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Human-Robot Collaboration With Commonsense Reasoning in Smart Manufacturing Contexts

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***Abstract*— Human-robot collaboration (HRC), where humans and robots work together to handle specific tasks, requires designing robots that can effectively support human beings. Robots need to conduct reasoning using commonsense knowledge (CSK), e.g., fundamental knowledge that humans possess and use subconsciously, in order to assist humans in challenging and dynamic environments. Currently, there are several effective CSK systems used for organizing information and facts, along with detecting objects and determining their properties. HRC is employed in various manufacturing tasks, such as paint spraying and assembly, in order to keep humans safe while increasing efficiency. Although there is a large array of research on HRC and on CSK, there is minimal research linking the two concepts together. This paper presents a novel system on human-robot collaboration guided by commonsense reasoning for automation in manufacturing tasks. This fits within the general realm of smart manufacturing. The primary focus is on improving the efficacy of human-robot co-assembly tasks. Evaluations conducted with online simulations and real-world experiments indicate that reasoning using CSK-based robot priorities enhances HRC as compared to simpler robot priorities, e.g., merely handling nearby objects. This system is modifiable and can be used for larger and more complex real-world tasks, thereby leading to improved automation in manufacturing. This paper demonstrates the scope of combining HRC and CSK, while future works will be able to further utilize the benefits of combining the two fields with significant impacts.**

***Note to Practitioners*—This paper is motivated by the human-robot collaboration problem in smart manufacturing. Robots operating by reasoning with commonsense priorities in human-robot collaboration enable faster task execution and better human work life. This can help balance work for humans and prevent injury. Adding robots to tasks accordingly does not necessarily decrease costs, but can limit human exposure to danger which is significant (and can also lower costs overall). Simulations and real-world experiments in our research using commonsense reasoning demonstrate how work is easier and better with human-robot collaboration. These factors are highly significant when tasks are repeated multiple times. The system is presented within automated manufacturing and is scalable for different real-world applications. Such automation is particularly helpful during recent times in the aftermath of the COVID-19 pandemic.**

***Index Terms*— Collaborative robotics, commonsense knowledge, human-robot interaction, UN SDG 9, smart manufacturing, task quality optimization.**

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I. Introduction

A. Background and Motivation

HUMAN-ROBOT collaboration (HRC) refers to the concept of humans and robots working together on tasks. It is an important part of automated manufacturing and would surely benefit from reasoning based on commonsense knowledge (CSK) such as determining where objects are typically located relative to each other [1]. For smart manufacturing, intelligent machines are given access to production data and use that information to control parts of production and logistics [2]. The adaptive nature of smart manufacturing allows for customizable products and flexible production. Smart manufacturing allows for rapid response to events [3]. This includes adapting to external changes and modifying manufacturing load through decision-making, even with incomplete information. Smart manufacturing also involves analyzing data for real-time decision-making and forming both predictions and models. Humans are quite important for smart manufacturing due to their ingenuity and collaborative robots supplement humans rather than supplanting them. Collaborative robots have a variety of benefits over traditional robots, such as being capable of working alongside human beings in the same space and being designated to handle multiple tasks [4]–[8]. Adding additional space for robots or getting multiple types of robots for multiple tasks increases costs, which can make collaborative robots less costly than traditional robots. Human-robot collaboration is important and requires robots to plan for dynamic real-world situations [9]. Commonsense knowledge (CSK), which is understanding objects, their properties, and how they relate to and interact with each other, is important for human-robot collaboration. Humans have commonsense knowledge due to real life experiences, such as knowing that icy ground is slippery and should be walked on carefully. Robots have a difficult time acquiring and reasoning with this knowledge, but need it in order to enhance collaboration with humans [10]. Commonsense knowledge and related works are used via many sources to manage information and to detect, interpret and manage objects [11]–[14]. There is still great potential for combining commonsense knowledge and reasoning with human-robot collaboration.

B. Contributions of This Study

This paper presents information on reasoning guided by commonsense knowledge and human-robot collaboration, specifically focusing on how the two areas are connected. This paper also offers the context of automation in manufacturing demonstrating how commonsense knowledge based reasoning can improve human-robot collaboration in tasks therein. We conduct simulation studies involving a human and a robot collaborating to construct a vehicle from a given set of parts. CSK is used to guide the robot's actions so constructing the vehicle is fast and simple for the human worker. In addition, this paper displays how in-person experiments conducted in real-world contexts confirm the benefits of human-robot collaboration guided by commonsense knowledge that are applicable for constructing a vehicle in the real world. This paper thus makes contributions to the domain of smart manufacturing, e.g., the use of various intelligent technologies within the context of industrial production [2]. While we address smart manufacturing in general, we focus on vehicle assembly in particular for the experiments in this paper. The conclusions of this study on reasoning with commonsense knowledge for human-robot collaboration can be potentially usable in other real-world applications as well with suitable modifications, though we focus mainly on automation in manufacturing here. It is to be noted that our studies in this paper have been conducted during the COVID-19 pandemic and we emphasize the role of simulations played in them that set the stage for efficiently performing real-world experiments. This is in line with the significant automation needed during such times and paves the way for further similar applications.

The paper is structured as follows. First, section II discusses related work in the area. Then, prerequisite information about commonsense knowledge and reasoning, as well as human-robot collaboration pertinent to our research is presented in section III. Afterwards, the methodology used in this work is explained in section IV. Further, the experimental evaluation is outlined in sections V and VI, describing online simulation experiments and real-world experiments, respectively. Based on this, section VII presents a discussion on our work. Lastly, conclusions and future work are presented in section VIII. The main contributions of this study are:

(1) Proposing a system for reasoning based on the use of commonsense knowledge in human-robot collaboration for automation in manufacturing, thus positively affecting the smart manufacturing domain.

(2) Conducting mathematical modeling for robot action planning and human-robot collaboration to provide task optimization in assembling an object from its parts.

(3) Demonstrating online simulation tasks along with real-world experiments to prove that humans and robots guided by CSK can be efficient in task execution while valuing human safety and comfort (by protecting humans, making them carry lighter parts, and making the collaborative experience pleasant).

II. Related Work

Artificial Intelligence or AI is the intelligence depicted by machines analogous to the natural intelligence biologically possessed by humans. In other words, AI pertains to machines (computers, robots etc.) that simulate "cognitive" functions which we humans typically associate with our real brain, e.g., "learning" and "problem solving" [15]. In this context, learning brings us to the realm of Machine Learning. As the name implies that machine learning is for making machines such as computers or robots "learn" analogous to humans. It can be more formally defined as the study of algorithms and mathematical models that machines can utilize to execute target tasks without specific instructions, by relying on patterns and inference. Thus, it can be considered a field of AI which provides the ability for systems to automatically learn from experience [16]. Machine learning is typically data-driven, and it leads to Data Science. There are several paradigms in Machine Learning, a highly significant one today is Deep Learning, which is a kind of learning algorithms employing multiple layers to progressively extract higher level features from raw inputs [17]. While Deep Learning can be used for several tasks in a variety of applications, it relies on prior knowledge or experience, often requiring huge amounts of training data. Thus, a machine when faced with a new situation for the first time may not be able to make decisions analogous to a human, due to lack of prior training. This issue can be addressed by the inclusion of commonsense knowledge (CSK) [10]. When machines are endowed with CSK, they can act in a more humanlike manner, and can make intuitive decisions closer to the thresholds of human cognition. A recent tutorial discusses the pros and cons of Deep Learning and CSK [18] with respect how they can potentially benefit from each other. It surveys numerous interesting works in CSK while also addressing Deep Learning models; and thereby emphasizes how the extraction and compilation of CSK is crucial in order to enhance modern AI systems. Given this overview, we now proceed to discuss related work as pertinent to this paper.

Researchers at the University of Bremen, Germany are developing a robot that handles tasks through using commonsense knowledge [19]. The robot's system stores entities' 3D positions at specified times, meaning the system's model can access every entity's position at a specific time and access a 3D image of the entire environment. This information can be used to connect detected visual patterns to spatial relationships. A simple example of this involves connecting 2D and 3D shapes to the objects' size and distance. Through connecting these features and properties, tasks can be made simpler. The work of these researchers demonstrates how commonsense knowledge can potentially makes robot task execution more optimal.

Until recently, humans and robots needed to work separately since humans could interrupt robots executing a task and robots could potentially be a threat to human workers [20]. Robots have become safer and more capable of working alongside human beings. Physical human-robot-interaction (pHRI) focuses on humans and robots interacting and is relevant to HRC. Prior approaches focus on planning out the individual basic steps rather than planning out the complete assembly of

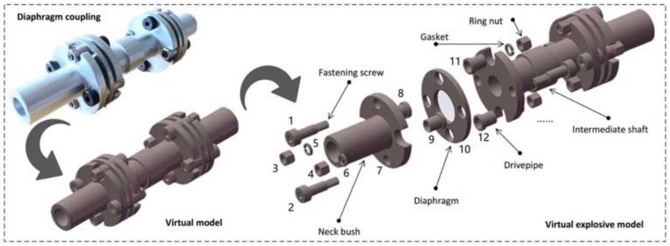

Fig. 1. Virtual model of a diaphragm coupling and its parts [28]. The human-robot collaborative disassembly (HRCD) system perception, cognition, decision, execution and evolution circle (PCDEE-Circle) can collaborate with a human to disassemble this type of coupling.

a product. Researchers developed a human-robot collaboration framework formed by three layers: the team level, the agent level, and the skill execution level.

The team level plans out the product assembly based on available agents, assembly parts and possible construction plans [20]. The main goal of the team level is to allocate tasks to human and robot workers by providing abstract task descriptions. When the planner requests an agent to take an action, that agent returns the cost for that agent executing the specified action. If the agent cannot execute the specified action, it returns a cost of infinity. The planner uses the costs it receives to determine the optimal actions to undertake. The agent level maps the abstract descriptions provided by the by the assembly task planner to abstract planning a layer above using the robot's motors and sensors. The agent level features other planning systems outside of the abstract planning that help a robot execute a task. This planning requires the robot to execute actions provided by the team level and provide information to the team level. Additionally, the agent level needs to be able to handle dynamic events such as interruptions and collisions. Finally, the real time level handles trajectory planning based on information from other layers. In addition, it executes reflexive actions based on dynamic events. A potential example would be slowing down to avoid a collision or stopping after a collision.

Non-specialist users are currently utilizing human-robot collaboration more frequently, and because of this, robot designers need to develop an effective interaction model [21]. Video games interfaces can be used to model robot interfaces since video games convey information in a simple to understand manner. One case where video game-based interfaces are shown to be effective is using an augmented reality cockpit interface rather than a virtual cockpit screen.

This paper has primarily focused on optimizing task execution, but robots also need to learn how to execute tasks, which grows more important as tasks become more complicated. This was not an issue for this paper's experiments due to their simplicity, but is much more important in the real world. Typically, robots use domain models and mathematical policies to learn how to execute tasks, which need to be precisely designed by experts. Robots need to be able to use learning from demonstration (LfD) [22], where they learn by watching another entity perform a task. This form of learning is much more intuitive and useful for non-specialists working with robots. Crucially, ordinary people can demonstrate task execution and robots can learn without the aid of experts. LfD comes in three main forms, teleoperation, shadowing, and imitation. Teleoperation involves a teacher operating the robot learner while its sensors save the inputs. Shadowing involves the teacher executing a task while the robot learns by attempting to copy the teacher's motions. Lastly, imitation involves a different entity performing the task while the robot learns by using its own sensors or sensors on the operator. Unlike shadowing, the robot only watches task execution during imitation. Through using these types of learning, robots can better understand how to execute tasks.

The realm of cognitive robotics extends to concepts such as object recognition. Machine learning techniques containing deep learning and neural networks play an important role here and the concerned systems can be augmented via the use of commonsense knowledge [23]. Spatial commonsense in particular is very useful here in generating benchmarks for object recognition [24]. This could particularly benefit applications such as robotic driving in autonomous vehicles [25] where the enhanced used of commonsense knowledge in object recognition and related tasks can bring the AI systems closer to human cognition thresholds so as to provide more adequate decision-making especially in situations encountered for the first time ever. Such aspects contribute to robotics and automation on a large scale.

Researchers at Cranfield University have been working on an Augmented Reality (AR) system for improving HRC [26]. AR has been applied in various fields such as customer technology, plant maintenance, and nuclear industry. The AR system is a handheld device that overlays a virtual animation of robot movements on the robot so the human operator can see how the robot will move. To test whether the AR-HRC system increased trust in robots, the researchers had people perform a maintenance task while using system and then answer a five-point Likert scaled questionnaire. The test involves picking and placing tasks of an electronic card. Importantly, the user can activate the AR system to see the robot's planned actions before it executes them. This helped increase trust, displayed by the fact that the average trust score from user surveys was above a three out of five. While the AR-HRC system has not been compared against a system not using AR, it still indicates that users trust the AR-HRC system. Using modern technology as AR can help improve HRC.

Robots are being used for agricultural tasks, demonstrated by a robot assisting in tree fruit farming [27]. The tree fruit farming robot has 3 modes, e.g., mule, pace, and scaffold mode. In the mule mode, the robot helps with tasks such as harvesting by following a group of workers. Its pace mode involves the robot executing a particular task over a given region. The scaffold mode makes the robot travel while it is acting as a scaffold on which humans can stand. The robot's helpfulness is ascertained by the fact that workers are able to trim the trees more than twice as fast in the scaffold mode versus using ladders. Also, this makes things much easier for humans. This is an excellent example of the robot's benefits in HRC and indicates how it positively impacts human workers, with respect to efficiency and comfort, making contributions to the realm of smart automation in general.

Sustainable manufacturing helps the economy, environment and society [28]. In terms of society, sustainable manufacturing generates new profits and allows for both better work and more work. Sustainable manufacturing uses disassembly as the main production mode of remanufacturing since it saves resources and energy while reducing emissions. While robots are able to handle some repetitive and dirty jobs in disassembly, there are other jobs that requires human beings. Because of this, human-robot collaborative disassembly (HRCD) is an effective form of disassembly. This paradigm falls in the overall realm of smart manufacturing since it contributes to sustainable living via intelligent manufacturing processes involving robots. Fig. 1 shows an example of diaphragm coupling and its parts, as deployed within the realm of smart manufacturing.

Robot intelligence is important for disassembly since robots need to be able to understand human intentions, their own motions and the product they are handling [28]. PCDEE-Circle is a HRCD system that uses "multi-modal perception, multi-target cognition, decision making, and both knowledge formation and evolution." PCDEE-Circle uses multi-modal perception to connect industry parameters to human actions and uses multi-modal perceptions to analyze entity actions and non-entity objects. From there, decision-making is based on reinforcement learning while knowledge formation and evolution are based on incremental learning and transfer learning that occurs during the HRCD process. A robot using this system works alongside a human in order to successfully disassemble a diaphragm coupling, which consists of several parts of varying sizes. The robot's successful collaboration demonstrates that HRCD is feasible.

Reimagining work in the age of AI explores how AI can be used to aid human-robot collaboration [29]. Previously, machines typically worked on static tasks apart from human beings and were designed for one task. However, those static tasks are really well optimized and very few automation improvements can be made. Currently, due to advancements in and AI and robotics, machines can work with people on various areas including smart manufacturing. Robots are now smaller, more flexible and capable of working safely alongside humans through using machine-learning algorithms. AI systems are not meant to remove humans from work, rather to work alongside humans. Robots will use data and machine learning to handle simple tasks while humans will use commonsense knowledge and reasoning to handle more complicated tasks.

Agriculture is a field that needs to become more efficient since the population is growing and there are 795 million people who do not have enough food [29]. Fresh water and fertile land are limited and difficult resources to manage. Precision agriculture uses AI and precise crop data to produce more food with fewer resources. Precision agriculture uses data from environmental sensors placed in the field, sensors attached to farm equipment, soil databases and weather data. Accenture is a company that developed Precision Agriculture Service to improve pest control. The service uses Internet of Things (IoT) sensor data to send suggestions, which farmers can manually choose to implement or a digital work management system can automatically implement. Another modern AI improvement in farming includes vertical farms [29]. In vertical farms, plants are grown in 30-foot stacks of trays, which allow for plant growth in more areas including urban settings and city warehouses. In Newark, NJ, a farm uses machine learning systems that analyze real-time plant data in order to maximize crop growth efficiency. The farm is expected to use 95 percent less water and 50 percent less fertilizer. In addition, due to being inside, pesticides are no longer needed. This will allow for more efficient farming.

Industry 4.0 predicts that humans and robots will work together seamlessly, and robots will aid humans with work rather than replacing them [30]. Robots need to be able to predict dangerous situations so fewer unexpected collisions can occur and robots can adapt to collisions. This requires robots to observe their environment and plan decisions effectively. Cyber-physical systems (CPS) are one of the linchpin technologies that will enable Industry 4.0. The 5C architecture states that implementing a CPS is made up of five levels, smart connection, data-to-information conversion, cyber, cognition and configuration. Smart connection focuses on sensing the environment and transferring environmental information between all entities. Data-to-information conversion focuses on a machine using environmental information to understand its environment. Cyber focuses on analyzing information from all machines to predict future behavior. Cognition focuses on translating analyzed data to forms more comprehensible to human experts. Configuration focuses on mechanisms that physically apply decisions determined in the cognition. This system will allow for effective human-robot collaboration.

While the 5C architecture is effective, it does not include safety component [30]. Because of that, CPS must also utilize scene monitoring, task modeling and planning in order to work safely alongside human beings. Scene monitoring focuses on continuously modeling the operator and the assembly processes' manufacturing components. This allows the CPS to be aware of where objects and operators are. Tasks modeling focuses on understanding present and future operator actions and assembly cycle states. This requires CPS to predict the operator's intentions through recognizing operator atomic actions and modeling transitions between them. Planning focuses on determining a plan that will complete action or movement tasks. The robot needs to base its order of actions around the predicted actions of the operator and the relative action transition model, which tracks the transitions between different actions. Through utilizing these safety systems, CPS will further human-robot collaboration, especially in more risk-filled environments.

While we have studied numerous works in the literature and presented a few of them here, to the best of our knowledge, none of these works focuses on the explicit adaptation of commonsense based reasoning in the context of collaborative robotics to enhance automation in the manufacturing domain. Our research makes contributions in this arena. We specifically propose a methodology that harnesses commonsense based reasoning in order to optimize robot action planning and arm movement for tasks in collaborative robotics, in particular vehicle assembly, thus making a positive impact on smart

Fig. 2. Collaborative robot working with a human to assemble an engine. [31].

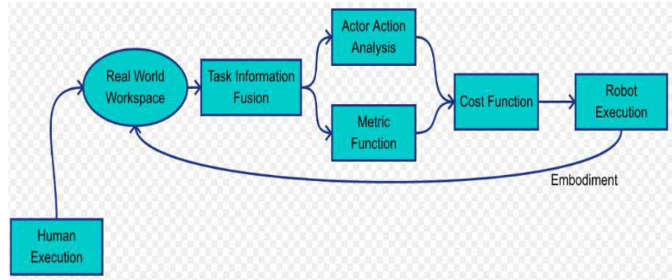

Fig. 3. Framework of proposed system for object assembly within smart manufacturing by commonsense reasoning in collaborative robotics.

manufacturing. This serves as a good starting point offering the two cents to the vast realm of human-robot collaboration and surely paves the way for more research along these lines.

III. Prerequisites on CSK and HRC

Commonsense knowledge encompasses pragmatics, which relates to general world knowledge, and semantics, which relates to context-specific knowledge. Pragmatic knowledge is often useful for corner cases that do not occur regularly. For example, if a power failure occurs in a factory where a collaborative assembly robot is working, the robot should stop its current task until being given new tasks. Otherwise, it could run into a person or object while lighting is limited.

The main goal of this work is to determine how robots can support humans through reasoning by using commonsense knowledge while efficiently working. As per that, the two objectives for robots collaborating with humans are:

1. Determine commonsense knowledge priorities that can support and protect humans in tasks involving human-robot collaboration.
2. Conduct reasoning with CSK priorities to achieve HRC with increased safety and comfort for humans while maintaining effective execution for productivity especially needed in smart manufacturing.

These goals must be such that they incorporate a good balance between human safety and comfort versus effective execution for high productivity. If too much focus is placed on effective execution, humans may have worse work lives while if too little focus is placed on effective execution, production will be significantly harmed. Because of this, determining a balanced set of commonsense priorities is critical. Safety is the most important priority; robots must handle tasks leading to minimal human risk. Other priorities include the weight carried, the distance traveled and the danger and fragility of the carried parts. Lastly, the total execution time is quite important.

Human-robot collaboration is widely used in automated manufacturing. With reference to this, Fig. 2 portrays an example of HRC in assembly tasks [31]. Note how a human and a robot work together on assembling an object from a set of parts. With reference to this, note that throughout this paper, the term ‘parts’ will refer to the individual components used to create a final product by being combined in a pre-determined manner, while ‘object’ will refer to the assembled final product. These terms are used to explain how human-robot collaboration for assembly occurs. For these collaborative tasks, the term ‘arm’ refers to a human with both arms and a robot with one arm, cooperating to combine parts into an object. The robot uses commonsense knowledge for reasoning in order to effectively select and move parts. The robot prioritizes heavier parts since humans can more easily and quickly carry lighter parts. Humans are also likely to have more difficulty with heavy parts and would therefore move more slowly. The robot arm prioritizes moving towards parts that are further away so that the work is easier for humans. The robot arm prioritizes carrying dangerous parts since that will keep humans safer. For example, the robot arm should carry sharp parts so humans do not cut themselves. At the same time the robot prioritizes carrying parts that are more stable since humans are better at handling parts that are fragile. The four main premises for commonsense knowledge based reasoning are:

1. Humans prefer carrying lighter and closer parts due to ease and comfort.
2. Humans will carry heavy parts more slowly than light parts.
3. Humans should handle less stable parts in order to avoid damaging them.
4. Humans should not handle dangerous parts as human safety is imperative.

Stability is defined as how likely a part is to remain stable if dropped, e.g., a wooden part is more stable than a ceramic part. Humans will handle heavier parts slower than lighter parts, especially if they carry the heavy parts all day. Humans will find it extremely frustrating if a robot mishandles an unstable part and not trust the robot to handle parts in the future. To avoid this scenario, humans will handle fewer stable parts. Since safety is the most important premise, robots will handle parts that are more dangerous.

The proposed system for human-robot collaboration guided by commonsense reasoning is illustrated in Fig. 3. It is to be noted that there may be conflicts between CSK premises 3 and 4 (listed herewith) occasionally. This overall framework for reasoning based on commonsense knowledge in human-robot collaboration is explained as follows. First, the human and robot executions affect a real-world workspace. From there, task information is gathered within the workspace. That information is used to inform actor action analysis and a metric function, which are then combined into a cost function.

The cost function in turn affects robot execution. Due to these conflicting priorities such as premises 3 and 4 herewith, and the need to determine how to best fulfill the premises for good HRC, mathematical modeling is used.

Robot semantics is about robots interpreting the meaning of the world, which is connected to presenting that meeting [32]. In particular, semantics is about robots understanding the meaning of locations, objects, other entities in the same environment and language. Human-robot interaction depends on both semantics and natural language ontology. For robots to operate in more complicated environments than manufacturing, warehouse transportation and mining, they need to be able to be able to interpret environments in complicated manners. The two main types of semantics are provided semantics, where robots are pre-programmed with information before deployment, and learnt semantics, where robots learn information before or during deployment. Semantics has potential in a wide variety of fields, including house cleaning, scientific exploration, intelligent transportation, and social interaction.

Pragmatics is about interpreting different forms of communication to a specific intention [33]. Some examples include, “Can you bring me my tools?”, “Please give me my tools?”, “I want my tools for work”, “Get me my tools already!” Currently, robots have been developed that can understand indirect forms of speech, but more work remains on allowing robots to appropriately respond based on the current social context. Robot pragmatics also includes having robots make requests politely when communicating with people. In addition, being brief while remaining informative is quite important. Being overly verbose is problematic as is missing information, so robot pragmatics need to be designed carefully. Social robots need to be able to adjust their language based on their context in order to communicate optimally. Different environments require different types of communication; a robot in a surgery room should be terser than one in a classroom. Pragmatics is important for developing social robots that can collaborate with humans.

The HRC system uses the CSK premises in order to conduct reasoning for potentially optimizing the smart manufacturing tasks, more specifically with reference to vehicle construction with the initial parts being shaped into a final object.

IV. Methodology

We propose a system based on commonsense knowledge used for reasoning in human-robot collaboration to achieve smart automation in manufacturing. The relevant background on commonsense premises provided herewith serves as the basis for this system. We explain its steps, e.g., robot action planning followed by robot arm movement accordingly.

A. CSK-Based Robot Action Planning Optimization

The knowledge base (KB) developed in our research focuses on human and robot priorities for selecting parts based on their properties, such as their weight, size, distance (the sum of the part’s distance from the arm and its distance from its final position), danger and stability. In order to follow the premise that humans prefer lighter and closer parts, the robot arm should prioritize heavier parts and parts that are further away. In order to fulfill the premise that robots should not carry unstable parts, humans will carry parts that are less stable. Lastly, in order to actualize the premise that humans should not carry dangerous parts, robots should handle parts that are more dangerous.

Algorithm 1: Optimization of Robot Action Planning

Input: Real-time parts, their properties, positions and priorities of arms

Output: The part that the current ami will target next

```
maxscore = 0; maxattrvals = [ ]; minattrvals = [ ];
selectedpart = None;
for (p = 0; p ≤ n; p++):
        for (a = 0; a ≤ t; a++):
                if (a(p) > maxattrvals [a]):
                        maxattrvals [a] = a(p)
                if( a(p) < minattrvals [a]):
                        minattrvals [a] = a(p)
for(p = 0; p ≤ u; p++):
        o(p) = 0
        for (a = 0; a ≤ t; a++):
                o(p) += r(amax) x a(p) maxattrvals [a]
                o(p) += r(amin) x minattrvals [a] / a(p)
        if (o(p) > maxscore):
                maxscore = o(p)
                selectedpart = p
return selectedpart
```

The steps for arms handling parts are described as follows:

1. Arms lock onto a part and indicate to other arms that they done so to prevent other arms form locking onto the same part.
2. Arms move to the part they have locked onto.
3. Arms move the part they are carrying to the final position.

Locking onto parts is used to indicate to other arms that a specified part is being targeted and that they should target other parts. From there, arms move to the parts they locked onto, grab them and then move to where they are supposed to be placed. This process is repeated until there are no remaining parts. An algorithm is used to define this behavior in order to aim for optimization of robot action planning and is displayed as Algorithm 1 herewith. This algorithm uses the real-time parts and their properties, and the arms’ positions and priorities in order to determine which parts to first select and how to move them to their respective final positions.

Each arm uses a scoring algorithm based on its position and the attributes of the remaining parts to determine which part to select. The scoring equations are:

$$W_a(s_p) = (min_a(s_p) + mean_a(s_p) + max_a(s_p))/3 \quad (1)$$

$$O_1(p) = \sum_{a=1}^{t} r(a_{min}) \times W_a(s_p)/(a(p)) \quad (2)$$

$$O_2(p) = \sum_{a=1}^{t} r(a_{max}) \times (a(p)/W_a(s_p)) \quad (3)$$

$$O(p) = O_1(p) + O_2(p) \quad (4)$$

In these equations, the set of parts is defined as s_p and the term $a(p)$ refers to a specific attribute for the part p. The term $W_a(s_p)$ refers to the weighted average across the set of parts for a specific attribute, formed by averaging the set’s minimum

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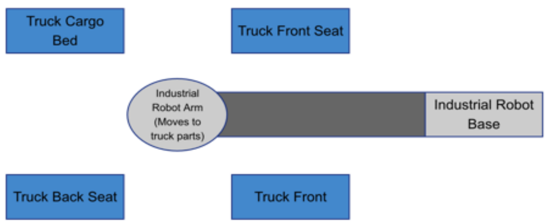

Fig. 4. The industrial robot arm and the layout of the parts it will transfer to the human (not to scale).

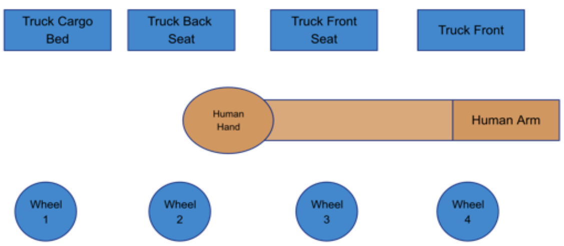

Fig. 5. The human arm and the layout of the parts once the robot transfers the truck parts to the human (not to scale). The robot starts with the parts in a rectangular configuration and then hands the parts to a human, placing each part in a straight line. The human and robot arm do not interfere with each other since even though they collaborate within the same environment, they are at a sufficient distance from each other where they will not collide.

value for that attribute, maximum value for that attribute and the average value for that attribute. $R(a_{min})$ refers to an arm's priority for minimizing a specific attribute and $R(a_{max})$ refers to an arm's priority for maximizing a specific attribute. The series $\sum_{a=1}^{t}$ is the series of all measured attributes. There are currently a few attributes being analyzed, but the system is customizable to permit adding other attributes. The relative attributes are important since the attribute of a part is compared against the weighted average for that attribute. The score is based on the priorities and values for attributes, including weight, danger and distance, so each attribute is used for calculations.

B. CSK-Based Human-Robot Collaboration

In human-robot collaboration such as a sample human-robot vehicle model co-assembly as shown in Fig. 4 and Fig. 5, an example outline of the process is described as follows. Note that we use this HRC in vehicle assembly as a running example in order to explain the further details herein. In this collaborative task, the robot first gives a cargo bed of a truck to the human. Thereafter, the human connects the two back wheels onto the cargo bed. Whilst the human conducts this task, the robot passes the back seat of the truck to the human. The human then affixes that back seat to the cargo bed of the truck. During this time, the robot delivers the front seat of the truck to the human. After that, the human attaches this front seat to the back seat of the truck. Simultaneously, the robot offers the front part of the truck to the human. As a next step, the human attaches this truck front part to the front seat of the truck. Finally, the human attaches the remaining parts, e.g., both the front wheels to the truck front as appropriate. This synopsizes the process of vehicle model assembly collaboratively executed by the human and the robot. Such co-assembly incorporates commonsense knowledge in the part ordering for adjoining the individual parts to assemble the entire model vehicle. This process is briefly illustrated in Fig. 4 and Fig. 5. The robot starts with the parts in a rectangular configuration and then hands the parts to a human, placing each part in a straight line. The human and robot arm do not interfere with each other since even though they collaborate within the same environment, they are at a sufficient distance from each other where they will not collide. Its details are elaborated next as per CSK-based-HRC.

Algorithm 2: Optimization of Robot Arm Movement

Input: Real-time parts, their properties, positions and priorities of arms
Output: The parts being placed in their correct positions

```
arm holdingpart = false;
for arm in arms:
    if not (arm.lockedon):
        bestpart [arm] = arm.determinebestpart();
        bestconnect [arm] = arm.detemunebestconnect();
        arm.lockonto (bestpart);
    if (arm.Jockedon);
        if (not arm.holdingpart);
            armarm.movetopart (bestpart);
            arm.pickup(bestpart);
        else:
            arm.movetoconnect (bestconnect[arm]);
        arm placepart (bestpart);
```

For robot arm movement in HRC, consider that humans and robots collaborate in the same workspace with the same set of parts denoted as *P,* and commonsense priorities denoted as *C*. Thus, each *P* refers to a part such as *wheel1, seat1* in vehicle manufacturing etc. while each *C* refers to a CSK priority such as distance, weight etc. Note that danger gets 1.5 times higher priority than the mean of all the other attributes. Here, *C(danger)* represents the CSK priority of this attribute while $C(x)$ *for* $x = 1$ *to* m represents the priorities of each of the other attributes. Furthermore, P_i represents the i^{th} part in the set P while $S(p_i)$ represents the overall score for moving a part to its correct position. This score is calculated by comparing the attributes of a part against the maximum and minimum values of the attributes of all the parts, along with the CSK priorities. P_s represents the selected part while t represents the total number of parts. Thus, human and robot arms select their next part to move using Equations (5) to (7) herewith.

$$C(danger) = \frac{1.5}{m} \sum_{x=1}^{m} C(x) \quad (5)$$

$$S = \{S(p_i) | 0 \le i \le t - 1\} \quad (6)$$

$$P_s = P(\text{argmax}(S)) \quad (7)$$

The optimization of robot arm movement is outlined in Algorithm 2 herewith. The output of this algorithm involves the parts being placed in their correct positions due to appropriate arm movement guided by the approach.

Within the task execution conducted using this approach, human movement speed is affected by the amount of weight being carried, so the simulation reflects this with the following

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formula. In the simulation, note that a human collaborating with a robot can either be un-encumbered, slightly encumbered, encumbered, or very encumbered. The variable E is used to represent how encumbered the human is, and the variable υ represents their normal velocity: when the person is unencumbered. $V(E_s)$ represents the velocity when slightly encumbered, $V(E)$ represents the velocity when encumbered and $V(E_\upsilon)$ represents the velocity when very encumbered. This knowledge will modify their movement speed for placing parts using the equations as follows:

$$\upsilon(E_s) = 0.66 \times \upsilon \tag{8}$$

$$\upsilon(E) = 0.5 \times \upsilon \tag{9}$$

$$\upsilon(E_\upsilon) = 0.33 \times \upsilon \tag{10}$$

In addition, this experiment primarily focuses on trajectory programming. Once a robot obtains a part and moves itself to where the connection area for that part is, connecting that part is treated as instantaneous. Future work could involve more task-based programming. This paper primarily focuses on how robots can be programmed to follow an optimal trajectory when gathering and inserting parts.

These algorithms and equations are used for the execution of tasks in our proposed system of reasoning based on commonsense knowledge in human-robot collaboration for smart automation in manufacturing tasks. We now describe its experimental evaluation considering vehicle manufacturing.

V. Online Simulation Experiments

We conduct online simulations as the first part of the experimental evaluation of the proposed system in this paper for which some preliminary results have been obtained in our early work [34]. We explain the simulation task setup and the corresponding results in the respective subsections herewith.

A. Simulation Task Description

Sample ranges of the CSK-based attribute values that correspond to aforementioned CSK premises of distance, weight, danger and stability, are depicted with an example in TABLE I herewith. Note that this is just one instance of values for the attributes and is not a predetermined order. These are as coded in the KB and used in our experiments. The cells here indicate the extent of the respective CSK-based attributes. The first row exemplifies the minimal permissible human attribute values for the respective columns corresponding to distance, weight, danger and stability, while the second row exemplifies its maximal ones. Likewise, the third row exemplifies the maximal permissible robot attribute values, and the fourth row exemplifies its minimal ones.

In our simulation experiments, the robot's maximization priorities are instantiated based on Eq. (1) through Eq. (4) to counterbalance the human's minimization priorities and vice-versa. This allows humans to work with parts they prefer and are better at working with, resulting in object assembly being faster, safer and more effective. Robots can then handle those parts that humans have more difficulty moving, such as heavy, large or fragile parts. The robot's priority ranges are limited in order to support human beings. This allows humans to work with parts they are best at working with, resulting in faster object assembly. Robots can handle heavy or large parts more effectively than humans; hence robots will handle those parts.

TABLE I

Human and Robot Attribute Ranges

	Distance (cm)	Weight (kg)	Danger (Level)	Stability (Level)
Min for Human	5	1	0	0
Max for Humans	600	55	30	30
Max for Robots	700	60	30	30
Min for Robots	10	2	30	0

B. Implementation of CSK-Based HRC in Simulation Contexts

We hereby describe how we implement our approach that entails reasoning based on commonsense knowledge embodied within human-robot collaboration. This is with reference to Eq. (1) through Eq. (10) formulated in Section IV of this paper. Accordingly, the tasks in our simulation experiments consist of programmed human-robot collaboration, with humans and robots combining the individual vehicle parts into an actual vehicle. In order to determine optimal CSK priorities, the simulation is conducted with various robot priorities and with limitations placed on these priorities. Human priorities are determined by common sense and remain constant while robot priorities change for different tests. The calculated CSK priorities based on Eq. (1) through Eq. (7) are tested against manually determined CSK priorities as well as the simpler priorities. The simpler priorities include: *blank*, where all priorities equal 0; *closest*, where all priorities except distance are equal to 0; and *norobot*, where only the human follows priorities. *Prioritiescsk* and *prioritiescskv3* refer to priorities as determined by our research team. *Combinationscsk* and *combinationcskv3* refer to the priorities calculated by the simulation system with minimum and maximum ranges, with each tested priority being a multiple of 50, for each robot priority in place. Priorities started at a lower multiple of 50 at the start of testing and ended at a higher multiple of 50 by the end of testing. *Thesis priorities,* are the final set of priorities used for the entire CSK-based-HRC implementation, which were calculated in a similar manner as the *combinationscsk* priorities. When testing to determine the effectiveness of priorities, each set combines five different sets of parts 1000 times, with a total of 5000 executions. The attributes that the human arm handles and the time are then averaged and stored. For these simulation experiments, distance is measured in cm, weight in kg and time in seconds. Danger and stability are measured as relative levels (which are unitless quantities).

The exact combination of priorities given to each attribute is shown next in TABLE II. Note that we include the attribute 'size' here since we initially store it in the KB for preliminary studies. However, we do not actually use the size of the parts within our experiments so far, thus its value is recorded as 0 here (except in the 1st sub-table where its value is shown just to maintain a default). The other attributes, namely: distance, weight, danger and stability are used for the experiments in this paper. Addressing the size of parts in the experiments

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TABLE II

LIST OF ALL PRIORITIES

prioritiescsk

Type	Distance	Weight	Danger	Stability	Size
human max	0	0	0	100	0
human min	100	100	50	0	100
robot max	100	100	150	100	100
robot min	0	0	0	0	0

prioritiescskv3

Type	Distance	Weight	Danger	Stability	Size
human max	0	0	0	50	0
human min	0	250	100	0	0
robot max	100	150	100	0	0
robot min	0	0	0	0	0

blank

Type	Distance	Weight	Danger	Stability	Size
human max	0	0	0	0	0
human min	0	0	0	0	0
robot max	0	0	0	0	0
robot min	0	0	0	0	0

closest

Type	Distance	Weight	Danger	Stability	Size
human max	0	0	0	0	0
human min	100	0	0	0	0
robot max	0	0	0	0	0
robot min	100	0	0	0	0

norobot

Type	Distance	Weight	Danger	Stability	Size
human max	0	0	0	50	0
human min	150	150	75	0	0
robot max	0	0	0	0	0
robot min	0	0	0	0	0

combinationscsk

Type	Distance	Weight	Danger	Stability	Size
human max	0	0	0	0	0
human min	100	250	100	0	0
robot max	0	100	150	50	0
robot min	50	0	0	0	0

combinationscskv3

Type	Distance	Weight	Danger	Stability	Size
human max	0	0	0	0	0
human min	100	250	100	50	0
robot max	0	250	150	0	0
robot min	100	0	0	0	0

thesispriorities

Type	Distance	Weight	Danger	Stability	Size
human max	0	0	0	0	0
human min	100	100	150	50	0
robot max	0	50	200	50	0
robot min	100	0	0	0	0

remains an aspect of future work. The first row for each table II section corresponds to the human's priority for maximizing an attribute. The second row for each table II section corresponds to the human's priority for minimizing an attribute. The third row for each table II section corresponds to the robot's priority for maximizing an attribute. The fourth row for each table II section corresponds to the robot's priority for minimizing an attribute.

In addition, the objects to assemble range from simple to complicated, allowing the simulations to test the approach on disparate sets of parts to be combined into an object, in this case a vehicle. Through this, a more general set of priorities can be determined and observations can be recorded for the simulation tasks in vehicle assembly.

TABLE III (Shown in APPENDIX) depicts a list of various sets of parts used in the simulation experiments as well as the specific attributes for each part. This is with reference to parts in assembling an object, in this case a vehicle. The parts here are the wheels, vehicle base, front seats, back seat, tires,

TABLE III

SOME TYPICAL PARTS AND ATTRIBUTES IN AN EXAMPLE CASE OF VEHICLE ASSEMBLY. THESE DIFFERENT SIMULATED VEHICLE MODEL PART ATTRIBUTES WERE USED TO TEST THE DIFFERENT HUMAN-ROBOT COLLABORATION MODELS

Attributesv1

partid	Label	isbase	Length	Width	Height	Weight	Danger	Stability
0	wheel1	FALSE	3	2	3	10	3	2
1	wheel2	FALSE	3	2	3	10	3	2
2	wheel3	FALSE	3	2	3	10	3	2
3	wheel4	FALSE	3	2	3	10	3	2
4	vehiclebase	TRUE	18	14	10	30	10	15
5	seat1	FALSE	4	4	5	5	2	4
6	seat2	FALSE	4	4	5	5	2	4
7	backseat	FALSE	12	4	5	15	5	8

Attributesv2

partid	Label	isbase	Length	Width	Height	Weight	Danger	Stability
0	wheel1	TRUE	6	3	6	2	3	4
1	wheel2	TRUE	6	3	6	2	3	4
2	wheel3	TRUE	6	3	6	2	3	4
3	wheel4	TRUE	6	3	6	2	3	4
4	tire1	FALSE	9	3	9	3	3	6
5	tire2	FALSE	9	3	9	3	3	6
6	tire3	FALSE	9	3	9	3	3	6
7	tire4	FALSE	9	3	9	3	3	6
8	frontmirror	FALSE	15	15	3	2	15	2
9	rearmirror	FALSE	15	15	3	2	15	2
10	vehiclebase	TRUE	54	42	30	15	10	15
11	vehiclebottombase	TRUE	54	42	30	15	10	15
12	seat1	FALSE	12	12	15	7	2	4
13	seat2	FALSE	12	12	15	7	2	4
14	backseat	FALSE	36	12	15	11	5	8
15	sunroof	FALSE	21	21	6	7	15	2

Attributesv3

partid	Label	isbase	Length	Width	Height	Weight	Danger	Stability
0	wheel1	FALSE	12	3	12	10	3	4
1	wheel2	FALSE	12	3	12	10	3	4
2	wheel3	FALSE	12	3	12	10	3	4
3	wheel4	FALSE	12	3	12	10	3	4
4	vehiclebase	TRUE	18	14	10	30	10	15
5	seat1	FALSE	12	12	15	5	2	4
6	seat2	FALSE	12	12	15	5	2	4
7	seat3	FALSE	12	12	15	5	2	4
8	front	FALSE	12	30	30	15	8	10
9	back	FALSE	20	30	30	15	8	10
10	roof	FALSE	48	30	12	20	12	4

Attributesv4

partid	Label	isbase	Length	Width	Height	Weight	Danger	Stability
0	wheel1	FALSE	8	4	8	5	3	4
1	wheel2	FALSE	8	4	8	5	3	4
2	wheel3	FALSE	8	4	8	5	3	4
3	wheel4	FALSE	8	4	8	5	3	4
4	wheel5	FALSE	8	4	8	5	3	4
5	wheel6	FALSE	8	4	8	5	3	4
6	wheel7	FALSE	8	4	8	5	3	4
7	wheel8	FALSE	8	4	8	5	3	4
8	vehiclebase	TRUE	50	14	10	30	10	15
9	seat1	FALSE	12	12	15	5	2	4
10	seat2	FALSE	12	12	15	5	2	4
11	seat3	FALSE	12	12	15	5	2	4
12	front	FALSE	12	30	30	15	8	10
13	back	FALSE	20	30	30	15	8	10
14	roof	FALSE	50	30	12	20	12	4

Attributesv5

partid	Label	isbase	Length	Width	Height	Weight	Danger	Stability
0	wheel1	FALSE	3	2	3	15	3	2
1	wheel2	FALSE	3	2	3	15	3	2
2	wheel3	FALSE	3	2	3	15	3	2
3	wheel4	FALSE	3	2	3	15	3	2
4	vehiclebase	TRUE	18	14	10	40	10	15
5	seat1	FALSE	4	4	5	10	2	4
6	seat2	FALSE	4	4	5	10	2	4
7	backseat	FALSE	12	4	5	20	5	8

TABLE IV
DANGER AND STABIITY VALUES FOR PART TYPES

Part Type	Danger	Stability
Wheels	3	2
Tires	3	6
Seats	2	4
Backseat	5	8
Mirror	15	2
Vehicle Base	10	15
Sunroof	15	2
Front/Back	8	10

TABLE V
AVERAGED VALUES OF HUMAN ATTRIBUTES AFTER 5000 EXECUTIONS

attribute options	distance	weight	stability	danger	time
cskoriginal	531.8	43.7	24.8	18.9	35.6
cskv3	551.4	39.2	25.8	19	34.8
blank	566.4	49.2	24.9	26.1	37
closest	501.6	49.3	25.6	25.8	37.8
norobot	508.1	52.7	28.1	28.4	36.7
combinations	523.7	40.6	26.1	20.5	35.4
combinationsv3	528.3	40.5	25.5	21.2	35.5
thesis	514.4	44.1	26.6	19.4	35.8

front mirror, rear mirror, vehicle bottom base, sunroof, front, back, roof etc. The attributes of these respective parts are: *isbase* (indicating whether the given part is a base or not, e.g., TRUE/FALSE), the *length, width* and *height* of the part in cm, the *weight* of the part in kg, and its *danger* and *stability* measured as relative levels.

Danger and stability are hypothetical values heuristically estimated by the researchers such that these approximately correspond to weight, and furthermore, they incorporate commonsense knowledge and reasoning based on the risk associated with the concerned objects as well as the extent to which the objects are stable. These values are therefore assigned based on the researchers' subjective commonsense reasoning mapped into objective values based on real-world knowledge in the given context. TABLE IV specifically describes how the various part types used in the context of vehicle assembly correspond to danger and stability with respect to objective values that are deployed in this work. These are the values used in our experiments on human-robot collaboration in this paper, conducted with examples from vehicle assembly.

Accordingly, each sub-table here depicts different versions consisting of a variety of parts and their respective attribute values. In each sub-table, the parts are indexed by their respective part ID values that are used to refer to the given part in the programming of the simulation.

We have conducted baseline experiments without CSK, the results of which appear in TABLE V in the rows, "blank", "closest" and "norobot". These depict our simulations without using commonsense knowledge in the experiments. The other rows in TABLE V correspond to the experiments entailing the use of commonsense knowledge. Hence, we have conducted experiments with and without CSK, the results of which have been tabulated herewith. TABLE V outlines the attributes the human experienced while executing the assembly task, such as the distance traveled and weight carried. The most important attribute to minimize is danger since human safety is critical while the most important attribute to maximize is stability since humans should handle the most stable parts. The other attributes should be minimized since they affect human workers and production speed.

C. Observations and Discussion on Simulations

The results of the simulation experiments are recorded as follows. Fig. 5 shows an example of car parts in their initial and final state with respect to our simulation experiments. This indicates an example of the outcome achieved with the simulation in terms of the actual vehicle assembly, e.g., the parts being assembled to form the object.

In these simulation experiments, the values of the average attributes that the human handles and the average execution times are summarized in the TABLE V as shown herewith. The attributes that are considered include the average distance traveled by the human being, the average weight carried by the human being, the average stability of the parts carried by the human being and the average danger of the parts carried by the human being.

These results display benefits of using CSK priorities for HRC. For example, in the *csk* row in Table V, the human carries less weight (compared to *blank, closest* or *norobot*), lessening the impact on human stamina and thus ensuring human comfort. Stamina is not an issue if work is only done for a minimal amount of time, but if work is undertaken for hours at a time, stamina degrading will result in humans working slower and negatively impacting their comfort. Having humans handle lighter parts will maintain stamina, and hence increase comfort which is desirable. Most importantly, danger is lowered with CSK priorities, especially in *combinationcsk* (and its *v3*), hence enhancing human safety. Execution time is also found to be lower with CSK priorities in comparison to simpler priorities. While the human travels a greater distance in *csk* (compared to *closest* for example), that is less important than safety. The human also performs tasks more slowly since the closer parts are occasionally heavier and this causes humans to move more slowly. The performance is more optimal for *combinationscsk* and *combinationscskv3* than for *prioritiescsk* and *prioritiescskv3*, since the values are determined algorithmically rather than by hand. The *thesis* priorities represent the newest research for this paper. Further optimization can be performed in future work as needed.

The simulation results herewith demonstrate that using commonsense knowledge for reasoning within human-robot collaboration makes work easier for humans while only slightly increasing the completion time in some cases. Humans are also safer since are carrying parts that are less dangerous on average. While work can be completed faster, oftentimes more danger is added, which can increase the chance of injury when tasks are frequently repeated. Having two humans collaborate to assemble the parts into a final object would

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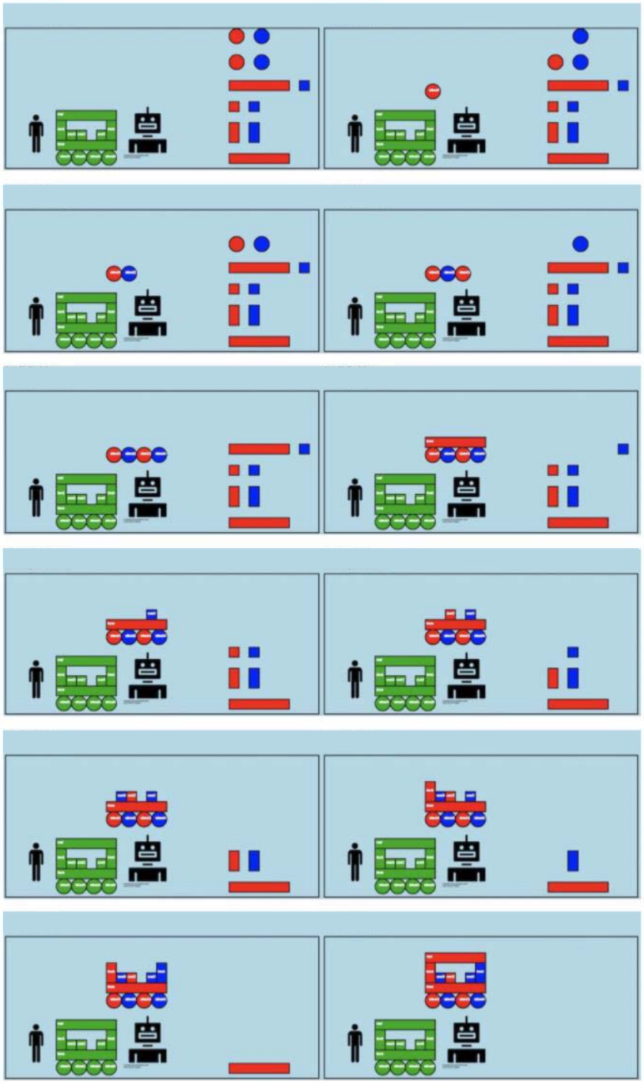

Fig. 6. An example of human-robot collaborative assembly in our typical simulation environments. The parts the human moved are marked as blue in the while the parts the robot moved are marked as red. Note that Figs. 4 and 5 cover real-life experiments using real-life parts for a toy vehicle while Fig. 6 refers to a simulated vehicle assembly online using hypothetical parts.

be an option, but they would eventually become tired and work more slowly than a human and a robot collaborating. When tasks are repeated several times a day in a real scenario, avoiding tiredness is important, especially since it can help with preventing injury. Adding more aspects of commonsense knowledge can be even more effective than shown in the current simulation.

VI. Real-World Experiments

We conduct in-person testing in a real-world task for our proposed approach of human-robot collaboration based on reasoning with commonsense knowledge, a subset of which is demonstrated earlier [35]. This is described in the following subsections.

A. Setup for Real-World Experiments

The real-world experiment involves a collaborative robot arm, a web camera, a workstation, a target object, and a shared workspace, similar to the simulation experiments shown in Fig. 6. In this experiment, a human and a robot will collaborate to assemble a vehicle model. A Franka Emika Panda robot, which is a 7-DoF collaborative robot with a two finger parallel gripper utilizing a pilot user interface and a Franka Control Interface (FCI) controller, collaborates with humans for this experiment [36]. A ThinkPad P15 with Intel Core I9-10885H processor and 64 GB Memory is used to run our CSK-based algorithms and communicate with the robot. The open source Robot Operating System is used for robot movement and robot system control [37], [38] while the MoveIt! package helps with operating in more realistic and dynamic work environments [39]. The CSK premises applied in the simulations are applied in the real-world experiments as well. For this purpose, a model vehicle with four base parts and four wheels is used, as shown in Fig. 7.

Fig. 7. Model vehicle type used for vehicle assembly experiments.

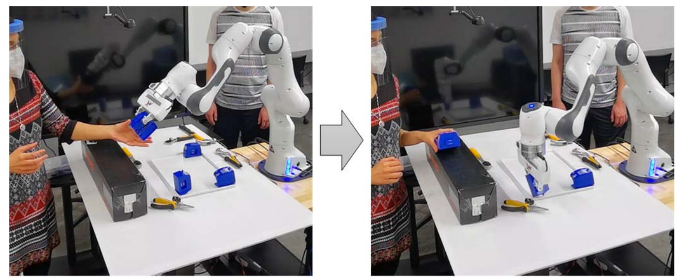

Fig. 8. HRC in vehicle assembly: snapshots from real-world experiments at different stages in left and right photos here (altered for privacy protection).

The base parts here are the cargo bed, the backseat, the front seat, and the front, with the wheels being attached to the cargo bed and the front. A robot arm collaborates with a human to assemble the vehicle by grabbing the base parts and delivering them to the human. From there, the human attaches the wheels to the base parts. This division of labor is efficient since the robot cannot effectively handle the wheels while the human can attach the parts, and the robot can lessen the human's work by handling the base parts. An example of the execution of real-world experiments is shown in Fig. 8.

B. Results Analysis

The in-person human-robot collaboration proves to be beneficial. For the real-world experiments, the robot and the human handle the parts in an optimized order. For example, in one instance of real-world experiments, all of the parts have a starting position, with the four base parts standing on the four corners of the white cardboard base in Fig. 7, and the four wheels being nearby the human worker. It is observed that in this example, the execution proceeds in the following order:

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1. Robot hands over cargo bed of truck to human.
2. Human attaches back wheel 1 and back wheel 2 to cargo bed.
3. Robot hands over truck back seat to human.
4. Human attaches truck back seat to cargo bed.
5. Robot hands over truck front seat to human.
6. Human attaches truck front seat to truck back seat.
7. Robot hands over truck front to human.
8. Human attaches truck front to truck front seat.
9. Human attaches front wheel 1 and front wheel 2 to truck front.

The order for handing these parts from the robot to the human is dynamically generated by the commonsense priorities described in section IV. Thus, commonsense reasoning is incorporated here during human-robot collaboration. This is done on a really small scale in our real-world experiments simply in order to illustrate the basic concepts in our proposed methodology. A similar process can be used in large scale industrial vehicle assembly with automated manufacturing using HRC. It is to be noted that we have used a limited dataset here because of the study occurring much during the COVID pandemic with operations in a remote mode. The intention of conducting advanced experiments with more decision-making as future work explained in the Discussion section.

Testing this assembly order shows that assembling the vehicle with aid from the robot makes the task easier than assembling it without assistance. While the task takes more time to complete with the robot's assistance, human stamina will remain higher for large-scale vehicle assembly execution, allowing humans to continue producing high efficiency and high-quality work. Maintaining stamina becomes more relevant when in a large-scale setting, where a task is executed hundreds of times. Because of this issue, the human-robot collaboration outlined in these experiments is a significant contribution.

This real-world validation leads to relevant inferences. Our study proves that humans and robots guided by CSK can be efficient in task execution while also valuing human safety and comfort by protecting humans. In addition, it is noticed that the robot arm is capable of verbally greeting the human worker and informing the human worker when it has brought a base part to them. This provides a pleasant sense of collaboration, which can be furthered by the human occasionally speaking to the robot. The robot arm makes the assembling of the vehicle more efficient and interesting. The real-world experiments, even more so than the simulation experiments, demonstrate the importance of task optimization in collaborative robotics, moving closer towards large scale real-world executions for industrial vehicle assembly. This work contributes to smart manufacturing, in manner analogous to other works [2], [3], [40], [41] in the literature.

VII. Discussion

It is to be noted that even though real-world experiments are conducted for our research in this paper, there is no subjective evaluation for this study due to the COVID pandemic.

The study is also limited due to the fact that the CSK system is tested in the real-world with one set of parts. The sets of parts can be assembled in various orders in this example, but the system should be able to handle cases where part order is more rigid with enhanced decision-making. The results still appear conclusive in that the robots utilizing commonsense knowledge can help in improving human-robot collaboration. Future work could potentially remedy some of these limitations.

The simulation conducted in this paper is modifiable, where more attributes can be added and altered based on the needs of the manufacturer. The system can be applied for larger and more complicated real tasks in the future. Currently, the arm used for in-person experiments does not detect the location of the parts; they are consistently placed in the same position. Future work can incorporate a detection system that would send the location of parts to the robot arm, which would then travel to the location and deliver the parts to a human worker.

Additionally, it would be interesting to conduct studies with CSK priorities changing in HRC based on different levels of trust, drawing upon interesting conclusions from related studies in the literature. This would further augment human-robot collaboration for a more enhanced experience.

While a robot handing a human partner vehicle parts is a simple example of human-robot collaboration, this still represents typical progress toward more complicated human-robot collaboration in smart manufacturing. There are currently experiments and implementations with far greater scope. In the future, our work on human-robot collaboration based on commonsense knowledge and reasoning could also incorporate more adequate object detection. Works such as [24] on generating benchmarks for object recognition using spatial commonsense, [42] on the detection of objects by transferring commonsense, and [1], [18] on conducting automated commonsense knowledge extraction with compilation could potentially be useful here.

Moreover, some experiments could be conducted in the future for subjective evaluation in real-world HRC. For example, this could consider factors such as the experience with in-person experiments being pleasant due to the conversation between the human and the robot. Other subjective evaluations could involve the manufacturing outcomes with respect to their reception by the real world. Some of this future work could potentially entail contacting domain experts from the industry in smart manufacturing. Their inputs on real-world experiments and feedback through surveys etc. would be valuable in further stages of the work emerging from this paper, on a larger scale.

In general, this paper deploys concepts from commonsense knowledge, proposes a system based on that for reasoning in human-robot collaboration and conducts execution in the application of vehicle assembly within the context of smart manufacturing. Such work is particularly significant during recent times considering the automation much needed during the COVID pandemic and its aftermath/recovery phases. Future work based on some of the aspects identified in this paper can provide even further enhancements from various perspectives, thereby making stronger impacts on robotics and artificial intelligence. We can address some future work in the context of helpfulness of robots in dealing with the COVID pandemic and other such adverse circumstances.

VIII. Conclusion and Future Work

This paper proposes and evaluates a system that harnesses the benefits of reasoning based on commonsense knowledge for human-robot collaboration in the context of smartmanufacturing. The simulations conducted in this work using vehicle assembly display how HRC can be improved by applying CSK in the reasoning, thereby resulting in a better work environment for humans while retaining high efficiency in the respective tasks. The in-person experiments conducted in real-world contexts further corroborate the simulations in demonstrating how the presented theory of CSK-based reasoning for HRC is effective in practice, with particular reference to vehicle assembly. With the robot arm's assistance, assembling the vehicle is significantly easier. Applying HRC along with reasoning based on CSK can thus help improve manufacturing especially since these tasks are executed multiple times. It therefore makes significant positive impacts on the smart manufacturing domain. Data gathering, including documenting execution time has been difficult due to the COVID pandemic, and will thus be part of future work. The experimental results indicate that the real-world execution time will be decreased since a robot working alongside a person will help that person's stamina and allow them to work faster. Future work can include testing more complicated forms of human-robot collaboration, documenting execution time, and incorporating object detection in human-robot collaboration based on commonsense knowledge and reasoning. This is expected to yield even better results and make further contributions to smart manufacturing.

Appendix

See Table III.

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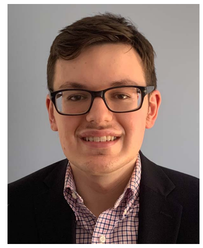

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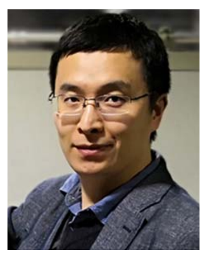

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