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Nathan Eskue and Marcia L. Baptista

Abstract The ability for humans to work in close contact with robots in a manufacturing environment has been limited due to safety concerns and the robot's inability to sense, react, and coordinate with a human without explicit, rigid programming. However, advances in **Deep Reinforcement Learning (DRL)** have shown considerable promise in developing processes that allow robots to work in a dynamic environment, solving problems and adapting to the actions and communication from human counterparts. This chapter explores the current state of the art for **Human Robot Interaction (HRI)**, discussing the tools, algorithms, and methods being explored. Representative use cases are discussed to better understand what can be accomplished in today's manufacturing environment and what challenges could be faced. The concerns around safety, ethics, and unintended consequences are identified. Finally, the chapter looks ahead at the obstacles that still need to be overcome before HRI can be fully scalable and widely used.

Keywords Artificial Intelligence · Deep Reinforcement Learning · Human/Robot Interaction · Manufacturing · Industry X.0

1 Introduction

The importance of Human-Robot Interaction (HRI) in Manufacturing is becoming increasingly important as its capabilities continue to improve, matching the critical needs of industry. Robots have long been able to outperform humans in tasks requiring precision, speed, and force. However, humans are still dominant in many areas, including experience, knowledge of a given task, the ability to adapt to new

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Fig. 1 Smart factory concept with AI automation system by using robots. Digital image. Envato elements item, License code 67B5WD9LPC. June 28th, 2024

information, understanding the surrounding control strategies, and overall intuition [1]. Because of these parallel sets of skills, **the best solution in many manufacturing environments is for humans to work side by side with robots, with robots adapting to human actions and behaviors** [2]. The last decade has seen many improvements in the field of HRI, increasing the potential for completing tasks more effectively than humans or robots individually [3]. This is encouraging for several reasons. First, it highlights that the potential for human-robot interaction in a manufacturing environment is extensive, with use cases that likely venture into today's science fiction. To reach this, there are a number of technical hurdles but the potential to maximize the strengths of both humans and robots into a collaborative force can create a strong sense of optimism for this field [4]. In addition to this collaboration performing better, we can also find use cases that are impossible with today's technology, such as intricate tasks that must be performed in hazardous environments [5]. As shown in Fig. 1, the cooperation of robots and humans has high potential for smart manufacturing applications. This chapter will explore the core elements of HRI, the use of deep reinforcement learning (DRL) in developing HRI, the challenges and limitations, and estimates of where this research will evolve in the near future.

As promising as HRI seems, however, there are significant challenges and limitations, especially when working to generalize and expand its use across manufacturing tasks. Because the practice of HRI centers around communication between humans and robots, many of these challenges involve the ability to effectively communicate and correctly interpret from both parties [6]. Humans demonstrating instructions to robots through visual guidance, spoken word, or even haptic interaction [7] is possible, but complex. Striking a balance between efficient, autonomous operation of robots, and a process that can be interrupted when necessary by human intervention can be difficult to achieve [8]. Safety of the human is a concern when any heavy machinery is operating nearby, especially when that machinery acts in a dynamic and sometimes unpredictable way. Other limitations include the ability for robots to complete delicate and sometimes subjective tasks [9], and for the success of a human-robot interaction on the manufacturing floor to be reliably replicated [10] in a way that meets the expectations for efficiency and effectiveness.

HRI is heavily dependent on Artificial Intelligence (AI) in order for the robot to sense, interpret, and act upon decisions that are productive toward collaborating with a human on a given task. Because traditional robotics programming does not allow for flexibility in its decision making, a smart factory with HRI must utilize AI to create this more nuanced decision making process possible [11]. The AI architecture developed for these increasingly complex decisions is fed through technological advances such as sensor networks and Internet of Things (IoT) devices [12], which provide large amounts of critical data as inputs for a trained AI model to interpret, allowing for correct actions to be taken by a robot. With a well trained AI model (see key components of such a model in Fig. 2), a robot can perform tasks efficiently while maintaining flexibility to modify its behavior depending on human interaction or even other elements, such as malfunctions in the manufacturing process [13]. Many different architectures have been created (for example, H2020 ASSISTANT [14]) to utilize AI for adaptive manufacturing environments, using insight from digital twins and other sensor clusters to create intelligent production planning and control.

Within the field of AI, HRI has been especially advanced through the use of Deep Reinforcement Learning (DRL). This form of AI, in the context of HRI, treats the robot as an agent and uses a structure similar to teaching a human how to accomplish a task. The method addresses perceiving the surrounding environment, estimating rewards for given actions [15], dealing with uncertainty in making a decision [16], and how to maximize particular objectives such as safety [17], reliability, speed, accuracy, etc. **There are many different considerations that must be considered when developing a DRL model, with an iterative simulation training process required in order to identify and eliminate unintended consequences**. Further, there are other learning elements that may arise as unexpected challenges. For example, learning to treat moving objects differently than static objects, and how to navigate each effectively [18]. The exponential rise in complexity as a DRL model is expanded is evident in the manufacturing environment, with more inputs, decisions, and actions required as robots work to accomplish more complicated tasks.

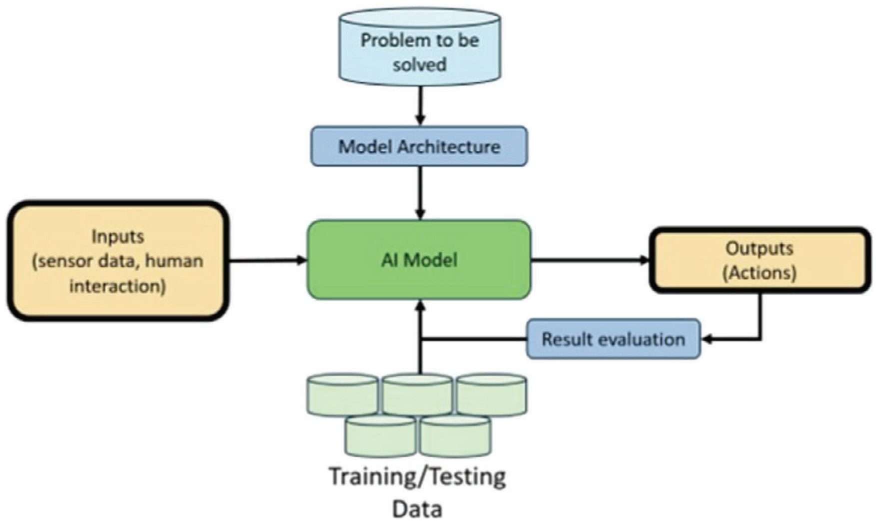

Fig. 2 Artificial intelligence components illustration. Digital image

2 Fundamentals of Reinforcement Learning (RL)

Before exploring how DRL can be leveraged to develop effective human/robot collaboration, it is necessary to understand what Reinforcement Learning (RL) is and why it is so well suited for HRI. **Reinforcement Learning is a form of machine learning that enables a model to learn optimum behavior through trial and error iteration**. Generally speaking, an RL model has an agent that can act, sense its environment, determine rewards, and evaluate what to do next. This type of learning is more intuitive than others because it mimics how humans learn a new task. The process by which an agent is trained is as follows. The agent takes action within the environment; it evaluates the action in terms of how it has changed the environment, and what rewards (punishments in this model are considered "negative rewards") were earned; it uses a decision making technique given this information to plan its next action; and the cycle repeats [19]. See Fig. 3 below for a simplified illustration of the RL process.

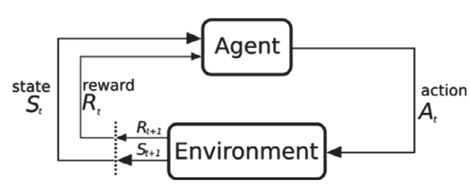

Fig. 3 Recurring neural network architecture. EBatlleP, CC BY-SA 4.0 https://creativecommons.org/licenses/by-sa/4.0, via Wikimedia Commons. June 28th, 2024

More uses of RL are being discovered and utilized, including robotics, planning and control [20], automated vehicles, internet of things security, energy management [21], etc. While the concept of RL will continue to be explored and improved to tackle key issues such as explainability [22] and evolutionary learning [23], the core concept remains the same as a robust and diverse tool for learning within an uncertain environment. **In manufacturing, RL for robots is especially fitting as the robots act as an agent, and often already have a number of sensors that aid in better understanding the immediate environment**. This, combined with the controlled conditions of a typical manufacturing cell, allow the infinite possibilities of decision making to be drastically narrowed down for the agent, simplifying the RL cycle and making effective computation possible. By simplifying the available actions, the environment, and the rewards gained, RL can even be expanded to include multi-agent situations, such as where multiple robots, each acting as an agent, can collaborate on a task without discrete programming instructions [24]. The complexity added in these scenarios can increase exponentially, requiring stronger methods of RL such as deep RL [25], continual RL [26], or other variations.

Another dimension of RL algorithms is the use of Model-Based or Model-Free architecture. The key difference between the two is that when evaluating the rewards and next action to take, **a model-based approach will use external information that contains objective information such as the probability distributions of rewards given a particular action** [27] (or discrete reward payouts if the situation is simple enough). A model-free architecture relies on the iterative cycle of action, reward, evaluation (of reward and environment), and planned next action. **The probability distribution of expected rewards given a particular action is gained through experience and learning, rather than an external set of rules.** These two approaches can be combined [28] in certain situations, which could potentially lead to additional benefits. Other than the availability of objective insight that can be developed into a model [29], there are a number of considerations when choosing model-based or model-free RL methods [30].

Researchers are heavily focused on reinforcement learning given its high potential to solve a wide range of problems. However, **the key types of RL algorithms typically fall within the categories of Q-Learning, SARSA (state–action–reward–state–action), or Policy Gradient**. Q-Learning (Shown in Fig. 4) aims to quantify the maximum possible reward by considering the rewards for various actions, weighing those against immediate action-rewards vs. longer term (and therefore less certain) action-rewards, along with a selected "learning rate" that helps to maintain an expected element of risk through exploring the unknown. This can happen in discrete steps or can be expanded to occur on a continuous timeline [31]. This element of curiosity allows the algorithm to effectively pay attention to the highest potential rewards, but allow for exploration [32] so that the agent can potentially discover unknown actions-rewards that may be even more beneficial. While similar, the SARSA approach has a wide variation in how it is executed, as there are many ways to assess the environment and calculate potential rewards [33]. Policy Gradient methods focus on using gradient descent to better direct an agent's focus toward

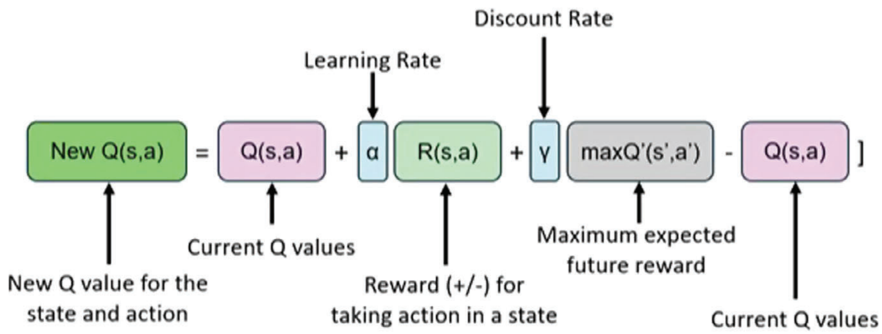

Fig. 4 Q learning components illustration. Digital image

maximizing a long-term cumulative reward [34] instead of maximizing immediate returns.

Using reinforcement learning in a manufacturing environment is impactful, but even a small amount of complexity and uncertainty can overwhelm traditional RL methods. **Using Deep Neural Networks (DNNs)** [35] **is a natural progression for handling increased complexity, as neural networks are ideal for taking in large amounts of feature-rich data and generating usable estimations for RL cycles**. This can create opportunities for Deep Reinforcement Learning (DRL), enabling new use cases that are more complex but are necessary to solve before a true smart factory can be realized. Using larger numbers of robots in a dynamic environment is a key goal for advanced manufacturing [36], and the use of deep reinforcement learning makes this possible, especially in areas where the processes and interactions can be simplified and controlled, avoiding as much uncertainty or external noise as possible. Deep learning within the context of smart manufacturing offers other opportunities as well, such as using recommender systems [37]. This is a format often used in areas like online retail, but could be tailored for other objectives such as recommending particular actions, specific tools to use, or pathways to take for robots using RL. Deep learning also suffers from the risk of providing output from a "black box", whereas a manufacturing environment with audit-driven regulations would require high explainability, even if working with complex environments like multi-agent decision making [38].

Various methods can be used to integrate deep learning with reinforcement learning. For example, Proximal Policy Optimization (PPO) can be used to empower robots with autonomous navigation in a complex environment, employing deep learning to improve collision avoidance behavior [39]. Other methods, such as Deep Q-Networks (DQN) and Actor-Critic Methods can be evaluated against each other and PPO to determine the best-performing approach. However, the results often depend on the specific goals of the problem being solved [40], as well as key elements of the problem such as training time, training timesteps, maximum value of episode-reward-mean, and others [41]. Because it can be difficult to predict performance, it can be beneficial (albeit resource-consuming) to develop a solution using a number of different techniques [42], evaluating their respective outcomes and selecting the method that best fits the needs of the particular problem.

3 Human-Robot Interaction (HRI) in Manufacturing

Human-Robot Interaction (HRI) is a vast and unique element of smart manufacturing. It is fast becoming a critical component of the fourth industrial revolution, but there is such a long roadmap for potential improvement that it will continue to be critical well into the fifth industrial revolution [43]. The growing capabilities of manufacturing, as well as marketing, supply chain, and logistics, place significant pressure on the ability of manufacturing activities to be flexible, efficient, collaborative, consistent, and sustainable in order to provide near single-unit customization in a just-in-time environment. To accomplish this goal, both humans and robots on the manufacturing floor must be extremely adaptable to changes in each manufacturing cell, performing different tasks potentially with each unit that is manufactured [44]. To accomplish this, **the elements of deep reinforcement learning can be applied to robotic elements of the manufacturing floor, along with the framework needed to create effective and safe** [45] **human-robot interaction**. Robots will be required to think, move, and act according to the manufacturing needs, but will need additional intelligence and sensing capabilities like computer vision [46] to be able to effectively interact with their human counterparts.

How does one measure “effective” human-robot interaction? This question is still being developed by both research labs and industry, but core requirements must include safety, trust, reliability, adaptability, and intuitiveness [47]. A successful system must be, at minimum, safe to use, effective in its goals, and able to change according to the needs of the human counterpart and the manufacturing job requirements. Ideally, **the robotic element must be able to efficiently manipulate objects, offer physical assistance to the human worker, but also be able to detect social cues from the human and adapt its behavior accordingly** [48]. This means, however, that the human in this system must have sufficient training to first know the robots capabilities, and to communicate with the robot in order to effectively interact and complete the necessary job. Either this, or the robot and subsequent intelligence guiding it must be incredibly adept at reading human social cues and adapting accordingly to assist toward the completion of whatever manufacturing job is being performed.

While working cooperatively with a robot can offer significant advantages in a manufacturing environment, this can also create stress for the human in a number of ways. **If there is a lack of trust toward safety, or if the human is not able to effectively communicate their needs to the robot, an HRI scenario can create more harm than good**. It is critical that the system is designed with this in mind, and includes proper human training of the system, and a robot that can adequately read human social and affective cues [49]. Another challenge in HRI is that many systems naturally skew toward the dominant control of the interaction held by either

Fig. 5 Automation technician engineer in manufacturing industry. Digital image. Envato elements item, License code AMDN2KT9PC. June 28th, 2024

the human or the robot. It is easier to develop systems where one party is dominant and the other party supports commands and actions, but far more difficult to develop a system where both parties share dominance. Figure 5, for example, shows a setup with a human-dominant structure. However, this balance likely leads to a much more effective system [50], where the human and robot act as teammates instead of one party acting as a low skilled assistant.

As technological and algorithm-driven improvements continue to develop, industry must find interim solutions to enhance the coordination between the human and robot. As intuition evolves toward a more acceptable level, the HRI can utilize elements such as AR-assisted motion previews for the human, showing where the robot is preparing to move in order to improve both safety and overall effectiveness of the system [51]. **Another approach that has shown promise is to break down robotic behavior into a series of tasks, utilizing reinforcement learning for each task and stacking multiple models in order to manage more difficult tasks in a way that supports time sensitive decision making** (which affects most manufacturing tasks) [52]. A key to solving these ongoing challenges lies with the setup of the manufacturing tasks and the processes that need to be completed. Developing interactions between humans and machines that are simplified, clear, and offer either previews or other intuitive cues, can help significantly to increase the effectiveness of HRI in manufacturing.

Fig. 6 Automated robot arms machine welding robots in industrial manufacturing factory. Digital image. Envato elements item, License code 3B2KUCNJFY. June 28th, 2024

4 Applying DRL to HRI in Manufacturing

In practice, applying deep reinforcement learning to human-robot interactions in manufacturing can take a number of forms. For elements where more control is needed or where HRI is not as advanced as the manufacturing process requires, **DRL has seen significant success in dynamically scheduling jobs for a given manufacturing cell in order to maximize the efficiency of the larger factory line** [53]. The reward for functions such as these can take the form of minimizing mean tardiness, or a collection of weighted rewards that includes measured efficiency, effectiveness, robustness, and generalizability [54].

While upon first glance it may seem that manufacturing tasks such as assembly, sorting, and quality control could be developed using traditional software methods, the ability to use DRL for these tasks opens the door to the many different dynamic environments and scenarios where these jobs might take place [55]. A robot using a strict program requires that each job be largely identical, with only minimal variation that can be detected and adjusted ahead of time. Even something as simple as components moving down an assembly line in a loose collection, vs. held in precisely paced jigs, could allow for significant flexibility on the manufacturing line.

While keeping consistency does allow even a DRL-trained robot to increase in accuracy, **designing a robot to be able to handle variation creates a much more robust environment, allowing it to perform as needed when elements of a process**

change unexpectedly [56]. Figure 6 shows a welding robot that must adapt its actions based on sensor input and AI-assisted decision making.

As mentioned above, DRL algorithms (for example, the deep Q-learning algorithm [57]) can excel at finding optimal policies to follow in a changing environment, adapting to the obstacles and elements in the area to accomplish its defined goal. Because any type of reinforcement learning brings with it uncertainty, using this method in HRI could potentially create safety issues. However, even this element can be developed as a high priority goal, and algorithms can be developed that emphasize the actions that work toward a goal while maximizing safety [58]. This emphasizes the **priority facing developers to completely understand the key elements of a given situation while applying DRL for HRI**. There must be metrics that the algorithm should maximize, such as the speed and accuracy of a task, but other goals or even full constraints such as safety elements must be given priority, otherwise injuries could occur and the trained robot would become a liability rather than an asset.

With many DRL applications, there are similarities in elements such as goals, methodologies, reward systems, or actions. While the specific context may be very different, **elements of a trained algorithm could be utilized in a new scenario without having to start development from scratch**. For example, an algorithm designed to identify and pick up boxes on an assembly line could potentially be transferred to also pick up other components. While the individual circumstances will dictate how much re-training is required, there has been progress made within the industry to increase the usage of transfer learning between DRL applications [59]. The efforts made to interact with humans effectively and safely are especially interesting and have potential value for transfer learning applications.

There have been increased efforts as well to utilize a safety-focused approach to DRL in scenarios with high risk and firm constraints. In addition to interaction with humans, DRL can be used to manage infrastructure elements such as microgrids [60] and HVAC systems [61] where there are a number of constraints that must be managed, all while working to minimize energy usage and overall cost. Because many different applications within a manufacturing environment have these key elements as robots work with machinery and humans, there are opportunities for direct transfer learning, or at minimum key lessons learned when developing new DRL algorithms within a manufacturing use case.

The ability to maintain manufacturing equipment itself is a large area of focus for DRL, utilizing elements of anomaly detection [62] and the game-like elements of goal pursuit found in RL to ensure that a particular machine receives the minimum amount of maintenance necessary to keep it running effectively, and with enough advance notice [63] of deteriorating performance that the maintenance can be scheduled outside of high demand time periods. This method has shown significant promise compared to the standard scheduled maintenance method, which risks both adding costs due to over-maintenance, and risking downtime when it cannot predict an increased chance of failure. By developing key sensor placements (often developed as part of an IoT system [64]) around the elements that most determine smooth operation, then building a DRL model to learn and identify upcoming anomalies, **predictive maintenance can save maintenance costs without risking factory downtime**. In the case of predictive maintenance projects, these problems often make use of time-based algorithms such as recurrent neural networks (RNNs) and long short-term memory networks (LSTMs). This allows for the passage of time to become a factor, creating trends in performance of the machine so the algorithm can identify and predict upcoming anomalies with better accuracy.

5 Case Studies and Applications

Use Case 1: Autonomous Assembly Line

Automated assembly lines have been active for decades, utilizing pre-programmed robots to complete repetitive tasks in a strictly-controlled environment. However, as many industries have evolved to more customization of their products to meet customer needs, or combining similar product lines to be produced on a single line, **there is a growing need for an autonomous assembly line that is both efficient and adaptable**.

The near future will see growing capabilities for robots to become more diverse in their capabilities (see conceptual illustration in Fig. 7), being able to sense the environment around them, determine how to complete a number of tasks, and do so both reliably and autonomously. However, the current state-of-the-art for AI is to create solutions where AI can excel, paired with those more cognitively complex tasks that humans can solve. **If done correctly, the pairing of humans and AI-driven robots can ease the burden for each partner and allow them to focus on what they do best**.

Within an assembly line, various tasks can be performed reliably with DRL [65]. Examples include sensing and detecting components, classifying what they are, developing a tool path to reach out and grasp a component, and developing a plan to combine and connect components together. However, there are elements of variation that can break a DRL if it does not have a way to exit the algorithm. For example, if two components are supposed to be placed together with 2–3 screws, but for some reason the robot is not able to successfully do so, it may cause issues on the entire assembly line. Depending on how the algorithm was developed, an edge case like this might cause the robot to continue attempting this process, to exert more force (and possibly break the components), or place the unfinished product in with the assembled pieces. This is an example of a more cognitive task that includes troubleshooting, perhaps some experimentation, and possibly out-of-the-box thinking. For example, the holes for the screws may be slightly misaligned. A robot empowered with an excellent DRL may still have no way to assess and solve this issue, whereas a human could determine the root cause and take action (e.g., set aside the defective part and continue work) within seconds.

In a use case like this, it is more effective to utilize HRI methodologies where a human can interrupt the robot [66], take the components to diagnose the issue, then

Fig. 7 Intelligent robotic operations. Digital image. Envato elements item, License code RDJTH-GAXZ8. October 06th, 2024

either give the components back to the robot to continue, or remove the components from the assembly line.

Studies have shown that this type of partnership between humans and robots is preferred, with humans continuing to handle more cognitive tasks while robots handle manual work [67]. When designing a HRI-based assembly line using DRL, it is critical to understand the strengths, weaknesses, and capabilities [68] of each party in order to design both normal and edge case scenarios that maximize overall performance. It is also important to develop these processes iteratively to ensure the solutions are valid, including line workers in the process to gain invaluable insight and better understand how to improve the solution.

Use Case 2: Collaborative Robots in Packaging

In the second use case, robots could be used collaboratively with human counterparts in the packaging operations at the end of an assembly line (see Fig. 8 as an example). This could take a number of different forms, but there are several key elements to consider, design for, and verify with the workers who will use the system. A key application for cooperatively packaging could be in cases where the components being packaged are especially large or heavy, and where the process would benefit from an industrial robot handling tasks that are not ergonomically sound [69]. When developing the scenario, the robot will need to not only sense the human colleague's position and movement, but will also need to detect, interpret, and act on commands from the human. In combination with the HRI elements of the scenario, **the process should be designed, as much as possible, to break down necessary tasks into simple, repeatable, and modular tasks so that the robot can more accurately act**

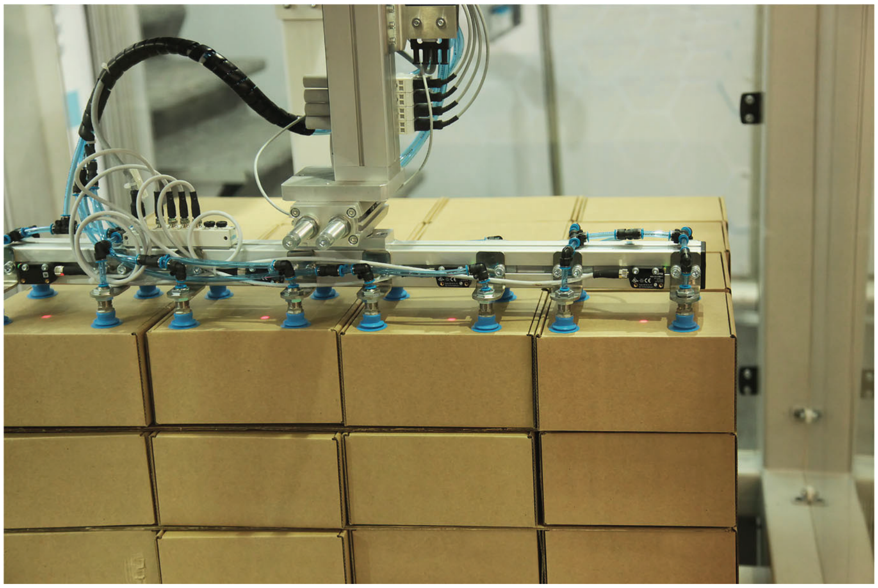

Fig. 8 Vacuum suction cups for industrial robots. Digital image. Envato elements item, License code NDEBVX9YW8. June 29th, 2024

upon them, possibly using a stacked series of DRL elements that are selected and executed as the robot recognizes commands and understands what needs to be done next.

This type of solution, where the robot completes physically difficult or repetitive tasks while being supervised by a human, has shown both effectiveness and a greater preference by the humans in the loop [70]. This again emphasizes the human acting as a cognitive member of the team, able to quickly evaluate and act upon scenarios that are still too complex for a DRL algorithm to effectively handle [71]. The ability to give basic commands that a robot can understand, then autonomously complete in a dynamic environment can provide a major boost for completing tasks that traditional robotics are unable to complete, and humans must do even if they are physically or ergonomically taxing.

Use Case 3: Quality Inspection and Control

Quality inspection and control are areas where various AI techniques have been used often, as the ability to detect anomalies in a controlled environment is ideal for many AI algorithms. Figure 9 illustrates inspection tasks driven by sensors and linked AI models. **HRI provides an entirely new dimension to quality inspection, bringing opportunities to areas previously impossible, and enabling the combination of humans and AI-guided robots to produce far better results than either party could on their own**. While the most simplistic application of AI quality inspection might involve a standardized assembly line of equally spaced, consistently oriented

Fig. 9 AI quality control performed by sensor-equipped arm. Envato elements item, License code BPWY27TGMV. October 06th, 2024

components (with consistent lighting, speed, etc.), the ability to employ both DRL and HRI can allow inspection to move away from the assembly line.

The use of robots traveling over a surface of a large product such as an aircraft becomes feasible (though not without its challenges), while the inspection and monitoring of construction sites with an inspector assistant quadruped robot is being developed [72]. Given this, **there are many applications where a robot assistant could enhance a human's ability to effectively and efficiently inspect a large product, providing DRL-based insights to detect anomalies, along with critical digital documentation of the process in the form of sensor inputs from the robot**. As with the other examples, the greatest results are possible when the strengths of both the human and robot are evaluated, and the solution is built with these elements as guiding principles [73].

This use case will continue to receive significant attention [74] as various innovations are developed, ensuring higher accuracy for inspection, minimizing both false negatives and false positive errors. **Pairing a human with a DRL-driven robot has also been improved through the use of multimodal human-robot interaction**, as algorithms are able to receive and interpret inputs from humans in a variety of ways, including voice, image, text, and even more subtle methods such as eye movement, touch, and bio-signals [75].

```python
import torch
from torch import nn # Import the nn sub-module from PyTorch

class NeuralNetwork(nn.Module):  # Neural networks are defined as classes
    def __init__(self):  # Layers and variables are defined in the __init__ method
        super().__init__()  # Must be in every network.
        self.flatten = nn.Flatten()   # Construct a flattening layer.
        self.linear_relu_stack = nn.Sequential(  # Construct a stack of layers.
            nn.Linear(28*28, 512),  # Linear Layers have an input and output shape
            nn.ReLU(),  # ReLU is one of many activation functions provided by nn
            nn.Linear(512, 512),
            nn.ReLU(),
            nn.Linear(512, 10),
        )

    def forward(self, x):  # This function defines the forward pass.
        x = self.flatten(x)
        logits = self.linear_relu_stack(x)
        return logits
```

Fig. 10 Pytorch Example from https://en.wikipedia.org/wiki/PyTorch, via Wikimedia commons. June 28th, 2024

6 Implementation Strategies

Although there are many clear use cases and opportunities to develop DRL for HRI, it is still left to actually build the models that will be used. How are these models built, tested, and deployed? **There are a number of tools that can be used to develop DRL, ranging from open source, free, but higher learning curves** [76]; to expensive suites of pre-built templates, friendlier UI's, and even professional support. Because transfer learning is still such a large challenge in AI, and especially in more complex algorithms such as DRL, there is not a dominant platform of AI development that is both easy to use and effective. This however will likely change in the near future, and the still relatively young AI development suite industry will grow considerably.

There have been a number of key development tools that have maintained significant popularity with companies, research labs, and academia. Some of the top platforms include PyTorch (see Fig. 10), TensorFlow, and OpenAI Gym, though these are just examples and should not be considered a definitive list. However, those development platforms that are open source and maintain large communities have shown consistent growth among the AI community, especially as many innovations and libraries [77] are posted for the community to share. **It should be noted that RL development, and especially DRL, is still a bespoke process, with each problem addressed in a customized way, complete with environment-related and communication-related challenges that the development team must solve** [78].

As a review, DRL is made up of an agent that can observe their environment; take specific actions; observe the effect of those actions and calculate the expected rewards; then repeat this process in order to achieve the intended goal. Because of this, training a DRL algorithm often takes place in a simulated environment [79].

Fig. 11 Robot with Gripper in a simulated environment. Digital image. Envato elements item, License code 4V39LEG2QU. June 28th, 2024

It is nearly always cost and time prohibitive to conduct this learning process in real time [80], and a proper simulated environment could offer thousands, millions, or even hundreds of millions of learning sessions in a reasonable time (depending on the complexity of the simulation and the computational power used) [81]. **When a simulation reflects reality well enough, an algorithm can learn a new task virtually in a way that will translate accurately to reality**. The implications of this cannot be overstated, although there are significant challenges to scaling complexity [82] and creating truly accurate simulations.

In order to bridge the gap between simulation and real-world manufacturing scenarios, the simulation environment must be able to accurately replicate those elements that create uncertainty or affect specific actions that the agent could take [83]. For example, if a particular cobot will be used for a simulation, the same cobot make and model should have an accurate digital twin within the simulation environment (for example, the model shown in Fig. 11, allowing all elements (power usage, force, actuation, degrees of freedom, end effector capabilities, etc.) to mimic as closely as possible the real robot that will be used in deployment of the trained algorithm [84].

These movements and a physics-accurate environment are critical for the simulated environment to learn how to accurately create tool paths in order to

solve a particular problem [85]. If the robot to be used is mobile, then the material that will be used in the factory floor must be replicated for grip, slippage, dust, small obstacles like safety tape, and anything else that could affect the movement of the mobile robot [86]. The accuracy of simulation applies also to how the robot will sense their environment.

Computer vision must be replicated, as must distance calculations, temperature readings, and any other sensor readings. Because of this, the team must consider not just the immediate area (e.g., an assembly line) but elements in the outlying area. **For vision especially, the lighting sources, temperature, and variation must be properly replicated in a simulated environment, otherwise the robot will not be properly trained to accurately see in the production environment** [87]. While a controlled environment like a production line can contain many challenges during simulation and real-world deployment, this challenge is exponentially more difficult if the environment is either more dynamic [88] or more extreme [89].

7 Evaluation and Metrics

In order to effectively develop deep reinforcement learning for human-robot interaction, it is important to establish strong metrics that can incorporate those elements that are important to both accomplishing the manufacturing tasks, as well as ensure safety and user satisfaction thresholds are met as well.

In most DRL algorithms the performance metrics (speed, accuracy, efficiency, etc.) are directly or indirectly built into the reward mechanism in order to encourage the correct behavior that will yield desired results. However, when working with HRI problems it is also important to consider the best way to evaluate elements like safety. Depending on the situation, the development team could hard code constraints that would interrupt the DRL-trained actions, such as slowing if a person is too close to a robotic arm. However, this method could quickly erode the performance metrics built up by the DRL algorithm. In some circumstances (see Fig. 12, this evaluation can be tested and simulated through VR environments.

Instead, it is best to consider the human interaction within the DRL training itself, building it into the reward mechanism along with performance metrics [90]. For example, **rewarding the algorithm when it accurately predicts human movements and avoids collisions could encourage a more collaborative interaction**. This type of training can be accelerated through the use of developing both digital twins of the robot and machinery involved, but also proper simulations of humans and the typical actions they might take in that particular scenario [91]. For example, Fig. 13 illustrates the concept of a full digital twin of an aircraft, providing AI-driven insights as to the health and performance of the vehicle.

Other studies have worked to quantify the quality of a human-robot interaction, weighing factors such as flexibility, performance, cost, and quality aspects for a given training session [92].

Fig. 12 Engineer is using virtual reality glasses to inspect the factory's mechanical control system. Digital image. Envato elements item, License code Y8976FWL3M. June 29th, 2024

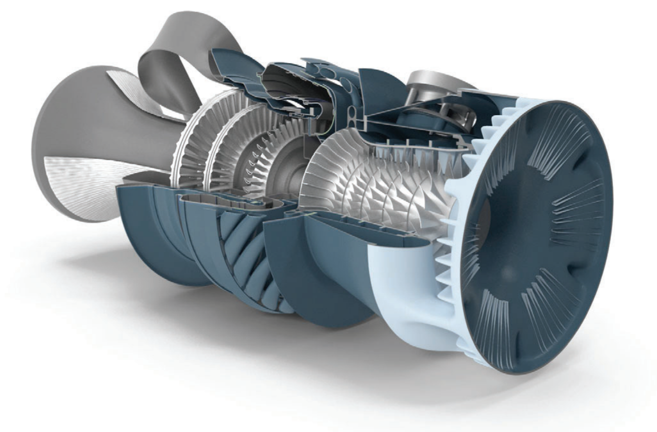

Fig. 13 Digital twin engine. Digital image. Envato elements item, License code TGXAVHB467. October 06th, 2024

Because DRL is so situational dependent, with seemingly small factors playing a large role in the effectiveness of a given trained model, it can be difficult to find a proper dataset to use as a benchmark test. However, there are a number of datasets that can be used as approximations for different scenarios. It is important to note that **when searching for a benchmark task and dataset, those datasets that provide a testing set, proper data labels, and have been made in real-world conditions should be prioritized** [93]. Regardless of the dataset and benchmark testing, it is important to understand what differences there are between the benchmark and the actual scenario for which a team would like to develop a DRL solution [94].

8 Future Directions and Challenges

Perhaps the largest obstacle preventing DRL from dominating the field of AI-driven manufacturing is the difficulty that arises when scaling solutions [95]. This challenge can be countered somewhat by working to simplify environments, tasks, available actions, and the uncertainty distributions of events. However, **as a single task is scaled up to more large-scale manufacturing setups (as shown in** Figure 14), **this level of complexity increases at an exponential rate, quickly overwhelming current computational limits available to many companies or research facilities** [96]. Another method to scale up more complex setups is to create modular tasks that can be separated into their own enclosed DRL solutions, with task hand-offs in between that can either be programmed traditionally, can be DRL solutions themselves, or can be managed by humans.

This challenge also extends within a given environment if the task itself is diverse, or even if the human counterparts who interact with the robot are diverse. In addition to looking different, being different heights and sizes, having different arm lengths or grip strengths, or any number of other physical characteristics, the behavior of

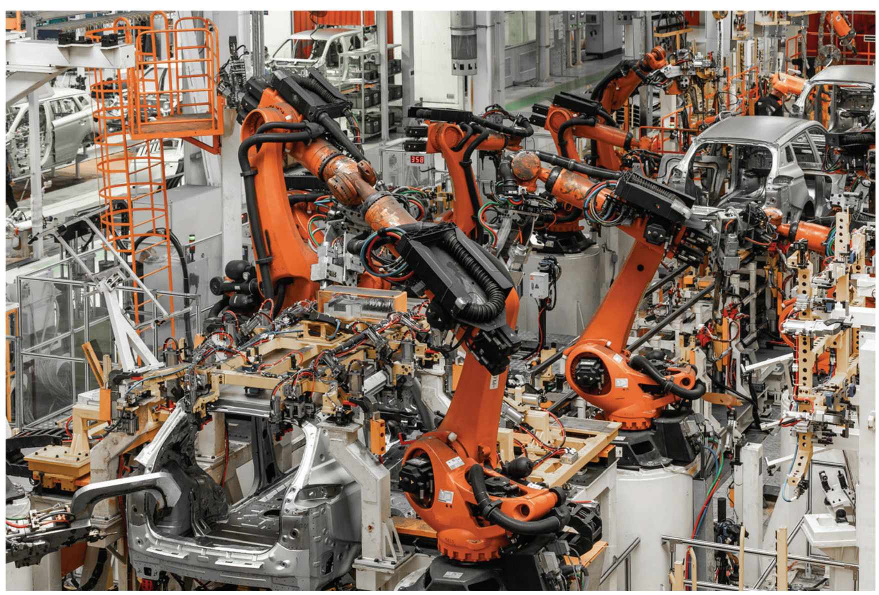

Fig. 14 Photo of automobile production line. Digital image. Envato elements item, License code 9S7TFJEQAM. June 29th, 2024

each person varies in terms of gestures, movements, even walking gaits [97]. While humans can sense and interpret these differences at a subconscious level, **a DRL without a very diverse training set could become confused and error prone if a human is behaving differently than what occurred during training**. As more and more differences are identified, the DRL training becomes significantly more complex and inefficient [98], preventing many real-world HRI scenarios from being deployable onto the factory floor.

AI development has already shown the potential for bias against particular people if those groups are either underrepresented or discriminated against in the training data [99]. This type of discrimination can be difficult to anticipate and detect, so additional testing (see Fig. 15 as an example of basic recognition and interaction testing) must be performed to ensure the data is representative of the people who will be affected by the algorithm, and that the trained behavior is consistent across sampled individuals. This type of discrimination, whether intentional or unintentional, can unfairly target based on ethnicity, gender [100], age, height, weight, or a number of other factors. The responsibility is on the developers of the algorithm, along with the organization who deploys and uses the algorithm, to ensure ethical practices from humans and DRL-driven robots alike [101].

The impact on the workforce and job roles is another important consideration for organizations. It is important to understand not just the purpose of a HRI solution, but its perceived goals and values among the organization. Even customers may have a say if the organization interacts with them in a HRI capacity, as [102] shows the

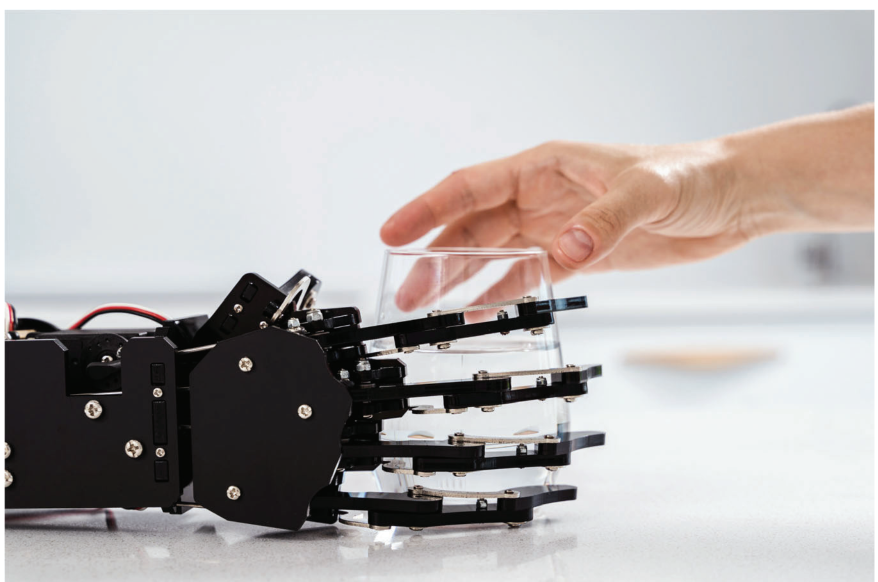

Fig. 15 Robotic extending a hand with a glass of water to a young woman. Digital image. Envato elements item, License code JSC2FAEKY3. June 29th, 2024

customers are much more favorable toward robot-related situations where the robot supports the growth of employees rather than as a replacement.

As AI in general continues to develop and evolve, there will be more opportunities for technology to improve the ability for DRL solutions, and for robots to better perceive and understand their human counterparts. With advances in online learning, **robots could conceivably identify users they see, and either gather data from available sources or directly inquire key characteristics from the humans themselves, updating their algorithms to better perform with a particular person** [103]. Other advancements could include the ability for humans and robots to interact using innovations such as ChatGPT [104] or voice commands given as natural language instructions [105].

9 Conclusion

In this chapter we introduce the concept of deep reinforcement learning, and how it can aid in human-robot interactions within a manufacturing environment. **Artificial intelligence has begun to transform many aspects of manufacturing, with applications ranging from optimizing supply chains, scheduling jobs, detecting anomalies, and sorting product lines**. Reinforcement learning, and especially deep reinforcement learning, can help an agent learn new tasks without explicit programming, creating new opportunities for robots to complete tasks that have a greater amount of uncertainty, decision making, and even human interaction.

The ability for DRL to bring flexibility to robotic task completion also opens the door to more complex human interaction, where humans and robots can work cooperatively, communicate instructions, and leverage each others' strengths. **This field, however, is still in early stages of development, with significant obstacles preventing scalability or complex tasks at this time**. There are strategies to break problems down into simpler, modular tasks, and to reduce the amount of complexity in order to successfully implement DRL for HRI. Simulation environments, a critical element of DRL, are also improving in their ability to more closely represent realistic environments. Physics-accurate scenarios with digital twins, representative lighting and textures, and simulated human interaction can help to develop accurate solutions for given DRL tasks. When transferred to a real robot, a well-trained DRL model can provide the robot with a strong understanding of the environment, actions, and the planning required to complete a task.

Along with technical hurdles, there are still ethical implications that must be explored and resolved. The training of a DRL, if performed with biased data, could result in lower accuracies when interacting with certain groups of people, creating a discriminatory level of service (whether intended or not). The ability to train a robot to interact with a representative number of people should be a priority as the field of HRI evolves.

Compared to many other technologies, DRL in complex environments is still incredibly new. However, the rate of interest throughout different industries, the clear value potential, and the amount of research being performed is clearly represented by the rate of continuous improvement and innovations developed on a regular basis. By understanding the capabilities and limitations of DRL, especially in the context of HRI, the field can continue to develop and solve the critical obstacles that prevent the widespread use of DRL. With new technological advancements such as greater processing power, the ability to use more natural communication methods (driven by large language models), more precise simulation environments, and modeling wide ranges of potential humans that will interact with trained robots, this field will likely grow exponentially in the next 3–5 years, becoming an integral part of manufacturing in large and small companies alike.

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