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# Industrial Applications of Cobots: A Review

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**ABSTRACT:** Bridging the Gap between Intuitive and Human-aware Programming for Industrial Collaboration, Collaborative robots (cobots) have been increasingly adopted in industries to facilitate human-robot collaboration. In this paper, an overview of collaborative industrial scenarios and programming requirements for cobots to implement effective collaboration is given. Then, detailed reviews on cobot programming, which are categorised into communication, optimisation, and learning, are conducted. Additionally, a significant gap between cobot programming implemented in industry and in research is identified, and research that works towards bridging this gap is pinpointed. Finally, the future directions of cobots for industrial collaborative scenarios are outlined, including potential points of extension and improvement.

**KEY WORDS:** cobot, Industrial applications, cobot programming

## I. INTRODUCTION

Mass customization in the Industry 4.0 era demands rapid adaptation to ever-changing customer preferences. This has fueled the trend of flexible manufacturing, requiring both automation efficiency and human adaptability. Despite this, it is challenging to program cobots for collaborative industrial tasks as the programming has two distinct elements that are difficult to implement: [1] an intuitive element to ensure that the operations of a cobot can be composed or altered dynamically by an operator,[2]and a human aware element to support cobots in producing flexible and adaptive behaviours dependent on human partners. In this area, some research works have been carried out recently, but there is a lack of a systematic summary on the subject While industrial robots excel at high-volume, repetitive tasks, their rigidity hinders customization.[3] Humans offer flexibility but lack the stamina and precision for sustained production.Human-Robot Collaboration (HRC) emerges as a solution, where cobots (collaborative robots) and humans work together in shared workspaces.[4] Cobots prioritize safety through features like speed and force limiting, making them ideal partners for humans.

This paper explores the programming features enabling effective cobots in collaborative industrial scenarios to review:

- Collaborative industrial scenarios: Identifying common applications for cobots.
- Cobot programming structure: Outlining a general framework for cobot programs, including safety considerations and human interaction.
- Three key programming features: Focusing on communication, optimization, and learning techniques for cobots.

### 1.1 Categories of Collaborative Scenarios

In this section categorization which classifies tasks based on the interaction between a cobot, an operator, workpieces, and the processes being performed is presented. The key factor is the degree of task intersection and dependency between the operator and the cobot (illustrated in Figure 1). This framework helps programmers and researchers understand the varying capabilities required for cobots in different industrial scenarios.[5]

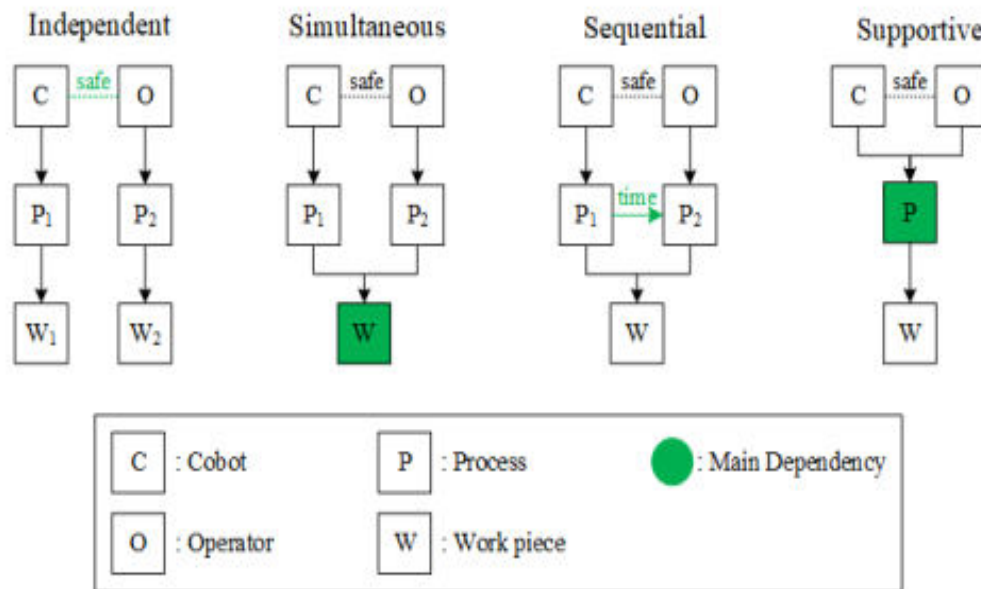


Figure 1: Degrees of collaboration in industrial scenarios [6]

The categories of Collaborative Scenarios are:

a. Independent:

- Operator and cobot work on separate workpieces (W1 and W2 in Figure 1) with independent tasks (P1 for W1 and P2 for W2).
- Collaboration lies in their shared workspace without physical barriers like fences.
- Safety relies on the cobot's inherent safety features and additional hardware/software safeguards.

b. Simultaneous:

- Operator and cobot perform separate tasks (P1 and P2) on the same workpiece (W) simultaneously.
- No temporal or task dependence exists between them.
- The cobot requires spatial awareness of the operator and their tasks to avoid interference.
- Concurrent operations on the same workpiece reduce transmission time and increase efficiency and space utilization.

c. Sequential:

- Operator and cobot perform sequential tasks (P1 and P2) on the same workpiece.
- Temporal dependencies exist between their processes.
- For example, the cobot completes P1 on the workpiece to prepare it for the operator's subsequent task (P2).
- Cobots often handle tedious tasks to improve operator work conditions.

d. Supportive:

- Operator and cobot work interactively on the same task (P) on the same workpiece (W).
- Their actions are interdependent; one cannot complete the task without the other.
- The cobot needs to understand the operator's intent and task requirements to provide appropriate assistance.
- For instance, the operator fastens screws on a toolbox while the cobot holds it in place, improving ergonomics.[6]

Table 1: HUMAN ROBOT COLLABRATION scenarios in their experiments

Scenario		Human Task	Cobot Task
Co-manipulation	[7]	The human guides the object's path.	The cobot handles the object's weight.
Fixture	[8]	The human polishes the held box.	The cobot hold the box in a position according to learnt human preference.
Handover	[9]	The human takes objects from the cobots and places them aside.	The cobot hands objects to the human. Handover pace changes according to the human's readiness to take an object.
Pick-and-place	[10]	The human chooses objects randomly to pick and place.	The cobot chooses object to pick and place while accounting for distance, reachability and the human's predicted motion plans.
fetch	[11]	The human takes the table part from the cobot and performs assembly action.	The Cobot fetches table part according to the human's progress in the assembly task.
Soldering	[12]	The human adjusts the pose at which the Cobot is holding the solder wire, and then he performs soldering.	The cobot holds the soldering wire at the tip of soldering, in human-controlled orientation and position.
Illumination	[13]	The human operates on parts on a table.	The Cobot, with a light source mounted as a tool, provide direct illumination on the human's work space while avoiding collision.
Inspection	[14]	The human screws bolts in holes.	The Cobot inspects if all holes are screwed and issues a warning in case of missing bolt
Drilling	[15]	The human specifies the drill location, during run-time.	The Cobot drills a hole in a specified location while having motion automatically constrained to drill bit's axis.
Surface Finish	[15]	The human specified surface to sand.	The cobot sands the surface, while having motion automatically constrained parallel to the surface.
Screwing	[16]	The human inserts bolts in holes on one side of a plate.	The cobot tightens the bolts from the other side of plate.

## II. SIGNAL RECOGNITION

Delving into the technicalities of signal recognition, whether it is gestures, speech, haptics, etc. is beyond the scope of this paper and will only be discussed briefly, as numerous relevant reviews already exist. Readers are referred to [17] for an extensive review on gesture recognition technologies in light of industrial HRC. Similarly, Benzeghiba et al. provided a review on speech recognition technologies [18]. To recognise gestures, the human skeletal frame, or pose, must be detected. Table 3 shows the advantages and disadvantages of different sensing technologies for pose detection. Given recent advancements in deep learning pose detection algorithms, such as OpenPose [19], the prospects of 2D cameras being the most suitable option is increasing.

For speech recognition, some have used Google API [21] or the Microsoft Speech API [20, 22] for speech to text transformation. In the case of natural language, morphological analysis is performed to identify word morphemes and understand context. For example, Mautua et al. [21] used FreeLing for morphosyntactic analysis while Nakata et al. [23] used the MOR and the POST program of CLAN. Nevertheless, Gustavsson et al. pointed out that relying on speech commands can be very problematic in the presence of background noise and chatter [20].

### 2.1 User Interfaces

Since cobots work closely with operators, cobots need to be equipped with intuitive UIs. These interfaces are used by operators to alter/create/customise cobot programs, whether off-line or on-line. The previous works related to cobot UIs and research challenges are discussed below.

### 2.2 User Interface Mediums

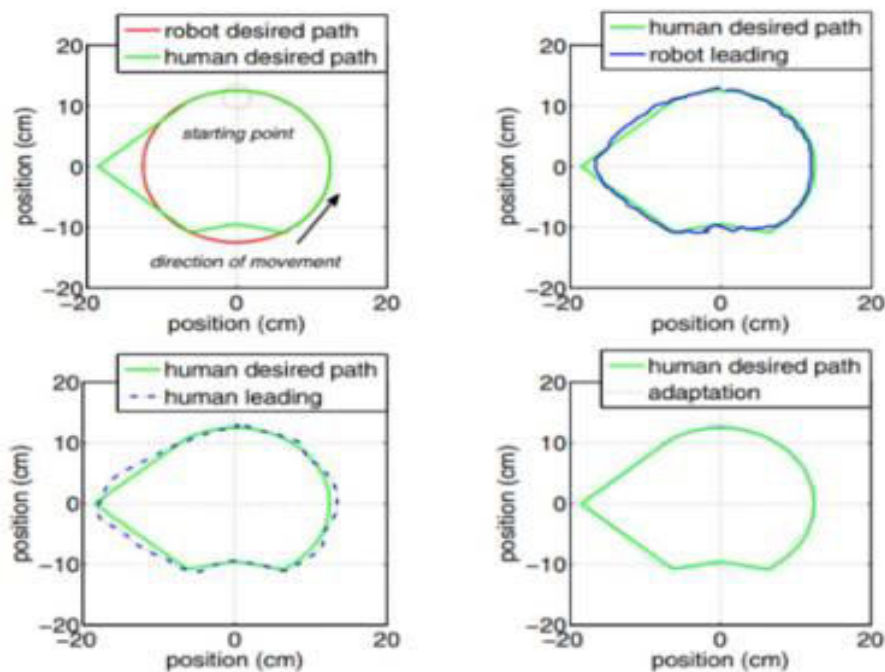
A UI is an essential differentiator of a cobot from traditional robots. Besides the user-interfaces being developed in research communities, several industrial solutions are already available. UIs are categorised such as:

- **Cobot teaching pendant:** Market cobots, such as Universal Robots (UR), ABB's YuMi and KUKA LBR iiwa, are labelled as intuitive and user-friendly due to their modular symbolic programming UIs. For example, the UR UI allows a user to specify way points and create arrayed motion patterns. The YuMi teaching interface is similar, with commands for both arms easily synchronised and parametrised. Teaching pendants are the easiest to utilise since they are built-in with the cobot. However, at a surface level, their capabilities are limited and do not enable human-awareness and action plan flexibility.
- **Icon-based programming:** A visual library of built-in functionalities can be utilised to create the program. For example, in MORPHA, the icons are connected to form a series of cobot commands. In LabVIEW, a data flow diagram is created in which values flow across the icons and trigger actions on hardware. Although an icon-based program is easy to build (in small scale programs), it is difficult to debug, maintain and alter. Therefore, they haven't been popular in the manufacturing industry [23]. Moreover, these methods haven't yet provided options to easily integrate the operator within the cobot's program so that the cobot is human-aware.
- **CAD-based programming:** Robot manufacturers and third parties have provided solutions such as V-REP, Visual Components and ABB's RobotStudio, in which performance can be validated and assessed. V-REP and Visual Components come with integrated human models that can also be programmed to help in validating the cobot's safety and collaborative functions around humans. In V-REP, a human can move according to a real-life actor through augmenting 3D sensor data, such as from Kinect v2, of a real-life human into the simulation. In Visual Components, the human can experience 3D simulation using VR which can be useful for training operators. However, since simulation has to match the real environment in order to achieve valid results, using CAD-based tools might be time consuming when changing work space design and reiterating the program, unless an automated method is devised to scan, map and build the environment.
- **Task-based programming:** This is the most popular research direction in intuitive cobot programming and will be further discussed in this subsection. The developed approach is based on a primitive-skill-task hierarchy [24]: Primitives are cobot motion commands or sensory inputs values, such as open gripper and sense torque. Skills are object-oriented and achieve goals such as pick object and tighten screw. Tasks are a sequence of skills and achieve the over all goal, which is the industrial scenario being implemented.

### III. REACTIVE COMPLIANCE

In reactive compliance, a cobot senses the forces exerted on its body and actively moves such that the forces are minimised. The challenge in reactive compliance is correctly mapping between the forces sensed by the cobot and the required motion to be done. Most cobots are not equipped with tactile sensors on their bodies, which makes it hard to interpret exerted forces and understand the intent behind them. The cobot, for example, can't identify the point at which contact with the human occurs and whether this contact is accidental or deliberate [25]. Magrini et al.'s work helps localise the forces being applied on the cobot [26]. That allows the cobot to respond to the contact force as desired or regulate it. Kouris et al. differentiated between collision and cooperation contact in a computationally efficient manner by thresholding the Fourier transform of the applied force/torque [27]. Gaz et al. differentiate between forces applied due to a polishing task and forces applied to move the cobot body by using a model-based approach [28]. This allows the human to smoothly and safely switch from moving the cobot compliantly and performing the polishing task.

#### Mixed-Initiative Compliance: Trading-off Between the Cobot's and Human's Plans



**Figure 2:** Results showing that path is smoothest when cobot switches modes between compliant and autonomous [29]. The switching occurs according to the human's exerted force with respect to the expected path. When the force is in accordance with the path, the cobot tends to autonomy. When the force opposes the path, the cobot tends to compliance.

### IV. OPTIMISATION

Optimality is a primary goal during industrial design processes (product, process and production line design) since it ultimately yields a “maximum” profit. The main challenge in HRC scenarios is to optimise around the human, i.e. modelling and incorporating the human in the cost function. This subsection reviews the works done on optimising different aspects to yield optimal and semi-optimal cobot action in different industrial HRC scenarios.

Since ergonomics is a main driver of implementing HRC, much has revolved around producing cobot behaviour that maximises humans’ physical comfort and health. Modelled human factors related to the human’s physical state include:

- Static ergonomic posture according to REBA: Busch et al. optimised cobot pose during handover to achieve human ergonomic posture [30]. They account for left/right handedness and avoid intimate body parts, all while keeping the human body in a safe comfortable posture according to the Rapid Entire Body Assessment (REBA).
- Muscle fatigue: Peternel et al. measured human muscle fatigue in order to adjust cobot's behaviours such that it handles more physical load and the human takes a more supervisory role [31]. The cobot does not take on all the physically-loaded tasks from the start since it needs to learn them from the human first. Hu et al. estimated dynamic human fatigue (varying with time as the human works more) per assembly action and accordingly distributes tasks between operator and cobot [32].
- Human joint torques: A key work in optimising co-manipulation for ergonomics is done by Peternel et al. a follow-up work of [33]. In both, the human's pose is optimised during co manipulation or handover task, such that the torque on the human joints are minimised. Table 4 highlights the main differences between the two works. An extension of these works would be to merge the benefits of both together by mathematically remodelling the problem.

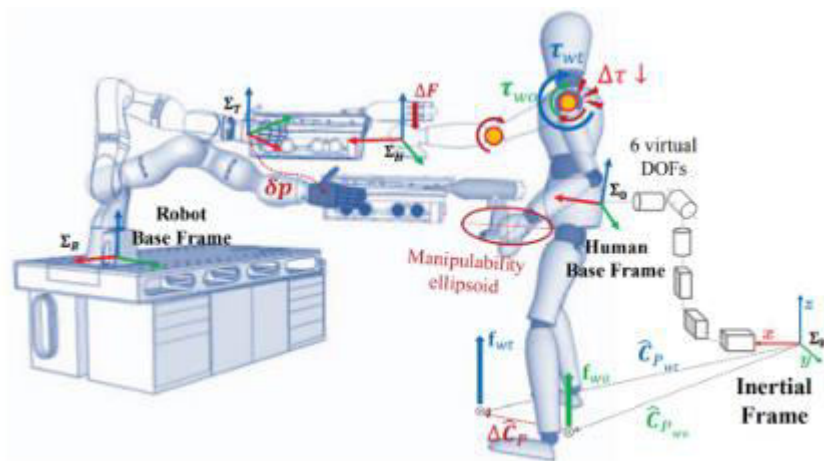


Figure 3: The force modelling used to calculate the human's joint torques [34].

The model is used to optimise the cobot's position such that the joint torques are minimised. Only the held object's weight is accounted for in the model. Reaction forces from tools, such as a drill, are not accounted for.

## V. COBOT LEARNING

Humans learn new tasks by observing them being done, by trying to do them and by asking questions and receiving feedback on performance. A human teacher serves to demonstrate a task, answer questions and provide feedback, all of which do not require programming skills. Researchers have attempted to enable a learner-teacher relationship between the cobot and the operator due to its naturalness and wide potential. In HRC, it is advisable to equip the cobot with learning capabilities since the operator might have to expand its skill set due to unforeseen working circumstances. Moreover, learning provides a balance between allowing the operator to make decisions first, then relieving him/her of the mental load as the cobot learns to operate autonomously.

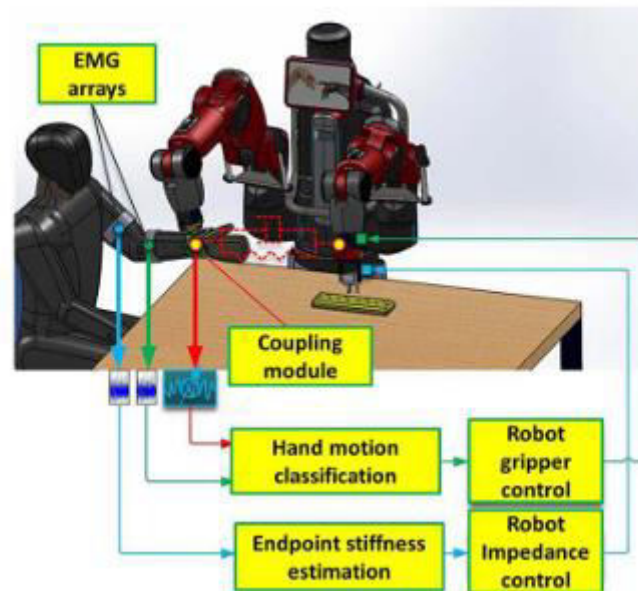


Figure 4: Demonstration-capturing interface designed by [35].

Encoding Information from Demonstrations LfD algorithms differ in what information they encode from the demonstrations, making it difficult to design one that caters for all expected variability in the environment and capture all requirements. Encodings can be motion-level or task-level. Motion-level encodings include:

- Motion with respect to obstacles: Ghalamzan and Ragaglia encoded obstacle presence from demonstrations, so that the reproduced cobot actions could avoid moving obstacles to reach a target location [36].
- Motion of two agents (humans or cobots) with respect to each other: Vogt et al. encoded correlation-based interaction meshes (Figure 4) from one human-human demonstration where one human led whereas the other followed. Then, they reproduced cobot motion that matches the human follower's pose with respect to the human leader while avoiding the correspondence problem [37].
- Constrained position and path with respect to objects and tools: Perez-D'Arpino and Shah encoded required postural (relative to work pieces) and path constraints for multi-step tasks [38].
- Compliance level (Stiffness) as a function of path: In a co-manipulation task, Roza et al. encoded compliance level (stiffness) given force and position inputs and could therefore reproduce co-manipulation behaviour with the right stiffness [39].
- Path dependent on position of landmarks: In task-parametrised LfD [40], the path of the cobot is encoded with respect to multiple landmarks as opposed to one. The importance/relevance of these landmarks to the path is automatically calculated from the variance of the path between multiple demonstrations. Task parametrised LfD has been used to generate trajectories for assembly tasks [41].

## VI. CONCLUSION

Human-robot collaboration and cobots are emerging technologies in supporting increasingly flexible and complex manufacturing processes. Among which, intuitive and human-aware programming technologies that can support cobots in collaborating with human operators more intelligently and adaptively, are the key enablers. In this topic, research has been actively conducted in recent years. In this paper, the latest research on cobot programming is summarised.

Firstly, an overview of collaborative industrial scenarios and programming requirements for cobot applications is provided. Then, the cobot programming technologies are categorised into three features, that are communication, optimisation and learning features, and relevant research works on the defined features are reviewed in detail. Communication features enable a collaborative human operator to transfer intent or commands directly to a cobot, thus



affecting its course of action to support collaboration. Optimisation features are algorithms developed by programmers on-line enabling a cobot to observe its collaborative operator and behave adaptively according to a pre-modelled optimised policy. Learning features allow a cobot to learn its own policy after receiving guidance from its collaborative operator. In the review, how intuitive and human-aware elements are considered in the communication, optimisation and learning features are elaborated. Furthermore, gaps from viewpoints of industrial requirements and the-state-of art research for cobot programming are identified. Finally, future research directions and recommendations for cobot programming to better support industrial collaborative scenarios are outlined.

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