaboration (HRC) [29]. During an HRCx task, neither the operator nor the robot shared task nor space [45], [46]. Therefore, this level is also called coaction [47] or coexistence [18]. On an HRCp task,

the operator and the robot operate in the same workspace. Nevertheless, they do not share the task [45], [46] limiting the synchronization to collision avoidance [16], [29], [48]. Additionally, HRC happens in a scenario where both, the task and the workspace, are shared simultaneously [29], [43], [47]. It allows completing complex tasks together between robot and operators [16] that only can be achieved by assuring the coexistence and safety first [29], [36], [49]–[51]. Three levels classification is accepted by several researchers who might name each level differently; however, the idea underneath each prevails [40]–[42]. Under the HR relation criterion, four and five level classifications which add groups to the levels mentioned above, such as isolation (no-coexistence) [13], [39], [43] and synchronization (sharing a task but not the workspace), respectively [18], [44] can also be found. An approach of a five-level classification can be appreciated in FIGURE 3. In this representation, the collaborative working modes (as HRC safety implications) meet with the interaction levels without disregarding the change of multi-human or multi-robot teams. Thus, whenever the complexity of agents which participate in an industrial operation grows, so does the complexity of a proper HRC [18].
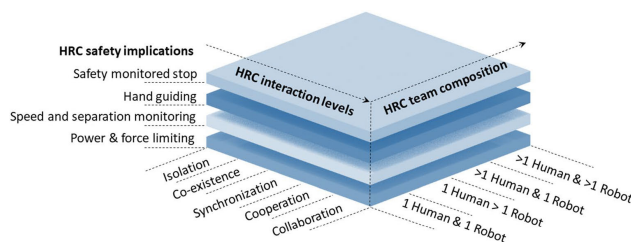


**FIGURE 3.** Architecture model for human-robot collaboration by Malik and Bilberg [18].

Some of the different classifications also consider higher interaction level topics such as pHRI (physical Human-Robot Interaction), cHRI (cognitive Human-Robot Interaction), safety in industrial environments, of CPS (Cyber-Physical Systems) for HRI [1], [14], [29]. However, in this work, they are not considered part of this level because they require the interaction of several factors in a more developed manner. So they have been included in higher levels of the presented classification instead.

Finally, the first of the proposed levels collects various classifications about the deployment of safe tasks. Implementing autonomy levels, human-robot relation criteria, and standard-based robotics makes it possible to program risk-free isolated actions for manufacturing applications. Unfortunately, developing safe, isolated tasks is not enough to deploy industrial collaborative scenarios. They require to be grouped and coordinated to ensure all the actions of an industrial process are safe.

### 2) OPERATION LEVEL

This second level represented at FIGURE 1 considers the operation aspects required for enabling collaborative scenarios. An operation can be described as a set of actions compound by various tasks with a particular target. This level collects and proposes the three first challenges related to operations for enabling collaborative scenarios in industrial environments.

In the literature, this level is usually camouflaged in a two-levels sorting compound by the pHRI and the cHRI. On the one hand, pHRI applications can be summed up into contact distinction and classification applications between operators and robots. For this aim, various studies have been developed in the field by applying techniques such as mathematical model matching or signal threshold filtering [52]–[57]. Developing a safe pHRI application based on these techniques depends on the integrated sensors the robot brings. Thus, some authors focus on studying the several collaborative suitable external sensors, and commercial robot integrated sensors [19]. On the other hand, cHRI includes technologies to allow natural interaction between robots and operators by gifting the robotic systems with cognitive skills. However, achieving natural interaction is not a simple task because it requires continuous monitoring of the surroundings and surveilling the communication flow direction to assure safety while interacting in the communication [58]. Researchers defend several approaches such as voice commanding, gesture recognition [59], collision avoidance and human-aware navigation, among other solutions to achieve natural interaction [1], [29], [60]–[62].

This manuscript pretends to extend the actual classification by filling the gaps detected in pHRI and cHRI standalone classification through the operation level group. First of all, the pHRI should not be restricted to contact management and distinction between operators and robots only [63]. The load management is also relevant because inappropriate handling might end in a load loss or a crash, unchaining risky or harmful situations for the operator. Besides, other collaborative operations requiring proper and safe physical interaction, such as hand-guided operations, can be included as pHRI topics. On the other hand, literature sorting for cHRI operations is a complete topic that integrates commanding operations and safety aspects. However, the commanding aspects such as gesture recognition or voice commanding do not influence safety facts or reduce production bottlenecks. As the purpose of these technologies is to ease operators commanding while executing operations and represent something complementary to safety, this work proposes to restrict collaborative scenarios enabling cHRI to just safety aspects like collision avoidance and human-aware navigation interactions. Moreover, in collision avoidance and human-aware navigation operational modes, the utilization of pierce-shaped tools or loads is also relevant. Once again, improper handling of both could end up colliding with the operator, compromising the safety of the operator by the load loss or the collision itself.

Therefore, this level is structured in three challenges identified for achieving operational safe industrial scenarios: the environment avoidance challenge, the object handling, and the physical contact management challenge. The challenges

are aligned with both the additional aspects to mind at industrial collaborative scenarios and the previous proposals. Firstly, the environment avoidance challenge addresses collision avoidance with surrounding objects or people, in movement or stopped, without a collision. Additionally, the object handling challenge manages the problem of adequately handling objects while executing trajectories and grabbing objects to avoid danger for the operator. Lastly, the physical contact management challenge includes handling the available physical interaction modalities between humans and robots.

The three-levels classification proposed pretends to extend the traditional classification to be more specific for enabling industrial collaborative scenarios. Thus, both sortings are complementary organizations that can coexist. On the one hand, the one defended in this manuscript gathers and extends safety aspects exclusively related to criteria required for allowing industrial collaborative scenarios. On the other hand, the traditional classification complements the one proposed in this paper by adding natural interaction between operators and robots.

### 3) WORK CELL LEVEL

As FIGURE 1 depicts, the third level of the representation corresponds to the work cell level. In this manuscript, the work cell level correlates with industrial subprocesses. Particularly, a subprocess can be defined as a set of industrial operations synchronized and coordinated to implement all the actions and achieve all the goals for a successful industrial workstation. Therefore, this level pursues to state the challenges and requirements to implement industrial collaborative work cells.

The higher the representation level, the more complex it is to incorporate acceptable safety behaviors on industrial systems due to the growth of the relevance of operator behaviors uncertainties. Thus, several tries of simulating or virtualizing human behaviors can be found. One of the most accepted approaches relies on the CPS applied to HRI to benefit from the advantages virtualized spaced offers while improving on-floor safety through real-time simulation of human behaviors [3]. By linking the simulation of the robot's surroundings to the operators' cognitive capacities, a new research discipline emerges, the Human-Cyber Physical Systems (HCPS). This way, industrial production improves due to reducing bottlenecks thanks to including human behavior on industrial control loops [64], [65].

However, virtualizing human behaviors is not an easy task because of the high complexity of non-consistently measurable cognitive skills models. Thus, these techniques cannot be applied to industrial scenarios, requiring less complicated techniques to synchronize and coordinate the several operations of the subprocess [66]. Therefore, an existing challenge relies on synchronization and coordination techniques that reduce non-controlled cognitive skills influence to allow the extension of collaborative working methodologies to any industrial scenario. Additionally, these scenarios must deal

with uninterrupted production systems, so adaptation mechanism becomes a necessity. Traditional adaptation techniques for autonomous manufacturing systems have been developed for several years now with high success rates in industrial environments. Due to that, this challenge will leave aside traditional adaptation challenges in favor of focussing on collaborative adaptation techniques [1], [14], [21]. Therefore, this works regard adaptation to operation distribution and synchronization to progressively reduce cognitive skills influence and improve production cycle times every new cycle.

To face the optimal operation distribution and its synchronization, the following two challenges have been identified: the task scheduling and management challenge and the task scheduling adaptation challenge (see FIGURE 1). On the one hand, task scheduling and management challenge is referred to how a task should be executed to guarantee worker safety even though when the robot handles non-safe objects is addressed. Complementary, task scheduling adaptation challenge addresses adaptation to task scheduling and management to improve production cycles on each iteration, leaving aside traditional adaptation mechanisms and methodologies such as FTC (Fault Tolerant Control) applied to production.

A collaborative work cell can be implemented by the synchronization and coordination of operators and robots' operations. Thus, the production will be optimized for shared workspaces where the operator and the robot coexist in a protection fence-free area. Even though addressing collaborative work cells denotes considerable progress, they are not enough to be considered the desired industrial collaborative scenarios.

### 4) INDUSTRIAL PROCESS LEVEL

This level integrates all the relevant aspects of the levels below as the highest level of the classification presented in FIGURE 1. It corresponds with the most complex level considered, and it is the level where the collaborative scenarios should be implemented. This level defines an industrial collaborative scenario as an industrial environment where collaborative work cells coexist with autonomous machinery workstations synchronized and coordinated to accomplish a whole industrial manufacturing process. Thus, a modern industrial collaborative process combines generic subprocesses based on autonomous and adaptive machinery with highly flexible subprocesses based on collaborative work cells.

There have not been found any specific approaches for managing the industrial collaborative scenarios that coordinate both types of subprocesses. However, some of the available techniques for work cell level might fit this level too. As this level requires a higher degree of synchronization between processes, it does not focus exclusively on robotic system requirements or safety aspects for robotics in safe collaboration. They are more production-oriented methods such as ERP (Enterprise Resource Planning) systems.

Since there are no particular challenges to address this level because there have not been found solutions for this particular

level of abstraction, it can be considered a challenge itself. Nevertheless, facing it is not a sole objective. Before addressing this issue, industrial collaborative levels challenges must be solved. Thus, the only requirement left will be high-level subprocesses coordination which is generally solved by advanced or integrated production techniques such as ERP. However, the enabling challenges for this environment have not been addressed yet, so their solution might unravel new challenges for this specific topic.

## III. SOLUTIONS FOR COLLABORATIVE SCENARIOS CHALLENGES

Section II proposed five challenges grouped in several levels of the industrial automation process: the contact management challenge, the object handling challenge, the environment avoidance challenge, the task scheduling and management challenge, and the task scheduling adaptation challenge. Each of the challenges mentioned above pretends to address a specific aspect to deal with to allow a safe implementation of collaborative scenarios in industrial environments.

In this section, the solutions found to address each challenge are reviewed. Thus, the state of the art of the identified challenges and the remaining gaps to be solved has been analyzed. It also aims to establish the basis for a critical discussion about the current state and possibilities of real collaborative scenarios in an advanced manufacturing environment. Additionally, each challenge is complemented with a table where the relevant information for each challenge is described to allow a critical discussion. Each table is composed of the following fields: level (subchallenge or problem to address), available level of collaboration for applications, physical contact (referred to whether the physical contact is allowed or not), advantages of the solution, disadvantages of the solution, available technologies for its implementation, approaches and reference summary. This way, the critical facts to bear in mind while developing collaborative scenarios can be quickly heeded.

### A. OPERATION LEVEL

In the following subsections, each of the challenges included in the operational level is reviewed from the one that concerns more danger (the physical interaction is allowed) to the one that is considered safer (the physical interaction is not allowed collision is tried to be avoided).

#### 1) CONTACT MANAGEMENT

In the era of Industry 4.0, more and more vision-based systems are being launched for industrial use. However, in a shared environment where the operator works side by side with a robot, eventually, a crash might occur. When this happens, the robot must react correctly without harming a human to preserve safety under any circumstance.

In this situation, the most common reason why the collision happens is because of an expected situation of close human-robot interaction. Nevertheless, it is not appropriate to forget that this contact between an operator and a robot

can happen intentionally. Thus, this challenge can be divided into contact classification, hand-guided tasks, teaching applications, or allowed pain threshold topics as represented in TABLE 1, depending on how the physical interaction occurred and the involved agents of the contact.

The differentiation between desired contact and non-desired contact is crucial to discern between the need for a collaborative working mode or an autonomous one. The contact classification, also known as post-collision strategies, aims to establish methods to automatically identify and classify contact between a worker and a robot on an industrial plant. The true potential of this field is to discern between desired or non-desired contacts to react to each situation appropriately [52]. Even though most commercial collaborative robots of the leading industrial manufacturers have intrinsically installed PFL (Power and Force Limiting) strategies, this functionality should be driven by a higher controller to avoid stopping the robot movements during operation. Thus, a minimum and maximum contact force will be assured while working. In this scenario, the operator interacts directly with the robot itself to accomplish a task. In these direct interactions between the robot and the operator, the contact classification algorithms are integrated and synchronized with the high-level robot controllers. Therefore, the contact management challenge will address the advanced techniques and methodologies to handle the collision classification. This will relegate inherent collision detection mechanisms already integrated into commercial cobots to a background plane. An example of such systems is the F/T (Force/Torque) sensors built in each of the KUKA LBR iiwa robot joints. These integrated sensors combined with the programming suite of KUKA (Sunrise Workbench) allow the development of advanced functionalities for contact distinction without disregarding the cobot's critical safety aspects and limits [3]. Thus, the following paragraphs review several strategies and algorithms that can be applied to upgrade simple thresholded monitored stops to improve their functionalities while preserving safety.

The first approach based on control strategies for these scenarios is the admittance control architectures [92], [93]. These types of control loops can be used to discern which kind of contact has occurred using an external F/T (Force/Torque) sensor [56]. Another similar approach is based on more generic admittance control loops for industrial manipulators suitable for scenarios where the industrial cobot has already installed integrated F/T sensors [67]. Another type of approach tries to improve the admittance control structures in these scenarios. For example, a solution based on a stable compliant motion control coupled with a variables admittance and adaptive control for moving environments has been proposed [68]. A similar approach consists of a vision-based adaptive impedance controller (inverse control strategy for admittance control) for advanced polishing tasks [69]. Adaptive controllers for safe pHRI are also exposed as solutions through an implemented adaptive damping controller, which fulfills the ISO10218 requirements by online

**TABLE 1.** Contact management sub-challenges.

| Level | Level Collab. | Physical Contact | Advantages | Disadvantages | Available Technologies | Approaches | Refs. |
|---|---|---|---|---|---|---|---|
| Contact classification | Coop. and Collab. | Allowed | Allow the presence of operators in robot's surroundings. Automatic switch between operation modes and safe modes. The operator can interact in a more natural way with the robot. | Cannot operate standalone. If it fails, the operator can be harmed. Precise modelling is required to classify the contact type. Model based on AI usage might introduce computational stress to the overall systems | F/T sensors External sensing skins (capacitive, inductive, among others) Current/torque sensors | 1) Admittance and adaptive control models 2) Sensored contact detection and classification 3) Mathematical/physical models matching 4) Neural networks (NN) models improvements 5) Current/torque signal filtering | [56], [67]–[71] [56], [72] [53], [54], [73]–[76] [77]–[81] [82], [83] |
| Hand guided tasks | Collab. | Required | The robot is more easily programmed The movement can be recorded for later use or learning how to move. | Not every tool is suitable for this kind of applications during operation. When the tool is spining or heating, there's additional risk to the operator. | Software/Programmatic robot skills | 1) Hand guided polishing 2) Hand guided painting | [84]–[86] |
| Teaching application | Collab. or Coop. | Required | The robot is more easily programmed. Enables programming complex tasks through learned movement primitives There's no need of inline experienced programmer in production | The applications to be developed are more limited Might increase complexity during software design faces | Commercial software tools Open Sourced software tools | 1) Waypoint/Movement teaching 2) Kinesthesic teaching | [87], [88] |
| Allowed pain thresholds | Coop. and Collab. | Allowed | Better adjustment of safety stop paremeters. Knowledge about safety application feasibility. Increase application safety | Increase cost of production/application (study/safety must be paid) Not all tools are suitable for collaborative applications | F/T sensors Current/torque integrated sensors Skin sensors | - | [89]–[91] |

limitation of tool velocity, pose and contact forces [70]. The last approach consists of an impedance controller-based solution for carrying through a stability analysis for single or multiple passive/active human models. Thus, load-lifting and handling tasks that require more than one operator can be executed [71].

The paragraph above displays the integration of the contact classification mechanism in control architectures; nevertheless, there are more straightforward solutions in the literature to just detect and classify the collisions through external sensors, for example, the usage of an external sensitive soft robotic skin for safe human collaboration. In this particular use case, the algorithm has been tested by wrapping both arms of a YuMi robot, so when an operator collides with one of the two arms, it stops [72].

Using external sensors is a reliable method to detect and distinguish between collision types. However, using external sensors means increasing automation costs. Thus, mathematical, physical, or statistical methods have been developed to classify collisions in real-time using only the information commercial robots provide and, once again, integrating these algorithms into the robot controller. An example approach exposes a frequency study analysis of applied external forces through a Fast Fourier Transform. Thus, the dynamic response speed is used to distinguish among collisions, or intended contact [73]. Another solution is based on matching strategies between physical-mathematical models of the robot's behavior and the robot's behavior in the real world. Thus, when the expected behavior does not follow the real one or vice versa, a collision is detected. Depending on how the mismatch is produced, a desired or non-desired contact can be discerned. The literature proposes two different models to detect collision avoiding the use of external sensors. The first one is based on the experimental estimation of joints frictional models and comparing the current torques with the expected without external influence [74]. Furthermore, the second one is based on a subspace projection of the robot joints and links. Thus, consider the effect of the load during a collision [75]. Another presented solution is based on

total energy and generalized momentum to detect and safely react after a collision using only proprioceptive sensors [53]. This approach has been improved by adding the projection to the null space of the robot to reconfigure the robot structure, avoiding injuring the operator in case of the contact lasts long than momentaneous contact [54]. Other works are prone to develop a universal algorithm for sensorless collision detection on robot actuator faults. Starting from a rigid body dynamic model, the study employs the generalized momentum and the joints friction to distinguish between external desired torque and additional undesired torque (which means collision) [76]. Another way to improve the models approach is to use neural networks to apply artificial intelligence (AI) techniques to model discrimination and classification. For example, a neural impedance adaption for assistive human-robot interaction based on barrier Lyapunov function [77]. Another similar solution exposes an adaptive impedance controller for HRC through a model-based reinforcement learning approach. To implement the controller, they proposed an Artificial Neural Network to learn uncertainties for HRI to generate a model that is going to be used with a Model Predictive Controller (MPC) combined with a Cross-Entropy Method (CEM) [78]. A multi-input-output neural network can also be an AI-based approach for discerning collisions. An example of this kind consists of trained neural networks from manipulator's coupled dynamics in human-robot collision detection [79]. A similar approach proposes a modified nonlinear disturbance observer based on neural networks for improving performance compared to robot dynamics models approaches [80]. Ultimately, there are solutions based on the measured currents of each joint. An approach of this type consists of a current model is trained, so when the model expected behavior mismatch with real currents data acquired, the system detects a collision [81].

In addition, filtering different magnitudes' measured signals can be used to distinguish between desired and non-desired contact thanks to self-computed thresholds. The literature gathers two similar examples based on a band-pass filter, high-pass filter, and low-pass filter. Thus, whenever

**TABLE 2.** Object handling sub-challenges.

| Level | Level Collab. | Physical Contact | Advantages | Disadvantages | Available Technologies | Approaches | Refs. |
|---|---|---|---|---|---|---|---|
| Visión-based object handling | Coex., Coop. and Collab. | Required (objects) | The robot gains the skill of interacting safely with objects | Control algorithms growth in complexity | RGB Cameras RGBD Cameras LIDAR Scanners | 1) Manipulation of non-rigid materials 2) Coordination between visual servoing and human detection 3) Vision-based optimal picking position detection 4) Load Stability | [94] [95] [96] [97] |
| Blinded object handling | Coex., Coop. and Collab. | Required | The robot gains the ability for interacting with objects without vision systems. The use of external sensors depends on the robot internal sensors. | Might require special or specifically designed tools (costs increment) Require more complex tasks design for recognizing the components | Soft-robotics actuators. Pressure sensor integrated grippers | 1) Human-robot object simultaneous manipulation 2) Haptic shared teleoperated control 3) Tactile object recognition | [98], [99] [100] [101]–[103] |

a signal overcomes the threshold limits, it means that contact has occurred. If that signal comes from a low-band filter, the contact is desired. On the contrary, if the signal comes from a band-pass or a high-pass filter, the contact is a non-desired collision [82], [83].

Depending on the application, the fact that the robot lets the operator moving it by hand guidance might be handy. Because of those situations, hand guidance is considered a topic of contact management and divided into two branches. The first one is the physical commanding, where the robot recognizes the haptic interaction. Depending on which interaction has been identified, the robot should execute one set of actions or another [84], [85]. In contrast, the physical guidance branch consists of manually moving the robot to the desired position instead of giving the robot a command [86]. In this second scenario, the robot is continuously in contact with the operator, while in the first one, the contact only occurs when the command is given.

In situations where the operator is hand-guiding over a trajectory of a robot, it might be helpful to record main target locations and record various in-between positions. Those types of solutions belong to the teaching application subchallenge. An accepted type of approach for this issue is kinesthetic teaching which consists of learning through physical activities. One solution is based on a system that combines pHRI with attentional supervision to support kinesthetic teaching for allowing learning from human demonstration [87]. Another approach consists of kinesthetic teaching for a dual-armed manipulator for a box tapping process based on learning from demonstration methods (LfD) [88]. The works above show that hand-guiding-based solutions are practical for teaching faster tasks to the robot without an experienced programmer.

The topics studied above highlight that in a shared environment, a collision might happen, and the systems must be prepared for not harming the operator [91]. All the research for diminishing, understanding, and classifying the pain and injuries when a crash occurs is gathered in the allowed pain thresholds issue. This subchallenge contains examples as a study on human morphological information to react safely in case of collision [89]. The last approach was improved by analyzing what would happen to the human operator if the collaborative robot carries a sharp or heavy object when the collision occurs [90].

As it has been reviewed, there are several solutions for handling various aspects of contact management. Handling the contact adequately is crucial for industrial collaborative scenarios to prevent any damage to the operator when it occurs. The most basic physical interaction is distinguishing between desired and non-desired contact to react appropriately to each situation. Mastering this contact distinction can lead to successful autonomous hand-guiding modes or teaching applications for reducing setup times. A safe and reliable operation mode for automatic change depending on robot dynamics must be combined with deep knowledge about the pain threshold to avoid injuring the operator. Only this way, a safe physical interactive environment can be achieved.

### 2) OBJECT HANDLING
Safety during pHRI not only on the capabilities of the robot to avoid harming the operator but also on their skill to manage the load gently. In many robotic approaches, the relevance of proper load handling is usually forgotten. It is remarkable not to forget that one of the main functions of a robot is to manipulate objects during production [104]. Picking an object of the scene and appropriately interact with it is even more relevant in human-robot interaction scenarios. In a shared environment, wrong object management could end up not only in a payload loss or deterioration but in damage or harm to the human operator too. Thus, proposals for adequate object handling are reviewed in this subsection.

In this scenario, several works prone their research to achieve this goal due to the relevance of correct robotic object handling tasks. As TABLE 2 represents, there are, mainly, two ways to interact with objects in the scene. The first one is based on vision systems, while the second one is a blind way; in other words, it is not based on vision systems; it interacts blindly with the object in the environment.

In the first situation, vision-guided object's interaction usually uses cases where a vision system aids the robotic system to pose where the item to handle is. An approach to solve this issue presents a use case for the proper manipulation of highly deformable materials. This solution includes an RGB streaming data system using Gabor filters and the combination of feature representation, visual feedback dictionary, and sparse linear representation, enabling complex manipulation [94]. Another approach presents a visual servoing system

**TABLE 3.** Environment avoidance sub-challenges.

| Level | Level Collab. | Physical Contact | Advantages | Disadvantages | Available Technologies | Approaches | Refs. |
|---|---|---|---|---|---|---|---|
| Collision Avoidance in Dynamic Environments | Collab. or Coop. | Excluded | Reduce the complexity of computation of Null Space Projection Methods. Reduce bottlenecks by collision avoidance. Online collision avoidance (during execution) | Need of aditional sensors such as wereables, vision systems, RGBD Cameras, LIDARs, among others. They are not enough reliable standalone (require physical contact safety management) | RGBD Cameras LIDAR Scanners Wereables Clothing IMUs Range Sensors (2D and 3D) | 1) Vision-based potential fields for attractive and repulsive vectors 2) Non-Contact sensitive skins and range sensors 3) Real-time trajectory modification based on minimum distance vector 4) Wereables-based online path modification 5) 3D- Occupancy grids planning and 3D- CAD based model planning 6) Minimum energy based model path planning | [105] [106] [107]–[109] [110]–[112] [113]–[115] [116] |
| Moving objects trajectory and operator intention prediction | Collab. or Coop. | Excluded | Predict Human Occupancy (Increase Safety). Optimize production by projecting operator occupancy in advance. It is less likely to change trajectories during operation | Higher Computational Cost. It is an estimation, it might fail. Requires coordination with physical contact safety techniques | LIDARs RGBD Cameras IA Sofware others | 1) State Machine human intention prediction 2) 3D simplified human model 3) Skelletoning and occupancy prediction 4) Statistical AI-based prediction models (HMM, GMR) | [117] [118] [119]–[121] [51], [122]–[124] |
| Real-time path computing | - | Excluded | Enable real-time obstacles avoidance | Requires high computational capacity | Non-Specific Technologies | 1) Online path computing techniques 2) Offline path computing techniques | [51], [123], [124] [125], [126] |
| Occlusion while navigation | Collab. or Coop. | Excluded | - | Increase the risks. Increase accident chance | - | - | [107], [108], [114] |

for transferring objects between an operator and a robot [95]. An architecture for image visualization where human is detected and the item is classified and tracked to estimate their poses is proposed. Then, the positioning information is used for planning and grasping the object. Another solution relies on the vision systems integrated into a dual-armed robot to stabilize load when simultaneous manipulation. It uses the visual feedback for one of the arms (the one commanded) to mimic the movement with the other arm [97]. In contrast, another approach type is based on depicting information from vision systems where a topological map is generated thanks to a dynamic density growing neural gas. Even though this last example is not specific to HRI, this kind of system for determining the best grabbing position can be helpful in human-robot interactive environments [96].

On the other hand, blind object handling consists of manipulating a load without any vision or range sensor aid, just by developing different haptic skills. An approach to this type of issue is based on object-shared manipulation between humans and robots. In these scenarios, a robot and an operator share a load simultaneously, so proposed strategies are based on force feedback control for object transportation while load stabilization [98]. A similar solution consists of a human impedance and motion intention controller to handle heavy loads [99]. Other approaches are based on applying AI techniques combined with soft robotics actuators to feel and detect objects by touching [102]. In this approach, the recognition of the object is tested through deep convolutional neural networks (DCNNs). Blind object handling is not only suitable for detecting an object, but it also can be used for recognizing by touching the environment of the robot. This type of approach is based on a control strategy for blind environment recognition where a tactile servoing control scheme has been developed [103]. Lastly, physical contact does not happen directly between humans and robots; they are based on haptic teleoperation. This kind of solution is based on some joystick the operator handles to telecommand the robot and accomplishing a picking task [100].

This subsection highlights the importance of proper object handling for enabling industrial collaborative scenarios. Incorrect management of the load or the tool might result in a load loss or a collision with the on-floor worker, damaging both. Therefore, an integral industrial collaborative scenario requires adequate handling to ensure operator safety and the integrity of the load in potential crash situations. This issue is magnified by the natural complexity of the grasping task itself. Picking an object depends on the object to handle, the gripper, and how both interact with each other (type of grasping, number of contact points, contact forces, grasping/hand dynamics, among others). A modern approach to palliate the effects of uncertainties in the grasping process consists of using AI techniques such as Deep Learning (DL) or Reinforcement Learning (RL). However, the inherently complex nature of different grasping processes makes this interaction even harder to manage [104]. Therefore, an integral industrial collaborative scenario requires adequate handling to ensure operator safety and the integrity of the load in potential crash situations.

### 3) ENVIRONMENT AVOIDANCE
Adequate physical contact management is required for enabling collaborative scenarios. However, continuous safety stops insert relevant bottlenecks in production lines. Besides, the best way to maintain the operators' safety is to avoid hitting them with the robot, leading to the collision avoidance challenge, denoted as environment avoidance. This section collects all the solutions and open issues found to afford the environment avoidance challenge for avoiding collisions while planning and controlling the robot in a shared environment between a human operator and a robot. These methods are mainly vision-based techniques to know how a dynamic surrounding scenario changes while the robot is operating.

As the TABLE 3 shows, addressing environment avoidance will come through tackling collision avoidance in dynamic environments (non-static obstacles), moving objects trajectory or intention prediction, and real-time path computing. When using vision-based sensors or range sensors

(such as LiDARs) to know the obstacles, another inherent problem is linked to this technology that must be handled, the occlusion problem.

The first goal to achieve safe navigation along the robot surroundings is collision avoidance in dynamic environments. In a changeable environment where humans shift from one side to another while developing their tasks, the first danger to warn about is hitting the operator or any object the worker handles. Even though the cobots are prepared to reduce risk and harm to an operator when a crash occurs, it is highly desirable to reduce the non-productive time to its minimum [1]. The main problems collision avoidance deals with are the high computational load of analyzing a 3D space in real-time, the high computational load of responding to hazardous changes in the environment with the calculation of new viable paths, and the management of non-perceived obstacles (occlusion) in movement or static classifies the found studies in six different groups based on the following issues: potential fields for attractive and repulsive vectors, real-time trajectory modification based on minimum distance vector, non-contact collision detection, wearables for online path modification, 3D-occupancy grids and 3D-CAD-based models planning, and minimum energy-based model path planning (see TABLE 3).

Starting with the first issue, the potential fields for attractive and repulsive vectors computation modifies robot trajectory in real-time without changing robot computed path by acting directly on the control signal. For example, Ceriani *et al.* propose a reactive task adaptation method based on hierarchical constraints classification. It combines a kinetostatic danger field for trajectory modification based on repulsive vectors with a state machine for commutation between the controller setpoints computed by the industrial controller and the modified ones [105].

Another approach is based on real-time trajectory modification through a minimum distance vector. This research branch employs repulsive vectors to modify in real-time the robot trajectory without changing the precomputed path. Some methods found in the literature use a filter to eliminate the robot from the picture scene, then computing the minimum distance between any object and its focal separation in the picture plane allow them to generate the repulsive vectors [107]. An improvement done by them was to modify their algorithm to take into account more than one object in the scene, reacting only to the closest moving obstacle [108]. Another approach based on using the minimum computed distance to the robot to generate a repulsive vector is also adopted by Zanchettin *et al.* [109]. They calculate the minimum distance between the robot and the closest vertices from the obstacle. Then, they generate the alternative paths based on the information received by a depth camera by sliding the path waypoint and adding additional waypoints.

Most of these works use vision and proximity detection systems to modify online the robot trajectory; however other researchers of the literature prefer to prone to use wearables technologies instead. A literature approach consists of 18 IMUs (Inertial Measurement Units) installed on a suit combined with a vision system [110]. Thanks to this suit, the controller computes the distance between the operator and the robot. On regular working mode, a visual servoing control technique is applied. However, whenever the operator surpasses the threshold, it stops and waits until the worker is out of the danger zone. Other strategies use data fusion from a depth RGBD camera and wearable motion capture. This strategy proposed by Liu *et al.* suggests an SSM strategy depending on the minimum distance to the obstacle [111]. Additionally, Safeea *et al.* propose an approach that combines the minimum distance repulsive and attractive vectors from the paragraph above with wearables for determining operators position. Thus, the robot not only avoids the obstacle, but it recovers as soon as possible the followed path [112].

Other strategies adopted by researchers are based on spatial occupancy as the 3D occupancy grids for planning paths and 3D CAD-based model planning. Mohammed *et al.* propose an approach that mixes a 3D model of the surrounding space and the human position on simulation. They compute the minimum distance to the robot and establish four reaction ways: warn the operator, stop the robot, moving the robot back, and modifying the path [113]. Morato *et al.* propose using six Kinect sensors to obtain a skeletonized human and robot surrounding model. They generate a collision space by giving volume to the obtained skeleton [114]. Operation in parallel with a virtualized 3D robot models can also be employed as a strategy to avoid a collision. This type of approach requires a suitable model of the robot and its surroundings to avoid collision properly. In case the environment is not correctly modeled, the collision cannot be avoided [115].

Lastly, some authors defend techniques based on the minimum energy model for planning robot paths. Lyu *et al.* propose the definition of a potential energy function around the obstacle. Thus, the robot will follow the optimal minimum energy path to accomplish its task [116]. In contrast, Ding and Thomas propose a robot-mounted exteroceptive range sensor to avoid the collision for redundant serial robot manipulators. The algorithm they detailed is based on quadratic programming definition of the main task based on its kinetic energy adjusting the movement by joint constraints and collision avoidance constraints. Thus, they can beware of more than one obstacle in the planning scene [106].

The methods studied above take into account just the actual position of the object generating the most suitable reaction. However, knowing how the surrounding obstacles behave and how they move is necessary because it allows computing more optimal trajectories and strategies for reacting to unexpected scenarios. The prediction of the robot's surroundings' behavior has been named as moving objects trajectory and operator intention prediction. This research brand splits into four distinct fields: state machine-human intention prediction, 3D simplified human model, skeletonizing and occupancy prediction, and statistical AI-based prediction models (see TABLE 3).

Beginning with the state machine-human intention prediction, it joins the approaches proposed by the literature, which apply state machines for determining the following actions of the human [127]. An approach suggests employing a Finite State Machine (FSM) to model human intention recognition. For determining which state is the most adequate for robot operation, the prediction of human movement is computed based on a planar simplification, and its speed [117].

The 3D simplified human model research branch gathers all the approaches that simplify the human body to treat them as an accessible object to model. Bascetta *et al.* propose a human operator simplification by using a square prism to represent the operator. They combine this representation with a particle filter and a mobile robot kinematic model. Thus, they can estimate the occupancy thanks to statistical methods as Hiden Markov Model (HMM), and a Kalman filter [118].

The skeletonizing and occupancy prediction techniques include all the works related to the 3D complex representation of operators as a dynamic obstacle. For example, Campomaggiore *et al.* propose a 2 RGBD camera system to track human movements. They use a 3D occupancy grid by generating a Point Cloud model of the operators, a clustering process (CP), and a Linear Kalman Filter (LKF). A fuzzy inference control considers the worker's relative speed to the robot to apply an SSM strategy [119]. A safety-aware trajectory scaling for HRC based on an RGBD camera and skeletoning techniques for tracking human pose is an approach too. They model the human body as robotic joints thanks to the skeletoning and establish rigid body limits thanks to the human occupancy representation [120]. Additionally, they improve their design by adding the velocity of the robot movement to clear the area regarding the close future robot positions [121].

The literature also proposes improving this kind of techniques by using statistical AI-based prediction models to determine the operator's movement intention in the robot's surroundings. An approach of this type exposes a method to recognize human motion based on an RFID sensor and a vision-based motion sensor, helped by an operator instruction sheet (OIS) to split the task between the robot and the operator. The human motion intention is recognized with an HMM (Hidden Markov Model) algorithm. Then, it has been tested on a car engine assembly task [122]. Another solution combines a standard motion-planning mode with a human-aware navigation planning mode. Thus, they propose the constrained bidirectional, rapidly exploring random tree (CBiRRT) algorithms and study its performance on a shared screw driving task [123]. Another approach is based on training offline a model using a Gaussian Mixture Model (GMM) for the implementation of a Gaussian Mixture Regression (GMR) model to generate online a 3D voxel grid of possible human occupancy [51].

Even though the works presented in this point have focused their efforts on analyzing future human position prediction, all the ideas exposed above can be applied to non-human moving obstacles in the space.

Collision avoidance and predicting surroundings behavior present a lack of sense, without a quick computation method for calculating robot trajectories. Even though the control system can avoid colliding with an obstacle or predicting its behavior, if the algorithms to compute robot trajectories are too heavy, the system might not be quick enough to respond to unexpected hazards. For avoiding the risky situations that can be generated when this happens, two ways of computing robot path trajectory have been studied: online computing and offline computing (see TABLE 3).

Online computing modifies the precomputed trajectory while the robot is moving along its path. This technique can be used to avoid obstacles or disturbances and change the trajectory of the robot to improve the performance of the movements of the robot [51], [123], [124]. An approach proposes an OTG (Online Trajectory Generator) for smooth cubic polynomial trajectories planner and controller for HRI, supporting the idea of achieving safety through a safe path generation and control [125].

On the contrary, offline trajectory computing methods focus on calculating a risk-free trajectory for the robot before any movement is executed. A solution found in the literature is based on introducing a novel automated offline programming (AOLP) system. That system relies on computer vision to recognize an object and position it for computing the shortest accurate path to pick the object [126].

The previous work is not specifically prepared for HRI; however, as Sidobre *et al.* state, one of the safest ways to guarantee on-floor safety is through the use of collision-free online planning [125]. This fact means that every research on developing collision-free path generator and control is suitable for its implementation on human-robot interactive scenarios, whether they are explicitly thought for HRI or not.

In this first challenge, several methods have been exposed to estimate and know the current and future positions of operators and objects. However, most of the researchers mentioned above had to deal with the occlusion problem. Occlusion happens when 3D, or 2D, capturing devices miss information from the environment because an object of the scene is hiding what is behind. This gap in the knowledge of the robot's surroundings can lead to a fault in control systems or even to a collision caused by one obstacle that has not been taken into account.

This trouble is prevalent in robotic systems equipped with only one vision system or range sensor. The literature approach employs a RGB-D camera sensor to take an overview of the robot and its surroundings. Then, the robot is filtered from the image, so only the surroundings are taken into account. The distance between each obstacle and the robot is computed in the camera plane by measuring perpendicular distances between each one and the focal ray of the camera. The control to avoid colliding with the closest obstacle is done based on the minimum of the computed distances [107], [108].

On the contrary, another point of view to solve this problem is to use more than one 3D camera, range sensor or mixing them up to compensate the blindsides of each system. Two already mentioned approaches use this kind of architecture. One of them uses 4 Kinect sensors to monitor the operator's position through a skeletonization technique [114]. The other is based on 2 Kinect sensors configuration to measure the closest distance between the operator and the robot through the generation of a voxel grid [113].

The review of the different approaches highlights the importance of two critical facts to bear in mind while developing successful applications for changeable environments. On the one hand, it is required to adequately recognize the possible obstacle of the surroundings and their collision risk. Without proper recognition of the possible risk entities or their moving intention, it would be hard to respond adequately to the changes in the environment. Computing on time and accurately obstacles positions depends on the computational capacity of the environment recognition system. These systems are usually based on 3D cameras or range sensors that must capture and process as quickly as possible the scene. Thus, the computational power of the recognition systems became a critical element of the collision avoidance reaction strategy because a failure or a delay could end up in a risky situation [1]. On the other hand, knowing the environment and their changes precisely is senseless unless the system responds on time. Depending on the allowed risk, the scenario, and the configuration of the robot, quicker responses will be required. Thus, this kind of strategy is usually combined with SSM techniques in order to support the overall system with a little more available response time [113], [119]. Therefore, to allow collision avoidance control algorithms for industrial manufacturing systems, the computational power required by the application and the required application accuracy must be balanced. Otherwise, the system will not be able to respond in real-time to unexpected changes in the surroundings of the robot, leading to situations where the safety of the operator is compromised.

This subsection detailed several solutions for evading the collision between operators and robots, from solutions based on quick computing for collision avoidance, passing through occupancy prediction solutions, to two problems to deal with, online path computing and occlusion. Optimal handling of collision avoidance is crucial to reduce production bottlenecks due to safety stops. Therefore, it is a critical challenge to deal with designing collaborative scenarios because it can rebound into production improvements. Besides, it also generates more robust systems against risky situations because the best way to avoid harming the operator is evading the potential crash situations.

After reviewing the possible solutions for the three first challenges, even when there are several solutions for each challenge, there are no unique solutions. However, it seems clear that the allowance of collaborative scenarios requires low-level handling of physical contact management and avoid the collision. Thus, production can be safe-guaranteed, but it

can also be improved in terms of quality. Lastly, a remarkable fact is that even when there are several types of solutions for each challenge, there has been a lack of solutions that combine more than one solution while facing the challenges.

### B. WORK CELL LEVEL

Section II states two challenges related to the work cell level. Both challenges are closely correlated because one of them is concerned about adaptation strategies applied to the field of interest of the other. Thus, this level tries to reduce non-productive times as much as possible in shared environments by an adequate task organization and distribution and adaptation to new situations or changeable scenarios.

#### 1) TASK SCHEDULING AND MANAGEMENT

Lower level safety measures are essential for assuring safety on shopfloor plants; however, most risky situations can be avoided with a proper administration of the operations between the robot and the operator. The proper operation distribution can also increase productivity by lowering bottlenecks while avoiding collisions [128].

With the arrival of Industry 4.0, production optimization techniques have grown. Industry 4.0 enables real-time production management, but it can also predict the production lines' unexpected behavior. In the situations where humans and robots are coexisting, cooperating or, even collaborating, the enabling technologies grow in the complexity of their application due to the non-contemplated situations workers' freewill produces.

Therefore, improvement in both production and on-floor safety will come to a correct implementation of Industry 4.0 enablers technologies combined with an optimal operation distribution among operators and robots. In this section, the solutions for the optimal coordination proposed in the literature are presented. As the TABLE 4 depicts, this challenge has been divided into the following solution types: collaboration in real environments, collaboration in simulated environments, human-robot teams, operator-robot trust models, and safe task control strategies.

Firstly, collaboration in real environment approaches are related to any human-robot interactive method implemented in a real or virtual industrial scenario. These solutions are mainly applications based on a single robot or a dual robot, where the operator and the robot distribute the task each must execute. It is essential to bear in mind the possible failures of the application due to the misplacement of the operator or any component the robot should handles. The key to solving the subchallenge relies on the proper distribution of diverse tasks to reduce to its maximum the failure chances due to uncertainties of the collaborative scenarios. Thus, the production bottleneck due to risky situations could be reduced.

One of the leading scenarios where the task distribution and management have been tested is assembly and disassembly processes. With the arrival of collaborative robots, these operations can be upgraded to solve unexpected situations during the assembly or disassembly, such as the

**TABLE 4.** Task scheduling and management sub-challenges.

| Level | Level Collab. | Physical Contact | Advantages | Disadvantages | Available Technologies | Approaches | Refs. |
|---|---|---|---|---|---|---|---|
| Collaboration in real environments | Coop. and Collab. | Allowed | They are scenarios where collaboration skills has been tested It is inspiring for Industry evolution They're good for testing behaviours on industrial collaborative scenarios. | Most of them are not a whole application. The limited testing conditions makes them non-suitable for industry. Test directly on shared scenarios could be risky | Collaborative robots Depth and range sensors AI accelerators Advanced software tools | 1) Hybrid cells for simultaneous or coordinated assemblies 2) Optimal task assignment scheduling based on ILP 3) Discrete Bees algorithm for disassembly remanufacturing tasks. | [55], [128]–[142] |
| Collaboration in simulated environments | Coop. and Collab. | Excluded | The safety and feasibility of the application can be tested before implementation Enable the usage of techniques such as digital twins If the models are properly implemented, it can speed up lines commissioning | It might double the efforts such as controllers tunning if the model is not accurate enough It's hard to do a real validation on simulated enviroments due to non-predictable human behaviour | Specific robotic simulation softwares such as RobotDK Open sourced simulation software tools (Gazebo, MoveIt...) Mathematical computation software platforms (Matlab...) | 1) Digital twin of the operator 2) Simultaneous simulation of robot and IMMA 3) VR pre-training for operators 4) Human Cyber-Physical Systems (HCPSs). | [143]–[153] |
| Human-robot teams | Coop. And Collab. | Allowed | Increment of production quality More task can be semiautomated New task types can be semi-automated Shared task can be semi or full automated | High increase of application and control complexity Increment of difficulty of a proper time and tasks distribution | Collaborative robots Software programming frameworks (ROS, WeBots...) | 1) Coordination through ARU or MFT for multi-robot systems | [154], [155] |
| Operator-robot trust models | Coop. or Collab. | Allowed | On an environment where the operator trust in robot actions, the production improves New jobs are generated for replace the ones already exists | If it is not achieved, the production decreases | There are no technology. They are more psychological aspects to care about the operators. | 1) Trust model based on PAS and affect 2) Trust measurement scale based on features such as safety or experience. 3) Trust issues and social psychological model to response to uncertainties. | [156]–[159] |
| Safe task control strategies | Coop. and Collab. | Allowed | A proper distribution of tasks execution secuences reduce highly production safety related risks. Production cycle times can be reduced so the overall production can increase. All the existing techniques for production optimization can be applied | A bad task distribution might end-up increasing production times and costs. A proper distribution of task and operation might require higher efforts in programming and synchronization. | - | 1) Simplified risk analysis based on historically occupied regions 2) Planning algorithms to perform optimal human-robot movements on shared environments 3) AR assistance for task developing or robot programming | [160]–[163] |

classification of damaged components. On the one hand, in the literature review, various examples have been found for assembling tasks with collaborative robots such as automotive assembly line proposals [129], screw operation in assembly tasks [130], hybrid cells for simultaneous assembly between an operator and a robot [55], [131], [132], use of augmented reality as a support system for operators on a collaborative assembly [133], dual-arm cooperative and flexible assembly [134] and the installation of heavy and bulky components [135]. There are also support activities to assembly task as a chaotic bin-picking task for low volume assemblies [136]. Another support activity for assembly lines consists of scheduling optimization through the optimal assignment of tasks. A solution of this type is based on an extended integer linear programming (ILP) formulation for two computationally more complex scenarios: an order-based heuristic approach and a matheuristic approach with different sequencing strategies [137]. Another solution consists of developing a Hidden Markov Model (HMM) for combining with a 3D occupancy grid; thus, the operator's workflow could be recognized [138]. This work is extended by a human-robot collaborative workspace design based on the use of visual and audio stimulus for the work coordination [139]. A final solution is based on a chain of four supporting blocks where the information is extracted and processed to generate and evaluate a collaborative assembly solution [140].

On the other hand, human-robot collaborative disassembly tasks are interesting for mitigating uncertainties due to the product's end-of-life condition for remanufacturing. An example of this type is an active compliance control [164] for the robot for disassembling press-fitted components [141]. Implementation of methods for planning using discrete Bees algorithms in disassembly remanufacturing

tasks is also valid for the actual subchallenge [142]. A final approach exposes a robotic task-oriented knowledge graph constructed by a natural language processing method for human-robot collaborative disassembly [128].

Even though several researchers have proposed their strategies to solve use case requirements for real industrial environments, combining the proposals with virtual simulations can improve the safety and productivity of the industrial plant. The first approach is based on human cognitive workload virtualization to integrate human mental capacities into industrial control loops by simulation [143]. Thus, unexpected human behaviors are expected to be better rejected. Examples based on the simulation for the automotive assembly process are also included under this branch [144], [145]. On a first approach, a digital twin model of the human operator created in Siemens Tecnomatix suite is proposed for testing a variety of solutions and what-if scenarios to improve planning and decision making [144].

On the other hand, a digital model, which combines the IPS (Industrial Path Solutions) tool for robot simulation and IMMA (Intelligent Moving Mannequins) for human simulation, has been proposed for the entire virtual verification of human-industrial collaboration before testing on real environments [145]. A suitable solution for this issue is based on the use of VR to develop digital human-robot simulated environments for improving the real-world process by virtual simulated data [146]. The other two similar approaches are based on VR (Virtual Reality) to develop training systems for operators in manufacturing scenarios [147], [148]. On the one hand, the presented Virtual Reality Training System (VRTS) is immersive and interactive based on "beWare of the Robot" game experience to enhance operator safety through previous execution of the task and awareness of the risks [147]. On the other hand, a VR digital twin is presented

to understand human reaction to predictable and unpredictable robot motions thanks to a new developed kinetic energy ratio metric to analyze those reactions [148].

The solutions reviewed right above are a glimpse of the actual panorama of human-robot interaction in simulated environments. However, a research branch about this topic is based on Human Cyber-Physical Systems (HCPSs), which introduces human behaviors models to respond better to human-based faults [149]–[151]. A variation of HCPSs relies on the addition of human cognitive skill into industrial control loops as Human-in-the-Loop (HiTL) techniques in order to react to unexpected human behaviors. This technique is used as a reinforcement for Cyber-Physical Systems during loop execution [152], [153].

On the other hand, complex tasks of industrial environments might require the synchronization or parallel actuation of more than one robot or operator at a time. In this situation, the operator and the robot should build a team for successfully finishing their manufacturing tasks. An approach that takes human-robot teams into account collects the requirement for building these teams while taking into account the application performance, operator performance, and robot performance separately for application validations [154]. Other proposals are based on a dual-armed robot, which is considered more than one robot coordinated by the same entity. In [155], a novel multi-criteria task planning method based on Average Utilization Time (ARU) and Mean Flow Time (MFT) for collaboration with multi-robotic systems.

The constant fear about system failure might end up in productivity reduction. To avoid this situation, the literature has researched how to develop accurate human-robot trust models to increase the operators' confidence in a shared environment [165]. A literature approach consists of studying critical factors that affect trust in a high-vulnerability HRI context to establish a structural equation based on trustworthiness, human-likeness, intelligence, perfect automation schema (PAS), and affect [156]. Building trust measurement scales for industrial HRC based on features such as safety, experience or shape of the robot are also considered as adequate solutions for industrial environments [157]. The studies mentioned before focuses on theoretical ways of building models and scales to measure trust between operators and robots. However, other works focus on the applied solution to industrial fields. An approach of this kind is based on trust issues and social psychological aspects to improve the response to unexpected situations [158]. Another model based on trust dynamics and control is proposed to regulate the task process while considering factors such as human fatigue [159].

Moreover, the literature defends a way for reinforcing the human-robot trust models through the natural interaction between robots and operators. In this type of interaction, the operator uses commanding structures that are intrinsically implemented in the interaction between humans, such as the voice or gesture commanding. Thus, the programming process of the task will seem closer to the shopfloor worker,

making them feel closer while working alongside their robot partners [165]. An adequate understanding of the task should be achieved to improve the confidence operators place in robot machines through natural interaction. Therefore, a straightforward task hierarchy is also supported to achieve natural interaction between humans and robots [157]. This way, high-level development of natural interaction between operators and robots might end up in a safe environment where traditional industrial robots and collaborative robots coexist while developing production together.

The last subchallenge, the safe control strategies, also help to reduce wasted times and production bottlenecks through the distribution of optimal task strategies and task operation scheduling without disregarding safety issues. So not only is the operation going to be optimally distributed, but the operator safety in different scenarios is going to be taken into account. In [160], simplified risk analysis based on a historically occupied space map by the operator for generating proactive strategies to respond to environment variations is implemented. This subchallenge also includes programming approaches and task plannification sequences distribution methodologies. The issues this topic addresses are task-based programming and sequence planning for collaborative assembly scenarios [161], planning algorithms to perform planning in human-robot shared environments [162] and augmented reality assistance for industrial applications robot programming [163].

This challenge collects a wide selection of various solutions of robots and operators' coordination in industrial real or simulated environments. This is remarkable because it aligns collaborative scenarios with technologies settled on Industry 4.0 and enables the possibility of benefiting from those technologies, such as the digital twins applied to robotics. However, the complexity of coordinating low-level safety in operations and high-level safety by scheduling the operations appropriately make the field at the early stage of development. Additionally, the relevance of trust models and the integration of human-robot teams at this level on industrial collaborative shopfloors has also been stated. These solutions are essential because they scale one level in the complexity of industrial scenarios' safety design by adding psychological aspects. However, the difficulty of adequate modeling of human behavior due to the unexpected conduct unravels the immature state of development in the field [66].

### 2) TASK SCHEDULING ADAPTATION

The last group of solutions collected is an improvement over the task scheduling and management challenge. They are related to adaptation capabilities that can be brought to industrial collaborative work cells. This topic tries to answer how production can be adapted to improve quality and avoid fault loss. Thus, SDGs (Sustainable Development Goals) 8 and 9 are preserved thanks to the maintenance of industrial operator safety as the production adapts itself to changes in production rhythms. As mentioned before, several techniques or methodologies which can be applied to non-stop,

**TABLE 5.** Task scheduling adaptation sub-challenges.

| Level | Level Collab. | Physical Contact | Advantages | Disadvantages | Available Technologies | Approaches | Refs. |
|---|---|---|---|---|---|---|---|
| Traditional non-stop production techniques | Coex., Coop. and Collab. | Allowed | Already tested tools for improving production. Production can be adapted to faults in robots actuators. | Intelligent adaptation is limited to adaptation laws | Software tools (Matlab, Tensorflow, Keras...) | 1) FTC (Fault Tolerant Control) 2) MPC (Model Predictive Control) 3) ILC (Iterative Learning Control) 4) Fuzzy Control | [3], [21], [64], [66] |
| Adaptation to real industrial scenarios | Coop. and Collab. | Allowed | Adaptation mechanism tested under the assumption of non-controlled disturbances. Improvements due to adaptation directly tested against real scenarios. | Increment of risks during tests and validations. Needs of an accurate model o the real system per se | Collaborative robots Software tools (Matlab, Tensorflow...) | 1) Self-supervised learning combined with vision-based object manipulation from imitation. | [166] |
| Adaptation to simulated environments | Coop. and Collab. | Excluded | Test the adaptation mechanism without any risk for the operator and machine. | Require a precise and accurate model of the environment for good results. The adaptation limit is tied to the adaptation mechanism and representative tests. | Specific robotic simulation platforms (RobotDK...) Open sourced simulation software tools (Gazebo, MoveIt!...) Mathematical computation software tools (Matlab...) | 1) Simulation and testing of a quintic polynomial for trajectory smoothing 2) Modularized parallel controller structure for motion planning and control on shared environment | [167]–[169] |
| Task adaptation in human robot teams | Coop. and Collab. | Allowed | Increment of the coordination between operators and robots through new cycles. The operators feels more comfortable with the robots (Increment in robot trust). | The complexity of application management and control presents an even higher increment The complexity of time and task distribution also grows | Collaborative robots Software programming frameworks (ROS, WeBots...) Tasks and operation optimization techniques | 1) Robotic long term autonomy through ROPA | [170] |
| Task strategies adaptation | Coop. and Collab. | Allowed | Through production cycles the task will adjust automatically to waste the less time possible. | If the adaptation mechanism is not good enough, the adaptation could end up in more time wasted. The chance of collision drastically increases the complexity of an adaptive task distribution strategy. | Task and operation optimization technique Adaptive task sheets | 1) Adaptation to skills and experience of the operator through a task distribution strategy based on levels of automation | [171] |

autonomous or intelligent production of Industry 4.0 can be used for collaborative robotics and HRI too. As it has been exposed earlier, this challenge leaves aside traditional adaptive techniques for non-stopped production to lead to adaptive techniques applied to task scheduling and managing techniques. Thus, TABLE 5 depicts the various types of solutions related to this challenge: adaptation to real industrial scenarios, adaptation to simulated environments, task adaptation in human-robot teams situations, and task strategies adaptation.

In the field of real industrial scenario applications, Nair *et al.* proposed an approach to combine self-supervised learning and imitation from vision-based object manipulations. An interactive method to learn through demonstration is exposed to tying a rope [166].

Other examples are based on adaptation in the simulation of human-robot interaction scenarios. In [167], an approach suggests a collaborative hybrid work cell that adapts its trajectory planning strategy to avoid colliding with dynamic obstacles in the environment. The reaction strategy considers human motion forms and a neural network using supervised learning to create the waypoints required for dynamic obstacle avoidance and a quintic polynomial for smooth trajectory optimization. Another approach introduces concepts for future intelligent production systems for designing decentralized manufacturing systems such as the relationships between the factory layout planning, production scheduling, and human-robot work distribution [168]. Another similar solution is based on developing an algorithmic safety set of measures for intelligent industrial collaborative robotics applications based on a modularized parallel controller structure to solve the motion planning and control problem in a human involved environment [169].

Another scenario where adaptation is being applied consists of the human-robot teams applications. In [170], an example of the literature exposes a robotic perceptual adaptation for dynamic environments in long-term

human-robot teammate collaboration is detailed. The proposed solution addresses the long-term autonomy of the system for shared environments by an innovative human-inspired approach called robot perceptual adaptation (ROPA).

Finally, the last issue of the actual subchallenge uses cases is related to the adaptation to task strategies topics. Hence, it focuses on the adaptation to the optimal way to solve the tasks improving it in each cycle. A solution of this type exposes a human-centered adaptation and task distribution strategy for industrial setups based on levels of automation. The adaptation in this occasion finds the skills and experience of the operator to adapt the production levels to it [171].

This challenge's solutions pretends to improve the performance methods exposed in the task scheduling and management challenge. However, the broad suite of various possible examples relative to this challenge and their low level of improvement makes task scheduling adaptation an under-exploited challenge. Therefore, there are not many solutions presented in the current challenge. Nevertheless, it is remarkable how the community intends to integrate continuous adaptation techniques to human-robot interactive scenarios where the robots adapt their behavior to continuous production cycles.

After reviewing the last two challenges available solutions, there are both promising and emerging research branches. Nevertheless, some suitable approaches have been presented. On the one hand, scheduling techniques to reinforce the safety between operators and robots is critical to reducing time bottlenecks during production. However, the psychological factors that take part make the challenges at an early stage of development. Moreover, the fact that even when adaptation techniques are broadly applied to other automation fields but not to the human-robot interaction boosts the idea of their lack of development. Despite the slow development in the actual challenge, it is believed to be compound by promising solutions to enable modern industrial collaborative scenarios.

## IV. DISCUSSION

The implementation of industrial collaborative scenarios relies on the five identifies challenges. These challenges, as defended earlier, are distributed into two of the four of the levels proposed. For each of them, a summary table is included. Additionally, the information of those tables is complemented in this discussion through the inclusion of FIGURE 4, highlighting the paper distribution for each of the identified challenges.

The three first challenges (physical contact management, object handling, and environment avoidance), belonging to the operation level, as shown by FIGURE 4 represent a greater distribution of collected papers. It means that the scientific community has invested more effort in these three challenges. This fact matches with the structure proposed for the suggested levels of autonomy because it means that the challenges corresponding to the lower levels are more developed than the higher ones. After all, the lower the level, the closer to basic human-robot interactive forms and more affordable is its implementation.
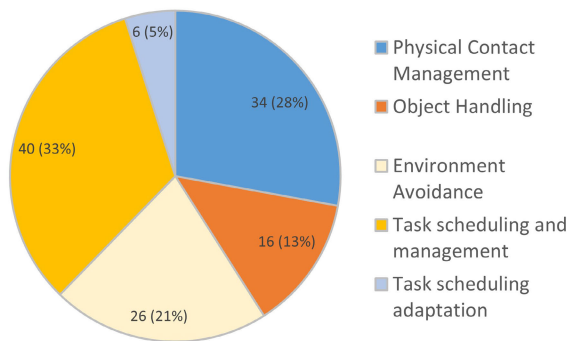


**FIGURE 4.** Distribution of solutions for the collaborative scenarios enabling proposed challenges.

The physical contact management collects the most quantity of operation level articles and considers all the applications where an operator maintains direct physical contact with the robot. The risks of these situations rely on the possible harm the robot might produce when an operator hits or grabs him. In order to minimize the danger of those situations, the literature proposes several algorithms for contact handling and automatic working mode switching depending on desired and non-desired collision discerning. Even though there are various examples, the safety aspect can only be guaranteed by a safe design of the robot and not by contact handling algorithms. On the other hand, teaching and hand guiding applications are also included in this challenge. This solution seems very promising for facilitating the future of robotics programming in daily tasks or teaching the robots how to grab the required workpiece. However, the challenge aim cannot be fulfilled until the algorithms are not performed well enough to consider the interaction natural and intuitive to the operators without disregarding safety, danger, and harming threshold.

The object handling challenge must deal with two different situations. On the one hand, vision-based object handling relies more on vision algorithms than on how the robot should handle the object. In this scenario, the success of the component handling highly depends on the accuracy of the vision algorithm applied to command the robot movements. On the other hand, blind object handling is relegated to positioning or morphology determination rather than managing where or how to pick components. This fact makes plenty of sense because, in a shared environment, it is undesirable to handle and move objects around the space without checking the existence of danger to harm an operator. Due to the reasons mentioned above, this challenge is still considered far from the required state to be suitable for collaborative scenarios. In order to consider this challenge fulfill, vision-based and blind object handling should be combined with auxiliary environment recognition systems to manage the load properly while carrying it. Thus, the load can be transported without the risk of harming the operator or losing it. It will even open a chance to combine the first challenge to ensure safety in contacts while the robot is loaded. This lack of development is also reflected in FIGURE 4 with a low percentage of articles found in the field.

As stated before, it is highly recommended to avoid colliding with obstacles and operators [172], even when the contact is assured to occur safely. This is desirable because avoiding the collision will increase the safety of the overall system and will reduce to their minimum the probable bottlenecks due to safety stops. Therefore environment avoidance challenge is a very catching and relevant topic for industrial collaborative scenarios with around 21% of the articles (see FIGURE 4). The literature shows how collision avoidance algorithms and obstacle intention prediction has gathered some attention. However, none of these algorithms are valid for its implementation unless it can ensure real-time computation to avoid the crash.

Leaving aside problems such as occlusion that can be easily solved, collision avoidance systems have some issues in avoiding the obstacles and predicting their intention. On the one hand, avoiding obstacles relies on the low computational cost that guarantees that the crash cannot happen. Otherwise, the system will fail, harming an operator. For instance, 3D vision-based or range solutions reduce time performance for updating the scene to increase the accuracy in modeling the surroundings. These approaches are also negatively influenced by the required time for postprocessing the scene to segment what can be considered an obstacle. On the contrary, techniques based on wearables for the operator or non-contact sensitive skins for the robot increase the accuracy for obstacle positioning; however, they introduce additional data to compute in the control systems. Furthermore, these solutions might not be suitable for manufacturing shopfloors implementation due to their extra cost. Lastly, techniques for path recalculation strongly depend on the performance of the scene segmentation algorithms used for obtaining the status of the surrounding in each cycle. However, they might

not be reliable enough for collaborative scenarios because of recalculation failures due to robot configurations or high computational costs. Due to all these facts, an economical solution to solve the timing issues these techniques introduced consists of adopting SSM strategies to manage the robot movement speed depending on the mutual distance between obstacles and the robot. Thus, the available response time will be increased the available response time as well as reduced the harmful risk in case this system fails.

On the other hand, predicting obstacle intention is based on probabilistic occupancy models. Due to that, they might not be ready for unexpected behaviors of human free will, causing once again the system to fail. These techniques usually rely on an accurate model to estimate unpredictable human behaviors for both state machine prediction approaches and statistical AI-based models solutions. However, it is relevant to bear in mind that these models are based on the occurrence probability of events. The fact that it cannot guarantee the prediction of human behaviors makes them unreliable for its industrial application. On the contrary, 3D simplified models or skeletonizing techniques increase the reliability and accuracy of predictions while increasing computational times due to the high load of the vision processing techniques. Thus, beating this challenge will come through reliable low computational cost algorithms, which also consider natural obstacle movement tendencies. Additionally, it should be considered possible malfunction due to control loss or blocking positions due to the singular configurations.

The first challenge of the third level, the task scheduling and management challenge, is referred to how the operations should be optimally distributed in an industrial environment. This topic collects real and simulated industrial approaches, multi-human/robot teams [173], and approaches for trust and control model solutions. This challenge aligns the possible application of collaborative robotics with other trending technologies of Industry 4.0. However, the high dependability of uncertainties such as workers' trust in robot operation and the lack of reliability and confidence in human-robot solutions makes this challenge far to be reached. This fact linked to the necessity of development of the previous challenges makes it hard to guarantee safety in the approaches of this challenge. Notwithstanding, this challenge gathers several pieces of research in human-robot interaction applied to the industrial scenario, being the challenge that collects the most of works.

The last identified challenge, the task scheduling adaptation challenge, is the last one of the identified challenges. Without considering traditional adaptive mechanisms for autonomous and unstopped production systems, task scheduling adaptation focuses on optimizing task scheduling and management to improve the results of the last challenge. Therefore, its lack of development might seem natural because of the low development state of the task scheduling and management challenge. Due to its low representation in FIGURE 4 it consecution seems a long-term goal. Combining traditional autonomous systems with adaptation

to task scheduling might be the cornerstone for future industrial collaborative scenarios.

In another vein, the upper-level classification proposed gathers no examples of any particular challenge for its implementation. Thus, it is considered that the enabling key leans on the previous implementation of the five identified challenges. At this level, the autonomous traditional manufacturing systems will be coordinated with collaborative industrial scenarios for intelligent, adaptive, and flexible production. This coordination might be considered as a challenge itself because of the high complexity both architectures bring.

A final contribution is presented, based on the conversion of traditional robots into collaborative robots. Some works implement the aforementioned conversion [55], [133], [134], [174]; however, a real industrial collaborative scenario can only be achieved by improving the performance of these studies and granting safety through the implementation of the five identified challenges. Thus, future factories will rely on collaborative robots for collaborative working modes, but they will use traditional ones for tasks that require more power or speed safely. However, combining cobots and traditional robots on industrial plants will not be intuitive because of the wide variety of needs for each of the different production requirements. For example, in automotive plants, industrial robots will be required to load heavy and oversized assemble objects while the combination of cobots and operators will handle the minor components assembly. Due to the heterogeneous needs of each industrial sector, the challenges to overcome for each particular industrial plant may differ. Nevertheless, it is relevant not to forget that this conversion can only be executed under the presumption and guarantee of maintaining safety in any manufacturing situation.

## V. CONCLUSION

All the challenges presented and detailed in this manuscript are distributed between the different levels proposed. The first level, which affords the basics of the interaction, represents no challenge due to their development in the field for several years. It resolves aspects related to safety design, the available levels of automation for the application and the essential human-robot relation that can be established. The reliable installation of cobots on industrial shopfloors is the best statement to affirm that this level is already safe enough to be considered achieved.

The two middle levels of the classification proposed are the ones gathering the five identified challenges. On the one hand, the operation level contains the three first challenges related to natural interaction between humans and robots for successfully accomplishing different operations. Thus, safe physical interaction with operators or objects can be achieved, as well as avoiding collision to reduce bottlenecks for safety stops. Even though it has gathered relevant interest from the scientific community, the complexity for guaranteeing human operator safety in every situation is not achieved yet. On the other hand, the work cell level defines a subprocess as an association of operation with a singular goal, and it collects

the last two identified challenges. Both challenges are related to distributing human-robot operations for wasting the least time possible properly while increasing safety. This can be achieved because an optimal operation distribution leads to reductions of possible conflict situations and reduced production spare times. However, the high degree in human actions' randomness makes these two last challenges unafforded yet.

As stated in the discussion, the upper level represents a challenge because of the high complexity the human-safe system architectures demand. This level tries to coordinate collaborative industrial scenarios with traditional non-stop productive environments. Even though it is still far to be reached, its consecution will lead to intelligent, adaptive, and flexible manufacturing systems.

From all the exposed work and discussion above, it can be stated that there is still room for improvement to fill the gaps required to achieve industrial collaborative scenarios. Even when the very low level of HRI has been firmly settled thanks to several safety standards, the more complex forms of interaction are still in development. This situation makes it hard to ensure operator safety in industrial environments without disregarding sustainability and autonomous production aspects, which is highly undesirable for modern industrial collaborative scenarios. Therefore, there is still work to do to integrate safety and autonomy in production to achieve an advanced and fluid interaction at any level in real industrial scenarios, which can only be filled by facing the identified challenges in this manuscript.

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