A Modeling Methodology Towards Digital Twin Development in Smart Factories for the Industry 4.0 Human Augmentation Experiments

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Abstract
Due to the rapid changes in the production environment and level of task complexity, workers are faced with more knowledge-intensive tasks requiring higher order thinking and better decision-making. Digital Twin has been identified as a promising technology for addressing the challenges of smart factories by integrating physical and virtual spaces allowing data simulation and performance enhancement. The goal of this research is to simulate a manufacturing assembly line work cell using BIM-enabled digital twinning methodology. The work cell focused on the integration of emerging technologies for human augmentation in Industry 4.0. First, the requirements for conceptual development of the work cell were identified. A physical space was then allocated and surveyed to develop the BIM model. Through simulation of the assembly line process, required components in the work cell, process duration, and interdependencies were identified. The simulation results can assist with identifying potential challenges to optimize the process in advance.

Keywords: Modeling, Industry 4.0, Digital Twin, Human Augmentation, Industrial Robots

1 Introduction

Industry 4.0 defines the start of the fourth industrial revolution in manufacturing and production towards digital transformation either with the use of Cyber-Physical Systems (CPS) or beyond CPS systems to connect the physical world of machines with the digital world (Soldatos 2019). In the first industrial revolution mechanical production was introduced and water and steam were used for operating the equipment. The second industrial revolution took advantage of electrical energy. The third industrial revolution used advanced electronics and followed digitalization. The fourth industrial revolution named as industry 4.0, integrated Internet of Things (IoT), smart objects, and big data to create efficient and intelligent production (Lasi et al 2014). The fourth industrial revolution is taking advantage of computer and digital information technologies to create intelligent manufacturing processes (Li & Liu 2019).

Many researchers have determined requirements for establishing industry 4.0. These requirements include standardization, management efficiency, infrastructure, security, work design, training, resource efficiency, organizational framework, human-in-the-loop, control systems, Industrial Internet of Things (IIoT), cyber physical systems (CPS), additive manufacturing, big data, cybersecurity, cloud computing, digital simulation, autonomous robots, virtual or augmented realities (VR/AR), and vertical and horizontal integration systems (Drath & Horch 2014; Fernández-Caramés & Fraga-Lamas 2018; Romero et al 2016).

Due to rapid changes in the production environment and level of task complexity, workers are faced with less routine tasks and more data-driven, skilled and knowledge intensive tasks requiring higher order thinking, more flexibility, and better decision-making skills (Ras et al 2017; Longo et al 2017). Smart factories with integrated intelligent systems enable the possibility of shifting human attention from routine tasks to more knowledge intensive and creative tasks. Therefore, it is significant to consider the proper integration of humans into this process (Longo et al 2017).

Importantly, Digital Twin has been identified as a promising technology for addressing one of the main challenges of smart factories: the integration of physical and virtual spaces. Digital twin allows the simulation, data retrieval, and data analysis to enhance data communication and product performance (Tao et al 2018). Furthermore, for the development of a digital twin, efficient computer-enabled modeling and VR is instrumental (Rasheed et al 2020). To that end, the goal of this research is to develop a modeling methodology for a digital twin of the manufacturing process enhanced with Industry 4.0 elements for human augmentation. This research also implements the proposed modeling methodology through the simulation of an assembly line. The research hypothesis is that by using BIM-enabled digital twinning approach, potential challenges can be identified to allow optimization prior to the work cell implementation.

In this paper we first provide an overview of human augmentation and the core elements of industry 4.0 that facilitate human augmentation. Then, we present a study to develop a modeling methodology for digital twin development in a smart factory. We implement the proposed methodology in our use case to validate the modeling methodology. The use case in this study is a work cell representing limited scale replicate of an assembly line equipped with human augmentation components. Our results enable the approach of developing a digital twin and digital simulation of a smart factory.

2 Existing Theories & Previous Work

To address a more human-centered design, researchers are studying human-machine interactions, levels of automations, and situation awareness while considering human factors from a different perspective. This will help humans to efficiently and rapidly respond to unpredictable processes by retrieving information from unforeseen events (Pacaux-Lemoine et al 2017; Säfsten et al 2007). An intelligent system can be updated and improved over time applying the user feedback and collected data. As a result, human will add value and intelligence to the system (Longo et al 2017).

The industrial system should be designed in a way that allows the allocation of tasks to human operator that matches its capabilities to result in a proper combination of human monitoring versus automated control (Sheridan 1995) to extend the capabilities of the operators and reduce workload and burden on the humans (Säfsten et al 2007). Human augmentation uses technologies and applications to improve human senses, actions, and abilities by providing necessary information to the human on-time. Such approach reduces the errors while still allowing the human operator to make decisions and control the process (Sheridan 1995).

In this research, we have focused on human augmentation within augmented senses and actions regarding five major features of industry 4.0 including (1) robotic systems, (2) internet of things, (3) cyber physical systems, (4) AR/VR, and (5) digital simulation. In the following sections, each feature has been described in detail.

2.1 Robotic Systems

Industrial robots can increase the productivity of the industry while decreasing workload on industry workers by performing various tasks in various fields (Li & Liu 2019). Industrial robots can be autonomously assigned to a specific task and they can be automatically controlled. Additionally, industrial robots are precise, reprogrammable, can be multipurpose, are able to move in three or more axes, and they can be fixed or mobile (De Pace et al 2020).

Collaborative robots (COBOTs) are industrial robots used for direct cooperation with operators without a need for traditional safety considerations. Some of their beneficial features include easy installation and reconfiguration, light weight, strength amplification, and possibility of guidance via virtual surfaces and paths (Afsari et al 2018). COBOTs can perform repetitive tasks and can augment human operator for performing vulnerable tasks more efficiently by reducing the workload on human operators (Romero et al 2016).

Another type of robotics used in manufacturing is the use of exoskeletons. Exoskeletons are defined as “wearable lightweight, flexible and mobile, representing a type of biomechanical system where the human-robotic exoskeleton powered by a system of motors, pneumatics, levers or hydraulics works cooperatively with the operator to allow for limb movement, increased strength and endurance” (Romero et al 2016 p31). Exoskeletons are used to increase human-technology cooperation to decrease physical stress, injuries, and accidents, while increasing human strength, productivity, efficiency, work quality, and safety.

There are four different levels of human-robot collaboration in industrial environments. In the first level, there is no shared workspace and task between the human operator and the robot. In the second level, there is no shared task and therefore, no contact between the robot and operator, but they share the workspace. In the third level, there is shared workspace and shared task without any physical interaction. In the final level, there will be shared task, shared workspace, and possibility of physical interaction (Anand et al 2017).

2.2 Internet of Things (IoT)

Industrial Internet of Things or IIoT technologies includes software, network connectivity, industrial sensors, actuators, or machines with sensing/actuation capabilities (Fernández-Caramés & Fraga-Lamas 2018) to link all the elements within a company (Wang & Wang 2016). These technologies are used to allow data collection, communication, and data exchange between physical devises, buildings, and other items using unique IP address. IIoT is used to analyze the data collected to make adjustments in the operations if required (Wang & Wang 2016).

Sensors provide active measurements and are therefore used to collect information from the environment, human activities, objects, and events and transfer them to valuable information for operator use. Human activities can be monitored and captured using wearable sensors such as tracking eye movement or capturing motor activity (Raisamo et al 2019). Additionally, using sensors are significant for controlling robots and providing instruction to them for performing and completing their required tasks. Also, sensors can help with understanding the state of industrial robots and their surrounding environment (Li & Liu 2019). Li and Liu (2019) have broken down the common sensors used on robots into five categories of tactile sensors, visual sensors, laser sensors, encoders, and other sensors such as proximity, inertial, torque, acoustic, magnetic, ultrasonic sensors, etc.

2.3 Cyber Physical Systems

The integration of physical and virtual world is one of the important elements of industry 4.0 which can be achieved using Cyber physical system (CPS) (Wang & Wang 2016). CPS is a system which uses human-machine interactions techniques and technologies to enhance human abilities (Romero et al 2016). CPS has the capability of analyzing and storing information related to a physical process using technologies such as IoT, sensor networks, and cloud to be able to provide real-time responses and feedbacks (Fernández-Caramés & Fraga-Lamas 2018; Wang & Wang 2016).

2.4 Virtual Reality and Augmented Reality

Augmented Reality (AR) provides the possibility of seeing a combination of virtual and real-world elements at the same time while virtual reality (VR) provides a view with virtual elements. Both AR and VR can be used in different stages of manufacturing process including design, maintenance, etc. to enhance productivity (Fernández-Caramés & Fraga-Lamas 2018). Using AR provides additional knowledge to the human operator regarding the working environment supporting skills and abilities of the operator (Longo et al 2017). The AR glasses can display information about the task and provide instructions. Additionally, AR can be used to support the collaboration between human operator and industrial robots by allowing the human operator to receive robot information such as joint values while also helping the operator to understand the intentions of the robot in terms of the upcoming manipulations (De Pace et al 2020). At the same time, if any faults exist, it can notify the operator (Dietrich et al 2010). Having access to such information can support the safety of the operator while providing useful data (Liu et al 2016).

2.5 Digital Simulation

Modelling the behavior of machines, products, or workers by processing the information collected will help to simulate the future process in order to identify requirements and predict issues and thus decrease costs while increasing quality. Digital twin concept is involved in this part of the process of industry 4.0 by simulating the real-world industry. It allows monitoring the operation (Fernández-Caramés & Fraga-Lamas 2018). A digital twin is an integration of model and data which represents a specific asset covering all its properties, attributes, and condition to simulate its behavior (Stark et al 2017).

Digital twin is a good option when the actual component changes over time which requires model modification (Wright & Davidson 2020). A huge amount of data is generated from multiple sources as a result of an industry operation. This data will be transferred to the virtual model (Qi & Tao 2018) to be stored, processed, analyzed, and managed using big data techniques. These techniques will help to extract meaningful information from the data received in order to optimize the physical component and process by predicting future issues, required resources, etc. (Fernández-Caramés & Fraga-Lamas 2018; Qi & Tao 2018).

3 Methods

3.1 Presented study, research question & hypothesis

The goal of this research was to develop a modeling methodology using BIM-enabled digital twinning for smart factories and determine if the proposed modeling methodology can assist with identifying challenges and optimizing the process prior to the smart factory's work cell implementation.

3.2 Applied Research Methods

To develop a digital twin of a smart factory focused on human augmentation, a modeling framework was developed in this research (Figure 1). This methodology starts with identifying required components and technologies in a smart factory that facilitate human augmentation.
In the conceptual development phase, researchers identified three major components of the study methodology for conceptualization of the work cell through the following developments:

A. Develop the space layout for a work cell in the smart factory
B. Develop 3D model of the space
C. Develop information flow and work processes

Major elements in the proposed methodology included 3D model of the factory space, space layout with required equipment, process model and workflow, and process simulation.

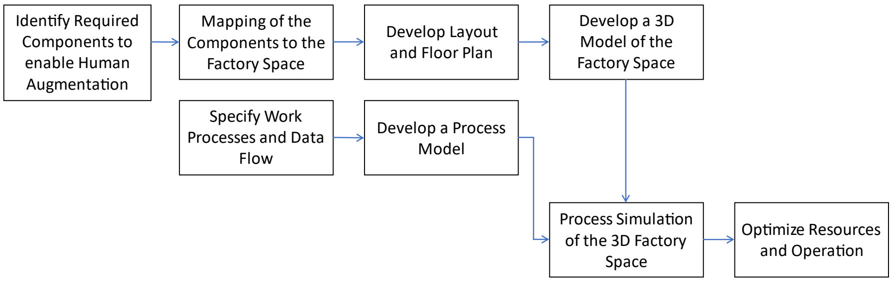

Figure 1. Modeling framework

3.3 Research Model

This section presents the implementation of the proposed methodology and validation of the approach through a use case. The goal was to develop a model as a digital simulation of space equipment and information flows focusing on human augmentation and core elements of industry 4. 0 including robotic system, internet of things, cyber physical systems, virtual and augmented realities, and digital simulations to improve manufacturing. As a result, an assembly line involving the assembly of parts and components was simulated as an example of integrating the core elements of industry 4.0 in the process. As discussed in section 2, there are four levels of human-robot interaction. However, in this study, level three, shared workspace with shared task but no physical contact, was excluded.

One of the laboratories located in Kelly Hall on Virginia Tech campus was selected for the implementation of the industry 4.0 for a smart factory work cell. Kelly Hall building is used for cutting-edge research projects in the fields of engineering, science, and medicine and it contains laboratories, offices, and workspaces. The room assigned to this study was the second room on the left side on the first floor of the building, marked in red in figure 2. It contained a main area with two small rooms. Figure 3 presents interior space of the room selected for this research.

Figure 2. Kelly Hall laboratory floor plan

Figure 3. Kelly Hall laboratory space

3.3.1 Surveying the Space

The laboratory in Kelly Hall was surveyed during several visits to model the space accurately using the CAD drawings provided by the building manager. In the discussions with the building manager, the location for the metal 3D printer that was going to be installed in the space was identified. Figure 4 specifies the location of the big metal 3D printer. So, the study used this location as a place holder for the 3D printer in the conceptual development process.

3.3.2 Developing the Space Layout

Through the studies and discussions with the project stakeholders, the work cell was defined to manufacture an assembly of parts and components while focusing on human augmentation in the work cell to examine different novel solutions to address industry problems. The work cell also needed to reflect the process model developed in next subsection.

Major components of the work cell included warehouse shelves, mobile robot, conveyor belt, assembly station for human-robot collaboration, collaborative robot arms, AR/VR Station, robotic assembly cell, a crane for moving big components to the robotic assembly cell with an exoskeleton station, packaging and transfer shelves, laser cutter, and metal 3D printer. The layout of space is illustrated in figure 4. This layout included the current allocated space for work cell and the placeholder for the metal 3D printer. Reserved spaces in the room were planned to be used for other work cells as well as teaching and learning spaces for students.

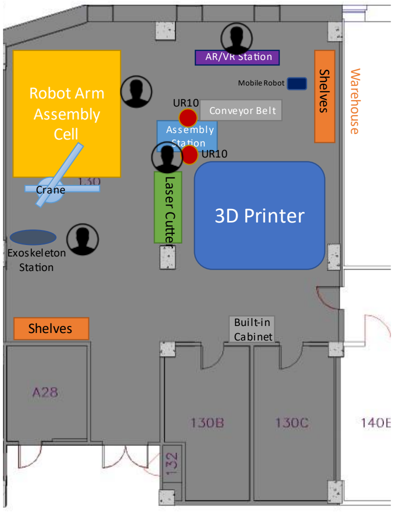

Figure 4. Designed work cell

3.3.3 Developing 3D Model of the Space

Based on the information from the space survey, the model of space was developed using Building Information Modeling (BIM) technology. Figure 5a shows the BIM model developed for the space using Autodesk Revit. The BIM model was then imported to Simio to add work cell equipment, components, and worker and to be able to simulate the process and conduct experiments. Figure 5b shows the Simio model developed in this study.

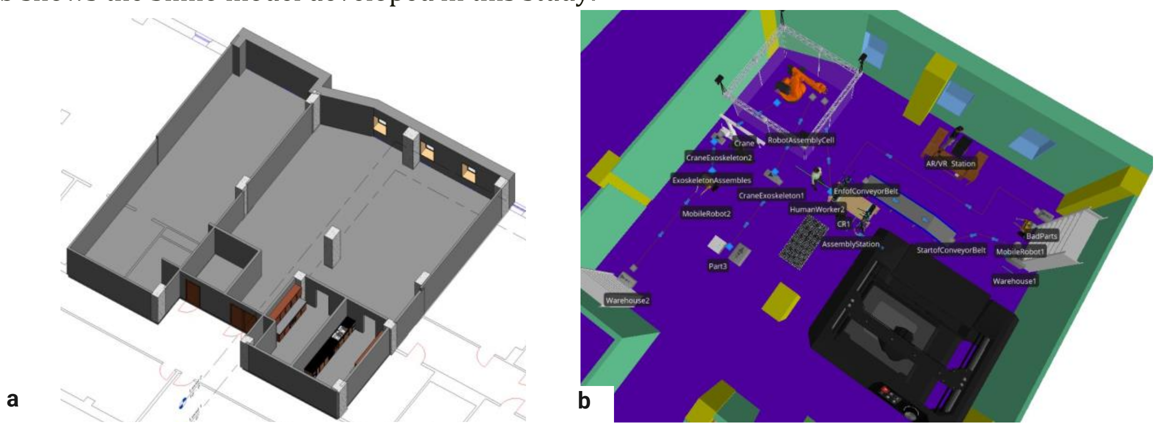

Figure 5. 3D model of the laboratory in BIM (left) and Simio (right)

3.3.4 Developing Information Flow and Work Processes

A process map was developed in Business Process Model and Notation (BPMN) using Visio to represent the proposed assembly line in the work cell that replicates parts of the real-world manufacturing process. Major components of the work cell included: warehouse, mobile robot, conveyor belt, assembly station for human-robot collaboration, collaborative robot arms, AR/VR Station, robotic assembly cell, a crane for moving big components to the robotic assembly cell with an exoskeleton station, packaging and transfer shelves, laser cutter, and metal 3D printer. Other elements involved in the design of the space were a conveyor belt for moving the components, two shelves for stacking the components (representing warehouse and packaging), and a robot arm assembly cell to assemble the components.

The process developed starts with the human operator monitoring the components (component1) for possible faults, and if no fault exists, the operator stacks them in the shelves (representing warehouse). The mobile robot (mobile robot 1) transports part1 from the warehouse to the conveyor belt. The belt moves the component forward until it reaches the first COBOT (COBOT1). The COBOT1 picks up the component from the belt and places it on the table. At the same time, other parts of the product are produced by the 3D printer and the laser cutter transported to the assembly table using collaborative robot 2 (COBOT2). Then, the human operator 1 monitors all parts including part1 from the warehouse, part 2 from the 3D printer for possible faults, and the part from the laser cutting process. Through human-robot collaboration, assembly of the parts are conducted. The output of this process is then checked and controlled by the human operator before being placed on the table. If no fault exists, COBOT1 places the product in the bin next to the robot assembly cell and the human operator 2 moves the bin to the robot assembly cell when permitted. The big part is also moved next to the robot assembly cell and the component is lifted using the crane and exoskeleton by human operator 3. After the assembly task, the crane lifts the final component and places it outside the robot assembly cell. Human operator 3 adjusts the assembly on the second mobile robot (mobile robot 2) while he/she is wearing the exoskeleton. Mobile robot 2 moves the assembly to the transfer shelves to be transported out of the work cell.

3.4 Experiment

The Simio model contains seven stations including the warehouse, assembly station for human-robot collaboration that combines the part from the warehouse with the 3D printed parts using two collaborative robots, robot assembly cell with a safety cage for big part assemblies, AR/VR station to control the robot assembly cell and help with process augmentation, crane with exoskeleton station to receive and transfer big assembly parts, packaging and transfer shelves to transfer the system output, and the metal 3D printer. Also, three manufacturing parts were included in this study: part 1 that arrived from the warehouse, part 2 that arrived from the 3D printer, and part 3 that arrived from outside of the work cell (e.g. engine inlet). The output of the system is the final assembled part.

The use case in the study simulation is shown in Figure 6. In this scenario, part1 arrived from the warehouse to the system at the rate of 60 entities per hour. Therefore, to calculate the mean interarrival time between entity 1 and entity 2 of part 1, $1/\lambda = 1/(60/hr) \times (60\, min)/hr$ equation was used. This showed that the mean interarrival time for part1 was one minute. Part2 arrived from the 3D printer which in this scenario the mean interarrival time for part2 was considered two minutes. Part3 was the big part (e.g. inlet engine) that arrived from the outside of the work cell. Its mean interarrival time was considered four minutes. The mean assembly time in the assembly station with COBOTs was considered as 1 minute and the mean assembly time in the robot assembly cage was also considered to be one minute. Also, in this scenario, the mean transferring time in the crane with exoskeleton station was considered to be one minute. The AR/VR station provided remote control for the robot assembly cage since due to safety concerns of robot arms with high payloads, human workers cannot be next to the robot while working and the robot should perform within a safety cage.

For the experiment, we set 100 replications (100 hours) for the system and we added the following responses:

- Assembly Station Utilization (AssemblyStationUtil)
- Robot Cell utilization (RobotAssemCellUtil)
- Crane and Exoskeleton Station Utilization for Arriving Parts (CraneExo1Util)
- Crane and Exoskeleton Station Utilization for Final Transferring Assembly (CraneExo2Util)
- Part 1 Time In System (TimeInSystem)
- Part 1 Number In System (NumInSystem)

Experiment response results were then represented in plots as represented in Simio Measure of Risk and Errors (SMORE) plots.

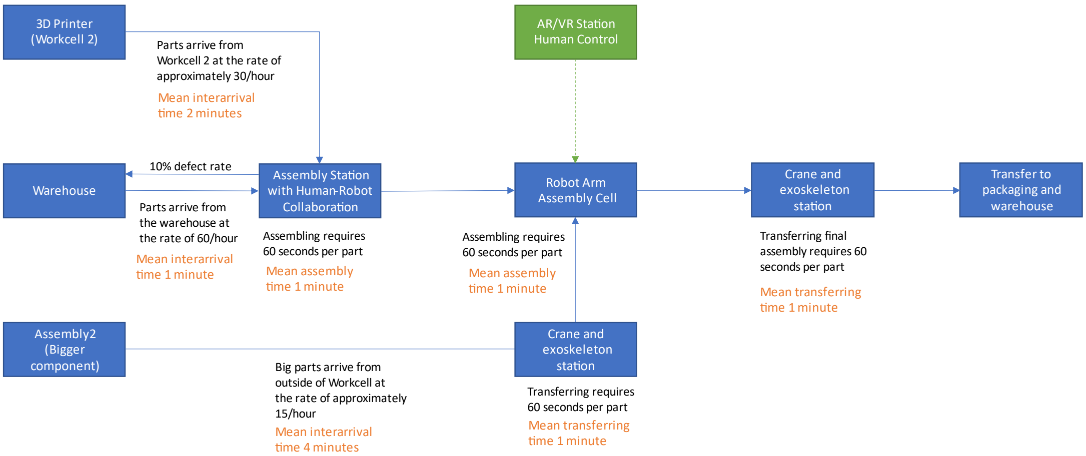

Figure 6. Use case in the study simulation

4 Findings

4.1 Collected Data

Table 1 summarizes the overall experiment result. In the 100 hours scenario, almost 1,502 final assembly were created and about 298 bad parts were detected. One interesting finding was that the human worker 2 responsible for transporting parts to the robot assembly cage, would walk about 22,997 meters on average during the 100-hour work cell operation.

Table 1. Experiment result statistics

Performance Measure	Value
Total assembly hours on average	100
Total entity output of the assembly process	1,501.97
Total part 1 created in the system	6,003.2
Total part 2 created in the system	2,997.48
Total part 3 created in the system	1,503.03
Human Worker 2 average distance travelled in meter	22,996.41
Number of bad parts	297.9

4.2 Analysis of the Collected Data

The results of the SMORE plots are represented in Figure 7a. In this experiment, we studied the utilization of the assembly station with the collaborative robots and the mean (or average) value of observations made was 49.95 percent while the range of all observations was between 47.19 and 51.81 percent. The mean confidence interval for the utilization of the assembly station started at 49.77 percent and ended at 50.13 percent where its half width was 0.178. The lower percentile for the utilization of the assembly station in this experiment was 49.44 percent with the median of 50.01 percent. In this experiment, we also studied the utilization of the robot assembly cell station which was in the cage (figure 7b), the utilization of the crane with exoskeleton station for receiving the parts from outside of the work cell (figure 8a), and the time spent for all part 1 entities to arrive in the system (figure 8b).

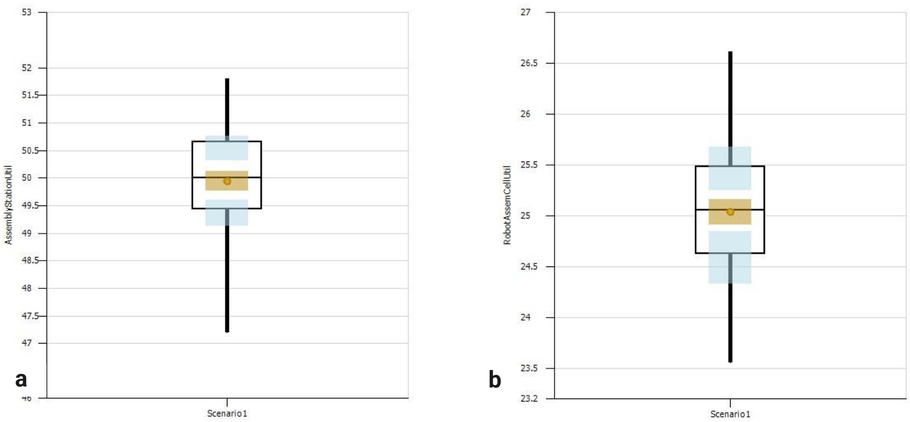

Figure 7. SMORE plots for (a) Utilization of the assembly station with the collaborative robots, and (b) utilization of the robot assembly in the safety cage

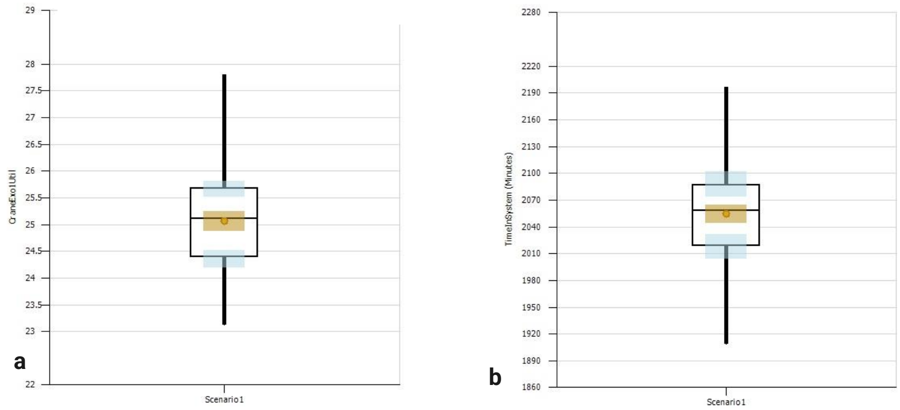

Figure 8. SMORE plots for (a) utilization of the crane with exoskeleton station, and (b) Part 1 time spent in the system

4.3 Discussion

Based on the results of this research, the developed modeling methodology assisted with simulating the work cell to identify required components in the work cell, the process duration, and interdependencies. Such approach can help with the optimization of the process by modifying the components, their duration as well as their relationship. Also, it will help with predicting future faults and addressing potential challenges prior to the implementation of the work cell.

5 Conclusion

5.1 Limitations

In this study, authors did not include re-assembly of the faulty assembled parts. Also, laser cutting part was not included in the process and only the 3D printed part, the big assembly part, and the base part i.e. part1 were included in the assembly process. Due to the pandemic delays of physical on-site equipment delivery and putting humans in the workspaces during the time of this research, researchers were not able to have a path to put the human operator inside the loop at the same time as the robots. Additionally, in this study, researchers did not include the implementation of different types of sensors to further support the process and simulation.

5.2 Concluding Remarks

Modelling and simulating the process of machines and products as well as the behavior of human operators within the industrial environments are beneficial in terms of data collection to identify and predict the future faults. Such approach enables the possibility of planning in advance to address potential issues and reduce the faults leading to cost reduction. Digital twin is a concept developed to simulate the real-world by integrating model and data. The data collected, stored, and analyzed will support process optimization. The goal of this study was to develop and analyze conceptual development of a smart factory work cell with focus on human augmentation using modeling and simulation approach to digital twin development. The modeling methodology developed in this study assists with identifying challenges and optimizing the processes prior to implementations. Modeling and simulation allowed the researchers to identify the duration of the tasks enabling the modification of the duration and the process as well as predicting future issues. The developed platform can also be used in courses and educational programs for teaching the fundamentals of modeling for digital twin in Industry 4.0 with emphasis on human augmentation.

5.3 Future Work

Future research will integrate human operators and robots at the same time in the loop to optimize the process. Additionally, it will integrate the sensors to collect additional data from the process and prepare a more accurate simulation. Future study will also test more scenarios based on actual use cases from the lab stakeholders and specify how the system can be optimized.

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