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Innovative robotization of manual manufacturing processes

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Abstract

Manufacturing industries are continually challenged to adapt to a competitive environment. Consequently, there is an urgency to opt for automation technologies to upgrade their manufacturing facilities and make them more flexible. Especially this relates to automating manual manufacturing processes, which is often challenging to structure to ensure repetitiveness and generalization to other processes within the facility. Consequently, innovating systematic approaches to identify robotization opportunities is an interesting proposition for manufacturing set-ups that would like to integrate collaborative robots on the shop floor and struggle with the decision steps to follow.

In this paper, a framework for supporting robotization effort for manufacturing set-ups is proposed. The methodology consisting of five phases, culminating in the identification of robotization opportunities. A case for manual milling manufacturing processes is demonstrated as a 'proof-of-concept'. The first step of the proposed approach focuses on task decomposition, in which manual manufacturing tasks are characterized. This is followed by task allocation to a robot and human agent based on intrinsic characteristics of the task to capabilities of the agent. Next, alternative layout configurations for candidate cell layouts are generated. In the final step, a candidate layout is selected and modeled in an agent-based simulation platform, considering factors such as realism, interaction safety between the robot and human agent, and interesting manufacturing metrics such as resource utilization and throughput rate. A final configuration is optimized, which visualizes a collaborative robot performs loading and unloading tasks alongside an operator performing highly cognitive tasks. For safety, zoning of the manufacturing cell is visualized, considering a working area separated by a safety fence.

Keywords: Robotisation; manual manufacturing tasks; structured decision making; manufacturing cell layout; agent-based simulation; safety

1. Introduction

The rapidly changing market conditions are posing challenges to the manufacturing industries to remain competitive in high-wage locations. The key factors that will help the companies survive in this globalized market are high-quality products, on-time deliveries, maintaining low production costs, and producing customized products [1]. Improving the manufacturing system's flexibility is believed to play a substantial role in attaining the factors above. Emerging technologies available in the manufacturing domain give the manufacturing companies ample choices to invest and gain benefits. Nowadays, most manufacturing companies look forward to solutions yielding maximum benefits while investing the least effort, time, and money. The trend of concepts like Industry 4.0, Cyber-Physical System (CPS), Internet of Things (IoT), Robotization, and Robotic Process Automation (RPA) shows the increasing reliance on industrial automation solutions to sustain competitive advantage among the manufacturing industries. Industrial automation holds the potential to assist the manufacturing industries in achieving sustainable competitive advantage [2].

Industrial automation focuses on automating production processes and systems by substituting human workers with mechanical, electronic, computer-based systems, robots, and information systems to operate and to monitor manufacturing

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[3]. The computer-based systems, information, and electronic systems automate cognitive tasks, whereas the robots and mechanical systems automate the physical task in manufacturing systems. International Federation of Robotics (IFR) reports a worldwide increase of 85% in industrial robots worldwide within five years (2014-2019), thus a total of 2.7 million industrial robots operating globally in 2020 [4].

Apart from providing economic benefits, the robot can perform tasks that require handling heavy objects, high precision, high quality, operating in dangerous conditions, and improving ergonomics. The innovations in the field of robotics broaden the scope of the application of robots in the manufacturing industry.

We often perceive the decision of integrating robots in the manufacturing system as either transformation into a fully automated or semi-robotized system or keeping it entirely manual [5]. While the robots excel in delivering high-quality work repeatedly, it does not provide high flexibility when the production demands change quickly. In contrast, Humans offer the abilities of adaptability, dexterity, and in-process decision-making skills. A manufacturing system can be a manual, fully automated, or Hybrid system (i.e., a combination of manual and automated systems). When the utilization of robots and humans is according to the process requirement, the manufacturing system attains the highest efficiency [6].

Thus, integrating robots with a manufacturing system in the absence of a structured framework may be fraught with risks, especially with overly relying on tacit knowledge of decision-makers at manufacturing facilities. Additional open questions include verifying prior to implementation, and the feasibility of a robotization solution considering safety aspects.

This paper addresses some of these open questions and, more specifically, the research question: How can decision-makers transform manual manufacturing processes into a fully robotized, or semi-robotized solution? To answer this question, we propose a robust decision-making framework to assist manufacturing facilities in identifying the potential of transforming the manual manufacturing process into a semi-robotized solution. We present a proof of concept whereby identified solutions can be visualized prior to designing/implementing an actual robotized manufacturing cell. Furthermore, the proposed framework allows decision-makers to evaluate the feasibility of robotization, from an implementation perspective.

Fig. 1 illustrates the framework we propose for robotizing manual manufacturing processes. The framework contains four sequential functions discussed in Sections 2 and 3. The arrows in the framework represent data and actors interrelating with the functions. The horizontal arrows represent the in- and output of data, whereas the vertical arrows indicate restrictions (could be subjective to change) and knowledge provided by actors.

2. Current state of research

2.1. Robotization of manufacturing

"Robotization" is the terminology used when a robot is employed to automate manual tasks. The manufacturing industry witnessed an increase in industrial robot adaption into its production processes due to its capability to perform tasks with high precision and repeatability. The ability of the industrial robot to work continuously helped manufacturers to increase output. Robots can work in dangerous and harmful conditions, thus improving the manufacturing system's working environment and safety. Thus, industrial robots' various advantages encourage the manufacturing industry to

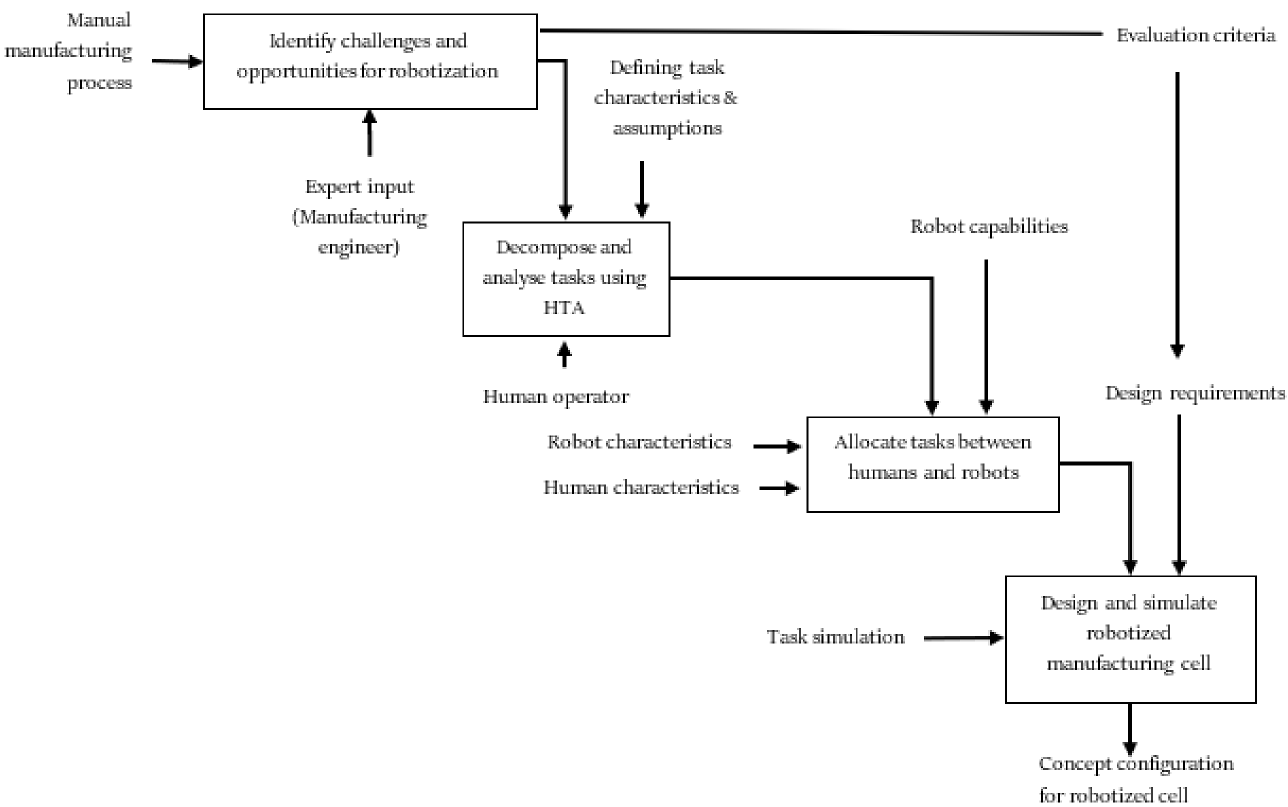

Fig. 1. Framework for robotizing manual manufacturing

incorporate industrial robots into their manufacturing systems to improve their productivity and profitability.

Robotization in manufacturing sub-divides into two parts 1) robotization of processing operations and 2) robotization of handling operations. Handling is the major robot application field found in all the areas of manufacturing [7]. The robotization of processing operations considers using an industrial robot to carry out tasks such as welding, painting, machining, inspection, and assembly operations. The handling operations such as pick and place, machine tending, packing, palletizing, and transporting utilizes an industrial robot in the robotization of handling operations.

The introduction of collaborative robots helped manufacturing industries to overcome the limitation mentioned above. A collaborative robot, also known as “Cobots,” is a robotic device that collaborates with humans. Collaborative robots share the workspace and work alongside humans without the requirement of safety fences. The combination of collaborative robot and human allows taking advantage of the robot’s ability to work with high accuracy with speed and repetitiveness, along with flexibility and cognitive skills of the human [8].

All the collaborative robots have an inbuilt safety system in the form of sensors and foam, which guarantees that the cobots will stop and safeguard humans when a collision occurs. Four types of collaborative robots are mentioned in ISO/TS 15066 based on human interaction with the cobots [9, 10]. This includes:

- **Safety Monitored Stop:** Includes measures to a human’s presence in a collaborative workspace.
- **Hand Guiding:** Hand guiding robot’s motion is only possible using direct input of the operator.
- **Speed and Separation Monitoring:** Influences the robot motion and adapts the manipulator speed when an operator enters the shared workspace.
- **Power and force limitation:** Limits the forces exerted by the robot manipulator to a level below thresholds that would be harmful.

2.2. Challenges and opportunities robotizing manufacturing

A robotic manufacturing cell presents an attractive solution as many repetitive and manual tasks are candidates for robotization. However, it is crucial to consider the criteria used to robotize tasks: task characteristics, robot characteristics, and robot capabilities. Task characteristics give information about the task, such as the task’s nature (i.e., Physical or cognitive), task time, and task complexity. The information about robot characteristics and capabilities such as accuracy, payload, reachability, degrees of freedom, and work envelope help check the robot’s suitability for performing a task [11].

As a first step for identifying robotization opportunities, Shepard emphasized the importance of task analysis as a means of understanding which task elements are suitable to be performed by a human operator or a collaborative robot [12]. More importantly, the analysis allows decision-makers to characterize manufacturing processes based on the capabilities of an agent, here the human operator or the collaborative robot.

3. Methodology

In this study, the methodology depicted in Fig. 1 is applied. The first main step evaluates challenges and opportunities for robotization, where expert input is important. For the case organization, suggestions on low hanging robotization opportunities were evaluated via brain storms, prior to agreeing on labor intense, but low cognition tasks.

The next sub-steps consists of task decomposition, analysis, allocation and designing a virtual workspace integrating industrial robots. The sub-steps are discussed further below.

3.1. Task decomposition, analysis, and allocation

For task decomposition, the Hierarchical Task Analysis (HTA) is a widely used method for structuring manufacturing tasks, and allowing decision-makers to extensive characterize manufacturing tasks. It does this by decomposing high-level tasks into lower-level sub-tasks up to basic task elements [13]. HTA method breaks the tasks into simplified sub-tasks. According to Kirwan and Ainsworth [14], HTA is the best-known task analysis technique to understand and analyze a manufacturing system.

In this study, existing manual steps were decomposed, from higher-level to lower-level sub-tasks, thus simplifying complex human-relevant task steps/actions into a sequence of simplified task steps. To support HTA, different data capture techniques are used and, most prominently, video recording (and analysis) of manufacturing processes or detailed process mapping.

For this study, we assume that manufacturing tasks have a hierarchical relationship, which often may not the case, especially for customized products where task steps are dynamic. However, since this project relates to a standardized product, whose tasks are static, we view the HTA as rather robust.

3.2. Task allocation

Once decomposed, tasks were allocated to either the human or robotic agent depending on the capabilities of the specific agent [15]. As an example, high cognition task elements are best suited for the human operator, with repetitive tasks allocated to a robot agent. For allocation, criteria were considered, such as payload (weight), cognitive demand of the task, cycle time, ergonomics, and investment requirements for actuators needed to substitute performance of the task step. Additional allocation criteria applied in the study, include product size, shape and weight ; cycle time, repetitiveness, task complexity; payload, repeatability, reachability and ergonomics; cognitive and physical strength [16, 17].

3.3. Designed robotized manufacturing cell

After task allocation, designing the work cell is the next feasible step. This involves designing a cell layout considering the positioning of the agents and trading off with system performance. The idea is to design a layout that optimizes workflow within the cell. For this study, an Agent-based simulation (ABS) was implemented, as it presents an attractive approach for designing and visualizing robotized manufacturing cell layouts [18]. It allows the modeler to represent the cell configuration realistically and experiment with alternative layouts before defining a more optimal configuration. Moreover, the optimization can consider manufacturing metrics and safety zoning to prevent unanticipated collisions with the robotic agent [19].

4. Implementation of use cases of milling processes

The proposed methodology was implemented for robotizing manual milling processes for press brake tooling for bending sheet metal. It consists of five (5) steps:

4.1. Task analysis

Task analysis is implemented to characterize manual milling task steps. The Hierarchical Task Analysis (HTA) method was applied to decompose manual tasks performed by the milling cell operator in a well-defined and sequential order. For collecting information, video recordings of the process were captured, and afterward, tasks were decomposed and tabulated.

Fig. 2. (a) cleaning the press-brake tool; (b) changing fixture for holding tool.

Fig. 2 illustrates examples of decomposed manual task steps based on video recordings of the entire milling process for press brake tooling. A hierarchical representation of the two sub-tasks is illustrated in Table 1, with Task 1 “preparing the press brake tool for loading on the milling machine” being the super-ordinate tasks, while sub-tasks (a) and (b) illustrated in Fig. 2 representing the decomposed sub-tasks, and sub-ordinate tasks.

Table 1. Illustration of hierarchical decomposition for a high-level manual milling task

High-Level Task	Sub-tasks	Sub-ordinate tasks
1.	1.1	**1.1.1** Hold the press brake tool with two hands
		1.1.2 Rotate the press brake tool to a vertical position
		1.1.3 Hold the press brake tool vertically
		1.1.4 Pick up the bottle of cleaner liquid from working table
		1.1.5 Position cleaner on cleaning fabric
		1.1.6 Spray the cleaner liquid on the fabric
	1.2	**1.2.1** Pick up the screwing drill
		1.2.2 Move it to the screw on the lower clamp
		1.2.3 Place it on the head of the screw
		1.2.4 Press the power button
		1.2.5 Once unscrewing is done, stop the drill

- **High-level task 1:** preparing the press-brake machine tool for loading
- **Sub-task 1.1:** Cleaning the press-brake tool
- **Sub-task 1.2:** Changing the fixture for the holding tool

Overall, the press brake tool milling was decomposed into five high-level tasks and a total of 148 sub-ordinate tasks.

4.2. Task criteria, rationalization, and allocation

Prior to allocating the sub-ordinate tasks to the specific agent (human or robot) based on capabilities, several allocation criteria were defined based on expert intuition and augmented by a literature search. The first criteria considered product characteristics, including size, shape, geometry, and weight, which influenced actuation aspects such as grasp-ability, maximum allowable gripper payload, and manipulation ease of the product by a gripper. Fig. 3 illustrates the tool geometry, which influences the ‘graspability’ criterion.

The second criteria considered characteristics of the production task. Cycle time, repetitiveness, and required precision were identified as important. It is important to note that the criteria were either quantitative or qualitative, influencing how each criterion was allocated to the sub-ordinate tasks. Table 2 illustrates an example of task allocation following a ‘quick-and-dirty’ qualitative assessment of the appropriateness of a criterion to the capabilities of an implementation agent.

Table 2. Illustration of hierarchical decomposition for a high-level manual milling task

Sub-ordinate tasks	Shape	Repetitive?	Grasp-ability?	Need to manipulate?	Agent?
1.1.1.	Cuboid	Yes	Yes	No	Robot
1.1.2.	Cuboid	Yes	Yes	No	Robot
1.1.4.	Cylinder	Yes	Yes	No	Operator
1.1.5.	Cylinder	Yes	Yes	No	Operator

Moreover, a task ‘rationalization is implemented to standardize decomposed sub-ordinate tasks, and ensure tasks are performed irrespective of product variety. Examples include standardizing the tool holding fixture, which influences the loading process of tooling by the operator on the fixture.

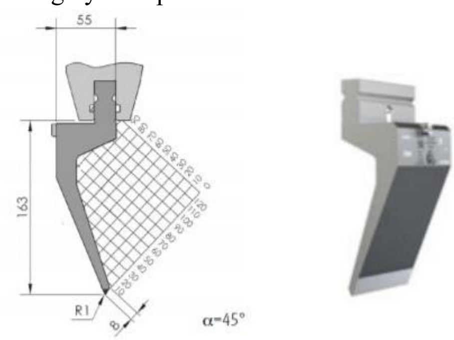

Fig. 3. Press brake tooling geometry.

4.3. Designing feasible conceptual cell configurations

After tasks were rationalized and allocated to the operator and collaborative robot, feasible cell configurations were generated, consideration capabilities and operator safety. generated and evaluated further on space, resource utilization, and operator access [20]. Fig. 5 illustrates one of the conceptual layouts considering the positioning of a robot manipulator picking and position press brake tooling on two milling machines. The operator prepares the tooling on a workbench and places it on a pallet. The robot arm subsequently picks the tooling from the pallet and position it on an automated pallet changer (APC), which feeds the tooling to the milling machine. After milling, the robot arm picks and places the tooling on the outbound APC, whereafter the operator picks and stores it on a storage system.
Following the design thinking approach, five concepts were
Agent-based simulation of cell configuration
In the next step, the five alternative concepts were visualized in Visual Components, an agent-based simulation software [21]. Input considerations for the model included parameters such as positioning and distance of the resources, task cycle times, operator walking speed, machine processing times, and operator schedules. Input values were based on empirical process times at the use case organization.

Several performance measures were defined to consider system performance to compare the modeled cell configurations. This includes resource/agent utilization, and production throughput. Fig. 5 shows the simulation model of one of the alternative layouts. Fig. 4 illustrates real-time statistics of the operator utilization for one of the configurations. Based on the evaluation of the performance measures, an optimal configuration was selected considering objective functions, including maximizing production throughput and resource utilization. Other considerations were space allocation while minimizing changes to the existing manufacturing facility.

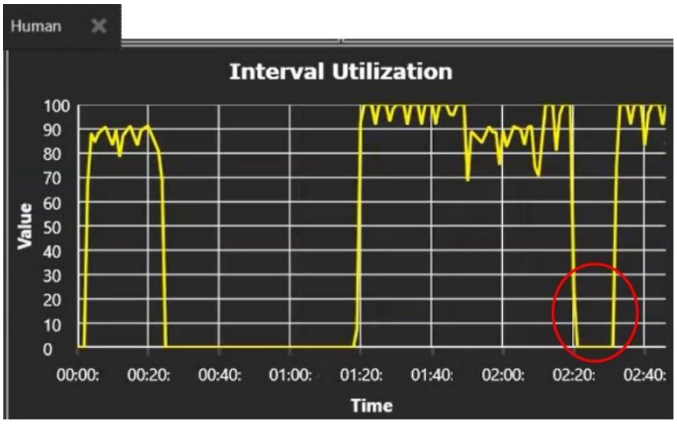

Fig. 4. Real-time statistics of operator utilization (red circle indicating breaks)

5. Discussion

In this study, we propose a structured framework for identifying robotization opportunities for manual manufacturing processes. This study addresses an automation challenge: how can decision-makers identify robotization possibilities for manual processes in a structured and time-efficient way? Furthermore, a question addressed relates to the implementation of feasible concepts, where in this study, an agent-based simulation approach is proposed. The proposed approach can be applied at both the starting phase of a new automation challenge or translating existing processes into semi or fully automated robotized solutions.

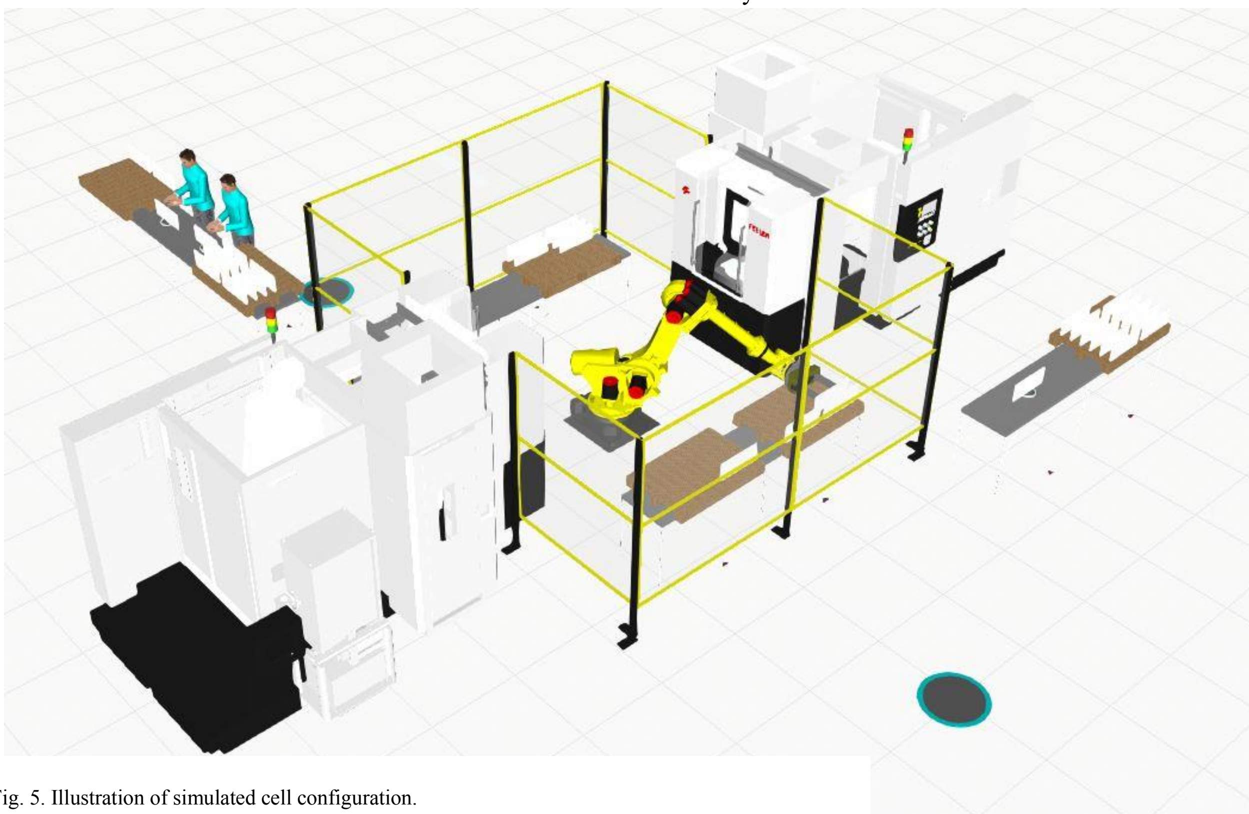

Fig. 5. Illustration of simulated cell configuration.

As seen in the study, to identify robotization opportunities, it is essential to understand the manufacturing tasks currently performed manually to identify the ideal task steps for robotization. This understanding is important for task allocation decisions (i.e., physical or cognitive tasks), thus forming the basis for allocating the task to the robot or the operator. The Hierarchical Task Analysis (HTA) approach is particularly useful to decompose the high-level tasks into sub-tasks and subordinate tasks structurally.

Furthermore, agent-based simulation is useful at the implementation phase, especially for modeling and visualizing alternative layouts of new semi-robotized solutions. The simulation also makes it possible to compare alternative configurations using performance indicators, including CNC machine's utilization, robot's utilization, operator's utilization, and the throughput for the alternative configurations. This provides valuable insights prior to actual implementation.

6. Conclusions

For future work, the study will define more dynamic and quantifiable criteria for allocating tasks to agents prior to designing alternative layout configurations. This would yield a robust allocation criterion, and better insights on task allocation. Additional work will focus on defining task analysis rules, and especially a 'stop rule for complex manufacturing tasks. Often, the hierarchical task levels can be extensive and may complicate the task allocation steps. Future steps to improve the modeling steps for the agent-based simulation will focus on developing dynamic models, considering stochasticity in manufacturing processes.

7. Acknowledgements

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