Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 207 (2022) 3646–3655

Procedia Computer Science

www.elsevier.com/locate/procedia

26th International Conference on Knowledge-Based and Intelligent Information & Engineering Systems (KES 2022)

# Modelling Uncertainties in Human-Robot Industrial Collaborations

Xiaodan Wang [a]*, Rossitza Setchi [a], Abdullah Mohammed [a]

[a]Centre *for AI, Robotics and Human-Machine Systems (IROHMS), School of Engineering, Cardiff University, Cardiff, CF24 3AA, United Kingdom*

**Abstract**

With the rise of Industry 4.0 technological trends, there is a growing tendency in manufacturing automation towards collaborative robots. Human-robot collaboration (HRC) is motivated by the combination of complementary human and robot skills and intelligence, which can increase productivity, flexibility and adaptability. However, it is still challenging to achieve safe and efficient human-robot collaborative systems due to the dynamics of human presence, uncertainties in the dynamic environment, and the need for adaptability. Such uncertainties could relate to the human-robot capabilities and availability, parts positioning, unexpected obstacles, etc. This paper develops time-based simulations and event-based simulations to model and analyse the dynamic factors in human-robot collaboration systems. The novelty of this work is the systematic modelling and analysis of dynamic factors in HRC manufacturing scenarios through the development of digital simulations of human-robot collaboration scenarios while considering the dynamic nature of humans and environments. A real-world industrial case study was redesigned into a collaborative workstation. The simulated scenario is developed using the software called Tecnomatix Process Simulate, which can help to visualise the dynamic factors and analyse the impact of the factors on the HRC. The simulation illustrates and analyses possible uncertainties in human-robot industrial collaborative workstations, which can contribute to the future design of HRC industrial workstations and the optimisation of productivity.


Peer-review under responsibility of the scientific committee of the 26th International Conference on Knowledge-Based and Intelligent Information & Engineering Systems (KES 2022)

*Keywords:* Human-robot collaboration; Collaborative robot; Digital simulations; Uncertainties; Human factors; Assembly system

## 1. Introduction

The fourth industrial revolution, known as Industry 4.0, is related to the integration of advanced digital technologies and artificial intelligence (AI) on many shop floors. Industrial robots have been successfully used to perform repetitive tasks with high precision [1]. However, there are tasks, such as complicated assembly work, that are less structured

* Corresponding author. Tel.: +44-07536-956238.
*E-mail address:* Wangx223@cardiff.ac.uk

1877-0509 © 2022 The Authors. Published by Elsevier B.V.

Peer-review under responsibility of the scientific committee of the 26th International Conference on Knowledge-Based and Intelligent Information & Engineering Systems (KES 2022)
10.1016/j.procs.2022.09.425

and too complex to be fully automated and thus cannot be totally performed by robots. Moreover, evaluation of performance and flexible adjustment by humans are sometimes necessary, which makes it impossible to fully replace humans with robots. Therefore, human-robot collaboration (HRC) systems are developed in industry to take advantage of effectively combining high human flexibility and high robot productivity. As the new production paradigm, human operators and collaborative, sensitive robots work closely in a shared workspace—precisely, efficiently and ergonomically.

Although collaborative humans and robots are now coming into widespread use in industry, there still exist great challenges in achieving safe and efficient human-robot collaborative systems due to the dynamic nature of humans, uncertainties in the unstructured environment and the need for adaptability. Assembly work is significantly important in manufacturing, which integrates various parts and components of a particular product. It is still limited to apply HRC in complex, continually changing and variety-oriented assembly lines. The environment of ordinary industrial robotics is structured and known, while in HRC systems, the robots are required to interact with operators who may potentially have different skills and capabilities in unstructured environments. Because of the dynamic nature of human operators, the unstructured workspace and other random disruptions on the plant floor (e.g. machine tool random failure) in HRC industrial systems, there exist many uncertainties in HRC systems, which require the collaborative robot (cobot) to accommodate high complexity and dynamic changes in the systems. The current practice is mostly a manual process that depends heavily on human expertise. The cobot is pre-programmed to perform repetitive tasks in limited assembly tasks. When assembly tasks change or any unpredicted uncertainties happen, the whole system may fail and need to be reprogrammed by robotic experts [1]. A large amount of research has focused on developing adaptive robot assistants for specific uncertainties (e.g. part positioning adaptivity). Limited studies have been performed to systematically summarise, model and analyse the impact of dynamic factors in HRC industrial workspaces. Therefore, there is a need to systematically summarise, model and analyse dynamic factors in HRC manufacturing scenarios, considering the dynamic nature of humans and the unstructured environment.

Keeping this challenge and the literature gap in mind, this paper aims to systematically model and analyse dynamic factors in HRC manufacturing scenarios through the development of digital simulations of human-robot collaboration scenarios while considering the dynamic nature of humans and the environment. The objectives of this paper are as follows:

- To present a summary of possible uncertainties in human-robot industrial collaborations
- To develop time-based simulations and event-based simulations to model and analyse the dynamic factors in human-robot collaboration systems.

The paper is structured as follows: Section 2 is a literature review about dynamic factors in human-robot collaborative systems. Section 3 summarises the important dynamic factors in HRC systems and explains how to model them in digital simulations. In Section 4, digital simulations are developed based on a real-world industrial assembly case study to visualise and analyse the dynamic factors in HRC workspaces. Finally, conclusions and future research directions are provided in Section 5.

## 2. Literature review: complexity and dynamic factors in human-robot collaborative systems

Manufacturing factories, which are committed to a continuous pursuit of productivity and quality, often meet challenges in coping with high production complexities and uncertainties. The application of HRC in complex, continually changing and variety-oriented manufacturing processes is still limited. One of the main challenges is that the HRC assembly environment is complex and dynamic. Some researchers have discussed system dynamics and human-robot coordination in implementing agent-based manufacturing systems. Because of the frequently changing situations—political situations change, delay in arrival of the materials, power supplies break down, failure in the production facilities, absence of workers, new orders arrival and changes or cancellation in existing orders—there exist great uncertainties in real-world manufacturing environments [2]. Since workstation layout problems affect the total manufacturing cost significantly, they can be considered a critical issue in the early stages of designing flexible manufacturing systems (FMSs), particularly in volatile environments where uncertainty in product demands is inevitable. The researchers proposed mathematical models for designing dynamic workstation layouts in uncertain environments [3]. Moreover, there are many stochastic events and high uncertainties in actual manufacturing systems. Disturbances such as machine breakdown in the production line can always result in the invalidation of original plans and schedules [4]. Many studies have focused on dynamic task scheduling because of the unexplored human-robot capability and availability: generating optimal task sequences considering the characteristics of humans and robots [5, 6], a real-time adaptive assembly scheduling approach for human-robot collaboration by modelling and incorporating changing human capabilities [7], real-time scheduling based on dynamic data-driven simulation (DDDS) [8], an event-triggered scheduling method [9] and agent-based scheduling [10]. To produce robust solutions when facing dynamic human interventions, task-and-motion planning algorithms are developed to support robot re-planning against human operators' interventions [11].

The dynamic nature of humans brings uncertainties into the HRC environment. Golan [12] summarised several factors that are likely to influence a worker's performance: fatigue, which is known to increase task completion time and the rate of error; learning, which indicates the proficiency of the worker; and attentiveness, which refers to the level of concentration on the task without being distracted by irrelevant information. These factors can significantly influence a human worker's efficiency and accuracy, and they can even cause errors or safety issues in HRC systems. Moreover, the dynamic nature of humans, changes in task sequences and human interference are common in workstations. Therefore, in HRC scenarios, robots are often required to dynamically change their pre-planned tasks to adapt to these dynamic factors and collaborate with human operators in a shared dynamic workspace.

Currently, manufacturing is transitioning from unplanned failures to failure prognostics that will remove problems before they occur. Therefore, there is a need to model and simulate the dynamic factors in HRC scenarios and validate the setup and robot programmes before developing complex physical systems. An answer to the complex behaviour of an HRC system is to somehow (re)-design the system in a simulation, predict the future under maximum known variables and implement it. Although HRC engineers value the idea of digital simulations and the benefits of digital validation, they rarely develop simulations in an event-based manner to model and analyse the dynamic factors in HRC scenarios. In the following section, key dynamic factors in HRC systems are summarised and a method for modelling the dynamic factors is explained.

## 3. Modelling the Uncertainties in Human-Robot Industrial Collaborations

### *3.1. Dynamic factors and uncertainties in human-robot industrial collaborations*

The human-robot hybrid work environment is complex and dynamic. Humans are complex. Not only as a group of humans, but even as individuals, they exhibit a complex behaviour that is often difficult to predict. Given the dynamic nature of humans and unstructured environments, human-robot systems do not always perform flawlessly. In cases where human and robot are collaboratively and continuously performing tasks, dynamic factors can affect the efficiency or even the completion of the production. In human-robot collaborations, humans and robots share the same environment to complete tasks. Human workers, robots, the shared tasks and the shared workspace can be regarded as four primary components in HRC systems. The possible dynamic factors in industrial HRC systems are categorised into human factors, robot factors, task factors and workspace factors, which will be described in what follows.

Due to the dynamic nature of humans, human factors bring dynamics into HRC systems:

- **Human capability:** According to the capabilities of humans, subtasks can be assigned to human-only, robot-only, and human-or-robot. The last type of task may be dynamically allocated to humans or robots. Moreover, during human-robot collaborations, human capabilities are subject to change due to factors such as experience, fatigue, workload, and environmental effects, which may lead to dynamic changes in task allocation.
- **Human availability:** The task sequence dynamically changes depending on the availability of humans. For example, robots may require waiting until the worker is available to perform a certain subtask.
- **Human task completion time:** The time consumption for every procedure an operator conducts is uncertain. This may be related to whether he or she is a skilled worker. Human fatigue level and concentration level also influence human task completion time.
- **Close humans:** The operator works closely around the worktable, requiring the robot to identify the distance from the person and adjust its moving speed.
- **Human mistakes:** Human mistakes may require reassembly, replanning new task sequences or the robot replans its motions and paths. For example, a human arm may suddenly block the robot's original trajectory.

Although the characteristics of the robots remain unchanged, some robot factors may still influence the HRC system:

- **Robot availability:** The robot availability affects task allocation and task planning.
- **Robot collaboration mode:** Based on the ISO 10218-1/2:2011 standard, the robot should move at a safe reduced speed (less than 250 mm/s) in collaborative environment [13]. Therefore, when the human and the robot are working closely, the robot should work within the collaborative speed which is 250 mm/s, and may quickly stop when people get too close.

The task may change frequently in real-world manufacturing systems:

- **Product modifications:** Companies tend to keep updating their products, so the task requirements may frequently change.
- **Task sequence:** Although there might be a list of assembly tasks, the tasks are not necessarily in sequential order and many tasks can be done in parallel. Humans have their own preferences; thus, they may conduct different task sequences.

Workspace uncertainties and the unstructured environment also encourage the collaborative workstation to be uncertain:

- **Part availability:** Parts or other tools may be unavailable due to the random errors of feeding devices.
- **Part location:** The positioning of the parts and their geometry are not always the same, affecting the robot's motion planning to pick and place.
- **Unexpected obstacles:** Some unexpected obstacles may exist, making the workstation unstructured. This can cause low production rates and collisions with robots or other resources, resulting in safety hazards.
- **Existence of other human workers:** Other human workers may also stay at the workstation. The robot should be able to detect close humans and decrease its moving velocity.

In the case where humans and robots are collaboratively and continuously performing tasks, dynamic factors can affect the efficiency or even the completion of the production. Robots are expected to be more human-compatible to cover more plausible, changeable scenes towards the enhanced intelligence of the robot that plays into this kind of collaboration. There is a need to model and analyse uncertainties for the trustworthy validation of any future modifications, thus making the HRC system more robust and truly adaptable. The next subsection explains how to model the five selected dynamic factors in HRC systems using digital simulations.

### *3.2. Modelling the uncertainties in human-robot industrial collaborations*

Digital simulations provide insights into complex production systems to develop and test operating policies before implementing them in the real world [14, 15]. In the field of industrial robotics, virtual simulation is a well-known concept to plan, predict, scale and safely test different scenarios in the planning, validation and optimisation of robotic systems [16]. Besides the classical use of simulations in product and system design, an emerging trend is to flexibly model the dynamics in a digital space to see, think and react to the environmental changes brought about by the dynamic and unpredictable nature of humans. This approach will help the HRC system evaluate, react and adapt to the impact of the dynamic factors in production.

Siemens Tecnomatix Process Simulate is a digital manufacturing solution for manufacturing process design and verification in a 3D dynamic environment. Digital simulations (time-based and event-based simulation) of both the components and dynamics of a human-robot collaboration system can be developed in Process Simulate. This section describes the characteristics of time-based simulations and event-based simulations and explains how to model the dynamic factors in these simulations.

There are two types of digital simulations in Process Simulate: time-based simulation and event-based simulation. Time-based simulation has a pre-defined duration of operation, and it is strictly defined in every scenario of a given simulation. Therefore, time-based simulation is first developed to verify the workstation layout. In event-based simulation, the logic of the process and the events that occur during the simulation determine the course of the simulation. The sequence of the operations is only one element of the complete logic definition. Event-based simulation is more realistic and enables the simulation of dynamic factors in HRC scenarios.

With the function of logic resources, transition conditions and signals, event-based simulation enables users to model and analyse the dynamic factors in HRC scenarios. First, material flow is defined, which consists of operations, links between them and information about parts and resources assigned to the operation. In event-based simulations, different operations are triggered by different signals. Logic resources can contain entry and exit values connected with signals as well as any number of parameters and constants. Logic block (LB) is a resource that contains a defined logic behaviour with respect to the control system, derived from one or more specified inputs and outputs in an equation or formula. To model the uncertainties in human task completion time, we assume that the human action's completion time can be described with a normal distribution (shown below), where the human action's completion time $X$ is normally distributed with mean $\mu$ and standard deviation $\sigma$.

$$X \sim N(\mu, \sigma^2) \tag{1}$$

Since the RANDOM() function is contained in the software as a recommended function to create a random number to represent completion time. Therefore, in this paper, this function is applied to simulate random task completion times for humans. Task transition logics are defined for each robotic task that examine the conditions to be fulfilled when activating or stopping the robot. Virtual sensors are equipped to detect the presence or position of assembly components and the human worker in the workstation and then output signals to trigger the next task. If the logic is fulfilled, the robotic task is executed. A logic-driven simulation offers extended control over the process, and additional logics can be defined to create what-if scenarios. Each robotics and manual task can be visualised and performed in the digital simulations. Logics are defined that ensure the completion of each task and initiate the next task according to different signals, thus forming an event-driven simulation.

## 4. Case Study

A real-world industrial case study of the assembly of three parts (pistons, extensions, and plungers) is redesigned into a collaboration workstation. Five important dynamic factors in HRC systems are modelled in time-based simulations and event-based simulations. The simulation results are analysed to illustrate the impact of the dynamic factors.

### *4.1. Case description and human-robot task allocation*

In the industrial case study, three parts are required to be assembled: pistons, extensions and plungers (Fig. 1). The conventional mode of production is manual, and current times for a skilled worker to assemble a piston, an extension and a plunger are 15 s, 40 s and 46 s, respectively. The HRC cell is supposed to reduce human hours while maintaining the same production rate. Each assembly task is evaluated for its ease of HRC automation. Task evaluation for cobot automation is different from conventional robotic automation, as additional parameters, particularly for safety implications, need to be considered. A complexity-based task allocation method [17] can be used to decompose each task into its attributes and assign an automation potential score, thus identifying the tasks carrying higher automation potential, assigning the right resource and balancing the assembly process. Importantly, the following criteria are considered to decide the task allocation of the robot:

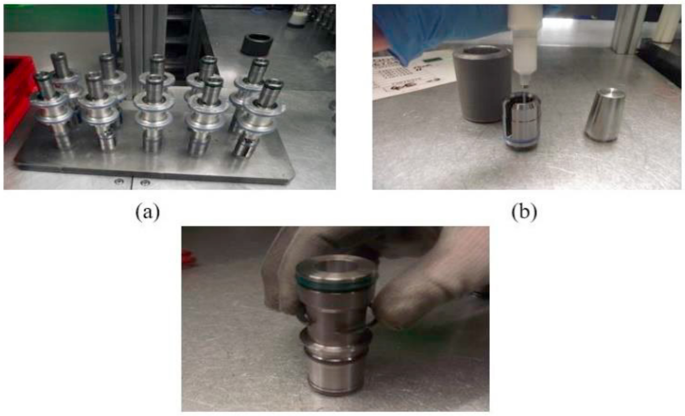
– The complexity of achieving the task by the robot
– The complexity of robot control
– Reliability of the robot deployment

Table 1 shows the final decisions on piston, extension and plunger assembly procedures and task allocations of human and robot.

Table 1. Assembly operations of pistons, extensions, and plungers

| No. | Part | Operation | Manual time (estimated) | Suggested resource |
|---|---|---|---|---|
| | Piston | | | |
| 1 | | Pick up piston and place in nest | 3s | Human |
| 2 | | Pick up "O" Seal and place into groove | 3s | Human |
| 3 | | Pick up "O" Seal and place into groove | 3s | Human |
| 4 | | Place in sizer | | Robot |
| | Extension | | | |
| 1 | | Pick up extension and place in nest | 3s | Human |

| | | | |
|---|---|---|---|
| 2 | Pick up bullet and place next to extension | 3s | Human |
| 3 | Pick up seal and place over bullet | 3s | Human |
| 4 | Pick up bullet and place over extension | | Robot |
| 5 | Pick up pusher and push seal down into groove | | Robot |
| 6 | Check seal is set in groove | | Human |
| 7 | Pick up extension and place in sizer | | Robot |
| Plunger | | | |
| 1 | Pick up plunger and place in nest | 3s | Human |
| 2 | Place three bullets next to the plunger | 3s | Human |
| 3 | Pick up seals and place over bullets | 3s | Human |
| 4 | Place bullet (1) over part | | Robot |
| 5 | Pick up pusher and push seal1 down into groove | | Robot |
| 6 | Place bullet (2) over part | | Robot |
| 7 | Pick up pusher and push seal2 down into groove | | Robot |
| 8 | Rotate plunger | | Robot |
| 9 | Place bullet (3) over part | | Robot |
| 10 | Pick up pusher and push seal3 down into groove | | Robot |
| 11 | Check and tag | | Human |
| 12 | Pick up plunger and place in sizer | | Robot |



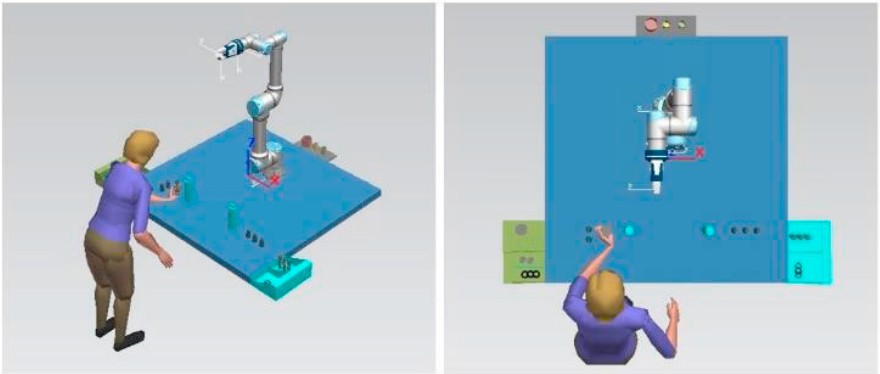
(a) (b) (c)

Fig. 1. Assembly parts. (a) Piston, (b) extension, (c) plunger.

As shown in Table 1, most of the pick-and-place tasks are allocated to the robot. Pick-up parts and place into sizers can be regarded as repetitive tasks, assigning these tasks to a robot can save human effort and help to achieve the same task in less time and work for a longer time with no interruption. It is challenging for robots to pick up a single item from a jumbled tray, so that tasks of picking up objects from the tray and placing them into sizers are allocated to human workers. Soft seals bring complexity for robots to pick up seals from containers and place seals over bullets with limited project time. Operations that pick-up seals and place seals over bullets require more accuracy, therefore, these tasks are kept manual to eliminate the complexity of the robot control.

## *4.2. Modelling and simulation of HRC industrial case study with five dynamic factors*

The proposed HRC assembly station comprises a robot manipulator and a human operator that jointly complete the assembly in a collaborative fashion. Universal Robot UR-5 e-series was selected, which has six degrees of freedom, a payload capacity of 5 kg and a reach of 850 mm. The robot is equipped with a parallel-fingers SCHUNK gripper EGP 64-N-N-B with a finger length of 40 mm. Computer aided design (CAD) models of the cobot and other resources (parts, table, trays, etc.) in JT format are imported into the simulation. The layout of the workstation is shown in Fig. 2. In time-based simulation, the assembly sequence is defined as piston-extension-plunger, while the time consumption is based on the estimated time from Table 1 provided by the industrial company. A Gantt chart of the time-based simulation is shown in Fig. 3.



(a) (b)

Fig. 2. Workstation layout. (a) Isometric view of the workstation. (b) top view of the workstation.

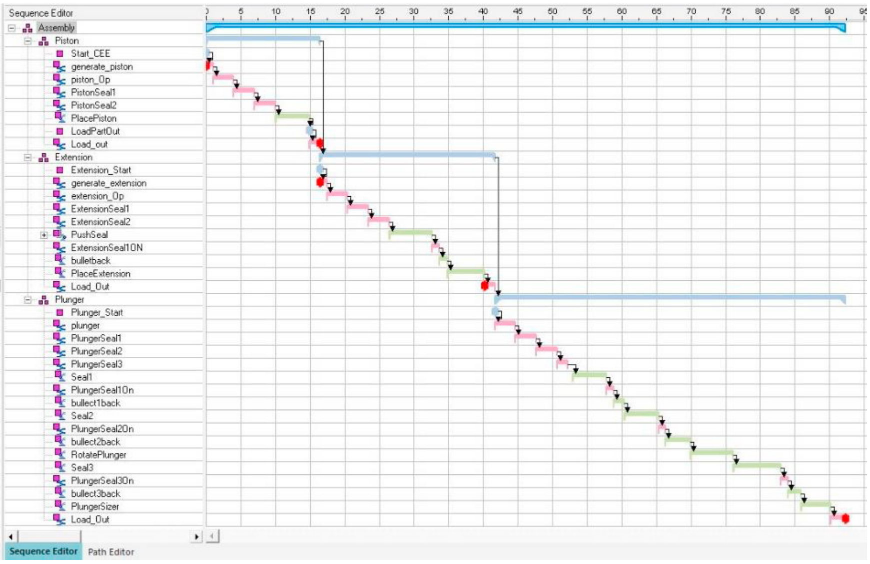



Fig. 3. Gantt chart of time-based simulation.

The following dynamic factors are modelled, simulated and analysed in the event-based simulations:

a) **Human task completion time:** Random functions are used to generate random task times based on the estimated average time. As for the piston, there are two key signals in the piston logic block. The entry signal named 'Piston' indicates that the assembly of the piston begins. Random function-TON(SR(piston, pistonfinish), RANDOM(4, 9))-is applied to the exit signal 'PistonReady' to set a random human task time. When the operator finishes the task, the exit signal will be triggered to indicate that the human task is finished, and the robot can begin its task. Similar random functions are also applied to the logic blocks of the extension and plunger.

b) **Task sequence:** The 'task sequence' variable is set to be random using the RANDOM(1, 3) function. This function generates random numbers to represent different assembly sequences. With the random task sequence variable, the robot can assemble the parts with different sequences according to the variable.

c) **Unexpected obstacles:** In this case study, factor of unexpected obstacles is modelled. A model of the obstacle is created in the parts, and when the sensor detects that there is an obstacle on the table, the input signal 'obstacle' will turn on. Then, the robot will first pick up the detected obstacle and place it in another location. The robot will choose a suitable path from predefined paths to avoid collision with other resources.

d) **Robot collaboration mode switch:** The human worker can switch the mode of the robot to industry (non-collaborative) mode or collaborative mode. The robot will automatically be set on industry mode and work at a faster speed. When the human worker switches on the collaborative mode, the signal 'collaboration_mode' will be triggered, and the velocity of the robot will decrease to a collaborative speed defined as 250 mm/s [13].

e) **Close human:** A digital human model is developed. The simulated human will work closely with the robot randomly, while the robot is required to detect the presence and location of the human with the equipped sensors including proximity sensors, photoelectric sensors, and joint distance sensors. Virtual sensor models are integrated to emulate physical sensors and are equipped to detect the presence or position of the human worker. When detecting that the human is working closely with the robot, the robot can adapt to the situation by decreasing the working speed from industry speed to a collaborative speed of 250 mm/s. Otherwise, the robot works at full speed when away from people.

The key signals are shown in Fig. 4(a). Besides the above-mentioned signals, 'Start_Scenario' indicates when the assembly starts; the 'humanwalkin' signal indicates that the operator is close to the robot, so that the robot needs to decrease the working speed; and 'Simulation Time' is applied to count the full assembly time in the simulation. Input and output signals for each operation with the transition logics are shown in Fig. 4(b). Finally, different simulations are generated to show the cycle time with different random dynamic factors.

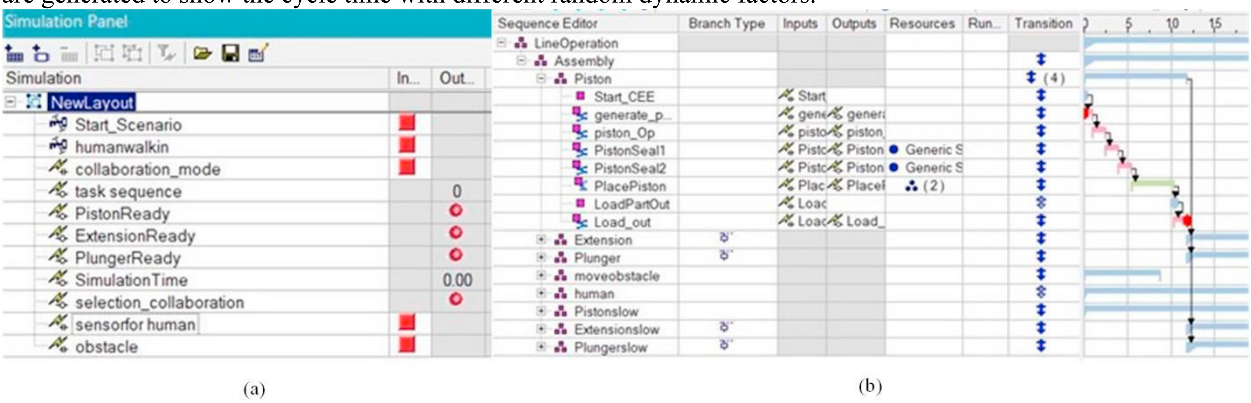



Fig. 4. (a) Key signals in event-based simulation. (b) Sequence editor with signals and transition logics.

## 4.3. Tests and analysis

Once the dynamic factors are modelled and digital simulations are achieved for the proposed HRC assembly system, the tests are performed to analyse the impact of dynamic factors on the HRC scenarios. As discussed in the previous sections, five dynamic factors are modelled and simulated in the event-based simulations. Through different permutations, there are 13 different HRC scenarios (Table 2) with different dynamic factors. By performing the assembly tasks in event-based simulations, an accurate estimation of the task times can be generated. Each scenario was run 20 times to record the simulation time for assembling one set of parts (including one piston, one extension and one plunger) under different dynamic factors, and the results are shown in Fig. 6.

It is worth mentioning that the No. 0 scenario can be regarded as a standard that was created in a time-based simulation, and the data of this simulation refer to the relevant data from the company assembling these parts. Therefore, the standard time of assembly of one set of parts (one piston, one extension and one plunger) is 93 s. Fig. 6 shows the box plot of the simulation times of the scenarios with different dynamic factors.

In the first scenario, the random human task time is simulated, and the average simulation time is similar to the standard task time. The second scenario indicates that the simulation is robust to changes in the assembly task sequence. When unexpected obstacles exist in scenario 3, the robot is able to move the obstacle into collision avoidance positions while the human focus is on own task, which saves idle time. When the collaboration mode of the robot is switched on, the moving speed of the robot remains at 250 mm/s, thus increasing the task completion time to around 132 s. In scenarios 5, 8, 10 and 12, the dynamic factor of a randomly close-human is simulated so that the digital human model works randomly close to the robot, which requires the robot to decrease the velocity when detecting a close human. It can be noticed that the simulation times of these scenarios are more scattered, indicating that human positioning and human interference can significantly influence the completion time or even the completion of the collaboration task.

Table 2. 13 different simulations with dynamic factors.

| No. | Random human task time | Obstacle existence | Random sequence | Mode | Random close human | Comments |
|---|---|---|---|---|---|---|
| 0 | | | | F | | Time-based, no dynamic factors |
| 1 | ✓ | | | F | | Random human task time |
| 2 | ✓ | | ✓ | F | | Random assembly sequence |
| 3 | ✓ | ✓ | | F | | Random obstacle exists |
| 4 | ✓ | | | C | | Collaboration mode: 250 mm/s [13] |
| 5 | ✓ | | | F | ✓ | Human randomly works close to robot |
| 6 | ✓ | ✓ | ✓ | F | | |
| 7 | ✓ | ✓ | | C | ×/✓ | C mode (collaboration mode): robot |
| 8 | ✓ | ✓ | | F | ✓ | moves with safe reduced speed as |
| 9 | ✓ | | ✓ | C | ×/✓ | 250 mm/s |
| 10 | ✓ | | ✓ | F | ✓ | F mode (full industry speed mode): robot |
| 11 | ✓ | ✓ | ✓ | C | ×/✓ | moves with full industry speed |
| 12 | ✓ | ✓ | ✓ | F | ✓ | |

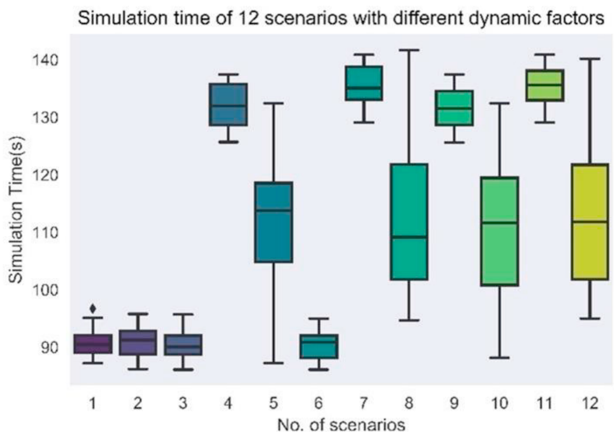



Fig. 6. Box plot of simulation times of scenarios with different dynamic factors.

Five dynamic factors with different permutations in an HRC assembly case study are modelled in event-based simulations. The simulations can create insights into operational behaviours and improve the system's productivity. Moreover, the simulated HRC system is robust to the simulated dynamic factors. Incorporating the uncertainties in the simulation can be useful for trustable validation of any future modifications, thus making the human-robot collaborative system more robust.

## 5. Conclusion

This paper systematically modelled and analysed dynamic factors in human-robot collaboration manufacturing systems through the development of digital simulations of HRC scenarios while considering the dynamic nature of humans and the environment. HRC manufacturing environments are complex and dynamic, which offers significant challenges to achieving safe and efficient human-robot collaborations. In this work, possible dynamic factors that bring uncertainties into HRC systems were summarised. Afterwards, five key dynamic factors in HRC assembly scenarios, including human task completion time, task sequence, unexpected obstacles, robot collaboration mode switches and close humans, were modelled and analysed in time-based simulations and event-based simulations.

Time-based simulation simulates a single production cycle from start to finish with a pre-defined sequence of operations, while event-based simulation provides an approach to model the dynamic factors by defining logics between the task operations, thus event-based simulation contributes to model more realistic and robust HRC systems. The system was robust to the uncertainties, and the impacts of the dynamic factors were analysed. The simulations can create insights into operational behaviour and improve the system's productivity. Moreover, incorporating the uncertainties in the simulation can contribute to the future design of HRC systems and can be useful for the trustable validation of any future modifications, making the human-robot collaborative system more robust. In the future, we will continue this research and expand the models to quantify the dynamic factors. We aim to develop methods to endow robots with the ability to adapt to the uncertainties in HRC systems. Moreover, the simulations with different modelled dynamic factors will be used to train the robot to learn how to plan and react to the uncertainties, thus making the robot truly adaptable.

## Acknowledgements

The authors would like to acknowledge the support of China Scholarship Council and the Centre for Artificial Intelligence, Robotics and Human-Machine Systems (IROHMS), operation C82092, partly funded by the European Regional Development Fund (ERDF) through the Welsh Government. Finally, we would like to thank Carlisle Brake & Friction, Inc. for industrial case conceptual contributions.

## References

[1] Yu, Tian, Jing Huang, and Qing Chang. (2020) "Mastering the working sequence in human-robot collaborative assembly based on reinforcement learning." *IEEE Access* **8**: 163868-163877.

[2] Shen, Weiming, Qi Hao, Hyun Joong Yoon, and Douglas H. Norrie. (2006) "Applications of agent-based systems in intelligent manufacturing: An updated review." *Advanced Engineering Informatics* **20**(**4**): 415-431.

[3] Moslemipour, Ghorbanali, and T. S. Lee.(2012) "Intelligent design of a dynamic machine layout in uncertain environment of flexible manufacturing systems." *Journal of Intelligent Manufacturing* **23**(**5**): 1849-1860.

[4] Zhang, Lin, Longfei Zhou, Lei Ren, and Yuanjun Laili. (2019) "Modeling and simulation in intelligent manufacturing." *Computers in Industry* **112**: 103123.

[5] Li, Kai, Quan Liu, Wenjun Xu, Jiayi Liu, Zude Zhou, and Hao Feng. (2019) "Sequence planning considering human fatigue for human-robot collaboration in disassembly." Procedia CIRP **83**: 95-104.

[6] Pellegrinelli, Stefania, Andrea Orlandini, Nicola Pedrocchi, Alessandro Umbrico, and Tullio Tolio. (2017) "Motion planning and scheduling for human and industrial-robot collaboration." *CIRP Annals* **66**(**1**): 1-4.

[7] Zhang, Shaobo, Yi Chen, Jun Zhang, and Yunyi Jia. (2020) "Real-time adaptive assembly scheduling in human-multi-robot collaboration according to human capability." *2020 IEEE International Conference on Robotics and Automation (ICRA)*.

[8] Zhou, Longfei, Lin Zhang, Lei Ren, and Jian Wang. (2019) "Real-time scheduling of cloud manufacturing services based on dynamic data-driven simulation." *IEEE Transactions on Industrial Informatics* **15**(**9**): 5042-5051.

[9] Zhou, Longfei, Lin Zhang, Bhaba R. Sarker, Yuanjun Laili, and Lei Ren. (2018) "An event-triggered dynamic scheduling method for randomly arriving tasks in cloud manufacturing." *International Journal of Computer Integrated Manufacturing* **31**(**3**): 318-333.

[10] Jules, Guiovanni, and Mozafar Saadat. (2016) "Agent cooperation mechanism for decentralized manufacturing scheduling." *IEEE Transactions on Systems, Man, and Cybernetics: Systems* **47**(**12**): 3351-3362.

[11] Li, Shen, Daehyung Park, Yoonchang Sung, Julie A. Shah, and Nicholas Roy. (2021) "Reactive task and motion planning under temporal logic specifications." *2021 IEEE International Conference on Robotics and Automation (ICRA)*: 12618-12624.

[12] Golan, Maya, Yuval Cohen, and Gonen Singer. (2020) "A framework for operator–workstation interaction in Industry 4.0." *International Journal of Production Research* **58** (**8**): 2421-2432.

[13] ISO Copyright Office. (2011) ISO 10218-1/2: 2011: "Robots and robotic devices–Safety requirements for industrial robots"—Part 1: "Robots"/Part2: "Robot systems and integration".

[14] Mourtzis, Dimitris, Michael Doukas, and Dimitra Bernidaki. (2014) "Simulation in Manufacturing: Review and Challenges." *Procedia CIRP* **25**: 213–29.

[15] Uhlemann, Thomas H.-J., Christian Lehmann, and Rolf Steinhilper. (2017) "The Digital Twin: Realizing the Cyber-Physical Production System for Industry 4.0." *Procedia CIRP* **61**:335–40.

[16] Schluse, Michael, and Juergen Rossmann. (2016) "From simulation to experimentable digital twins: Simulation-based development and operation of complex technical systems.", *2016 IEEE International Symposium on Systems Engineering (ISSE)*: 1–6.

[17] Malik, Ali Ahmad, Arne Bilberg. (2019) "Complexity-based task allocation in human-robot collaborative assembly." *Industrial Robot: The International Journal of Robotics Research and Application* **46**: 471–480.