Empowering operators with a human-in-the-loop/on-the-loop simulation-based digital twin: the case of a smart learning factory

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Abstract: Industry 5.0 has shifted the focus towards empowering humans and human-technology integration within industrial systems. Interactive Decision Support Systems (DSS) are a key tool for improving overall performance. This paper presents the prototype of a simulation-based digital twin as a support of a DSS that implements both Human-in-the-Loop (HITL) and Human-on-the-Loop (HOTL) approaches. An interactive human-machine interface, interconnected with a self-configurable simulation, assists frontline workers in comprehending a production system characterized by high variability, uncertainty, complexity, and ambiguity. By enabling frontline workers to run simulation models directly from the shop floor, the system empowers them to work alongside machines (in-the-loop) and make informed decisions in real-time, adapting to changing conditions and optimizing processes (on-the-loop). The Analytic Hierarchy Process (AHP) methodology allows to evaluate the adoption of the combined Human-in/-on-the-loop approach over the HITL, based on the complexity of the activity to be executed. A use case is developed at an Industry X.0 Learning Lab at the University of Calabria.

Keywords: industry 5.0; simulation; human-centricity; smart operator; digital twin

1. Introduction

In the transition towards Industry 5.0, manufacturing systems are evolving to emphasize human needs, skills, and capabilities as invaluable assets (European Commission, 2021). This shift acknowledges that human inventiveness, dexterity, and decision-making abilities are essential in enhancing the performance of smart manufacturing systems (Madzik et al., 2024) and should be enhanced through collaboration with digital technologies (Alves et al., 2023). The integration of humans into cyber-physical systems (CPS) has led to the development of Human Cyber-Physical Systems (HCPS) (Lou et al., 2024a), which orchestrate interactions between physical assets, cyberspace, and people throughout various stages of production. HCPS leverages the strengths of both machines and humans, leading to increased effectiveness in dealing with dynamic and unpredictable tasks (Peng et al., 2024). However, research on HCPS in the context of Industry 5.0 is still in its early stages, in particular regarding the effective integration of humans, and their roles, within the CPS (Lou et al., 2024a, Sgarbossa et al., 2020). Despite the value of humans, two aspects have to be considered:

- *Human limitations* (e.g., sensitivity, response times, and retention capacity), *and variability in skills and knowledge* (Mabrok et al., 2020). This can be critical for the system and may lead to lower performance. Designing Decision Support System (DSS) that can successfully help workers handle the challenging duties of HCPS is therefore imperative (Hu et al., 2024; Domin et al., 2023). However, the literature presents a lack of studies providing DSS in the context of SMEs, which, in comparison to big enterprises, are facing several challenges in developing and implementing DSS, such as a lack of human and financial capital resources (Zarte et al., 2019);
- *Underestimation of shop floor operators' capabilities* (Lou et al., 2024a). This leads to the information overload of managerial figures (Phillips-Wren et al., 2020), even for operational aspects, and operators' replacement with automated systems. Instead, the workforce and operations manager should be empowered by assistance systems (Sgarbossa et al., 2020), which, however, deserve further development (Rauch et al., 2020). Even this aspect is relevant for SMEs, where human availability is limited and has to be optimized. Concepts like Human in the Loop (HITL) and Human on the Loop (HOTL) have emerged to facilitate the design of human-centric solutions, enhancing varying skill levels and limitations, highlighting the need for systems and tools to optimize human-system interaction (Schirner et al., 2013; Nunes et al., 2015).

Therefore, this paper aims to navigate the matter of SME operators' empowerment, in line with a human-centric perspective, by proposing a simulation-based DSS for Human-in/-on-the-loop (HI/OTL) combined integration of humans in HCPS. Also, an application of the AHP methodology is proposed to define a prioritization of the adoption of the HI/OTL approach against the HITL, based on the activity to execute.

The paper is organized as follows. Section 2 offers an overview of the paper's theoretical background, exploring the HITL and HOTL paradigms. Section 3 highlights the methodology and the tools used for the proposed solution. Section 4 explains the characteristics of the prototype developed. Section 5 discusses the implication of this work and section 6 concludes the work.

2. Theoretical background

2.1 Simulation as decision support on the shop floor

The advent of smart manufacturing indicates a significant paradigm shift, revolutionizing production methods and transforming the work environment for operators on the shop floor. This paradigm will require that the operators are equipped with efficient support systems that assist them in making informed decisions (Torres et al., 2020). The application of simulation as a Decision Support System (DSS) is widely researched. They offer the possibility to deal with process uncertainty creating models for complex systems and contributing to enhancing productivity, quality, and decision-making accuracy (Ferreira et al., 2020). These systems are designed to provide decision-makers with the necessary tools for making informed choices aligned with organizational objectives and goals (Jung et al., 2024).

Leveraging on digital technologies to implement a DSS at the shop floor management level can create synergy between humans and technologies (Clausen, 2019). In the context of Industry 5.0, improving field operators' awareness can lead to different benefits for a company (Cimino et al., 2023). Furthermore, it was proved that it can empower operators to address complex issues and make data-driven decisions, enhancing overall efficiency and productivity (Listl et al., 2021). Moreover, centralizing knowledge assets and offering proactive support through simulation can reduce cognitive overload among workers by providing personalized, context-specific information based on their operational needs (Belkadi et al., 2020).

2.2. Human-in-the-Loop vs. Human-on-the-Loop

In the context of smart production, a 'loop' can be defined as a cyclic process of interaction and feedback involving human operators, automated systems, and decision-making mechanisms. This loop encompasses both the physical execution of tasks and the cognitive processing required for decision-making, ensuring continuous improvement and adaptation. The main difference between HITL and HOTL lies in the degree of human involvement (Figure 1). More specifically, HITL involves continuous physical interaction and feedback between human workers and machines. In particular, operators interact:

- *actively* with the system to execute a task, working synergically with machines, equipment, and other operators.
- *real-time*, providing input for the correct execution of the system, which relies on human judgment to complete tasks or make critical decisions.

This allows the operator to execute tasks efficiently, being supported and supporting the operations on the shop floor (Lou et al., 2024b).

Instead, HOTL refers to high-level decision-making and knowledge-based interaction between human experts and the cyber system (Lou et al., 2024b). Operators have a *supervisory* role rather than being directly involved in every decision or action (Figure 1). To support the operator, solutions adopted are DSS, simulation, data analytics, and more, with which they interact in order to control the system and process status. For example, Lou et al. (2024b) developed a system for the disassembly planning of an automated vehicle control box. Here, the HITL-CPS paradigm is used to guarantee the completion of disassembly activities, while experts can select the best disassembly plan using the HOTL-CPS paradigm and allocate relevant jobs to the robot and operator.

Still, in their work, Lou et al. (2024b) suggest that future studies should focus on addressing irrational actions by operators and managing uncertain disassembly conditions, such as robots disassembling rusty bolts. These challenges underline the need for advanced tools that integrate human expertise with automated systems in dynamic production environments. A simulation-based digital twin as a support of a DSS, which implements both HITL and HOTL approaches, can provide a robust framework to meet these demands.

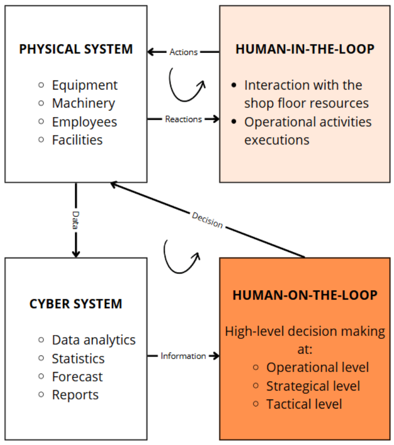


Figure 1: HITL and HOTL approaches

3. Materials and methods

3.1 Conceptual framework

Based on the considerations reported in the previous paragraphs, the conceptual framework of this study is shown in Figure 2. The integration of the two frameworks is possible through the use of a supportive level that integrates simulation software with a Shop Floor Management Tool (SFMT). This layer collects data from the physical system and provides detailed information for decision-making. The HOTL loop facilitates the decisional level by gathering data about the physical system and providing simulated data to the operator. This information is based on the HITL loop at the physical level, where equipment and employees work cooperatively, supported by the SFMT, which provides accurate information based on the decisions made. As such, this work aligns with the first pillar of Industry 5.0, human empowerment and inclusivity.

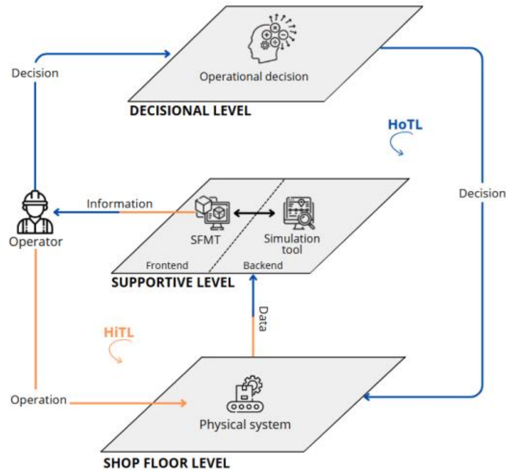


Figure 2: HI/OTL conceptual framework

3.2 Case study

The use case presented in this work is developed in the case of an Industry X.0 Learning Lab at the University of Calabria. Figure 3 shows some of the digital equipment, sensors, and automated systems that are available at the lab to produce beer. The brewing production system is operated by engineering students with no or limited knowledge about the process or equipment. As such, it is possible to compare them to low-skilled industrial operators. The use case regards the brewing process initialization, which is characterized by different activities shown in Table 1. The proposed system aims to shift the decisional authority from expert workers to empowered low-skilled workers regarding the picking of materials from the inventory. In particular, the operator has to decide when to pick the raw materials from the inventory and prepare them for the process to start (e.g., weighing).

Figure 3: Industry X.0 Learning Lab at UNICAL

Table 1: Characterization of process initialization production step

Process step	Process initialization
Description	Setting up and preparing all the necessary resources to start a production process. This stage ensures that all resources, materials, and equipment are available to produce the final product.
Activities	- Order review and planning - Process capacity management - Inventory management - Production scheduling - Equipment set up - Picking planning

3.3 Workflow

Effective utilization of simulation models requires advanced technical skills in system modeling and statistical analysis, which are typically not within the expertise of frontline workers. However, empowering them with the ability to autonomously explore and understand system dynamics can significantly enhance process efficiency. This approach integrates their existing knowledge and competencies with insights gained from 'what-if' scenarios. To facilitate this, we have developed a self-configurable simulation model. This model allows operators to adjust simulation parameters before each run and comprises interfaces enabling users to interact with simulation inputs and outputs.

The developed system is characterized by a continuous interaction between an SFMT and a simulator of the brewing process, using a database to enable communication (Figure 4).

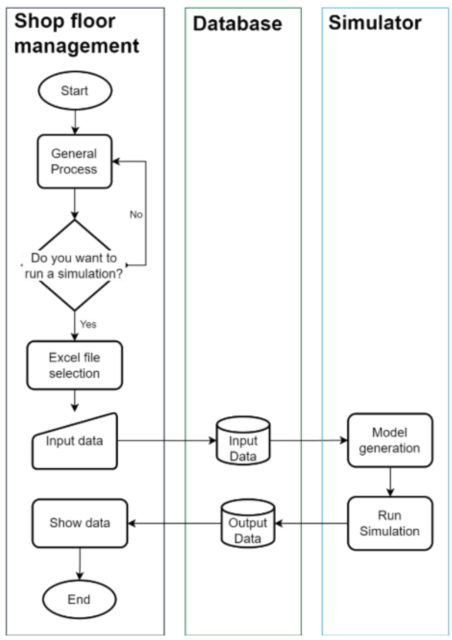


Figure 4: Workflow of the proposed system

Input data regarding the system entities involved in the scenario to be tested needs to be selected from the database (e.g., machines, raw materials, order scheduling, etc.). After feeding and running the simulation, statistics are given as output and saved into the database, which will be visualized in the SFMT by the user. This implies that the user interacts indirectly with the simulation model, thereby simplifying the cognitive effort in using a simulation model.

3.4 Prototype development

A prototype was developed to test the integration of the supportive tools and the data exchange. To this end, we decided to use TULIP as SFMT to provide the user with digital work instructions, and AnyLogic, to run what-if simulations. To integrate TULIP and AnyLogic, the connection through an Excel file was developed. Thanks to APIs, Excel can be easily integrated through HTTP calls to Microsoft's Graph API in TULIP, simplifying the workflow between the software and speeding up the prototyping phase.

Within the Excel file, we structured two distinct worksheets. The first sheet, used within TULIP, serves as a platform for users to insert parameters essential for AnyLogic's simulation. The second sheet functions as the output repository, where simulation results are recorded. Users can conveniently access these results through the TULIP interface. Thus, the workflow guides operators through a systematic process: initially, they are directed within TULIP to input accurate information into the Excel sheet, ensuring the integrity of data fed into the simulation; subsequently, they access the output sheet to visualize the simulation outcomes. The interaction of the different parts of the system is represented in Figure 5.

Regarding picking planning, based on the list of customer orders, the user can simulate the production process, analyze process bottlenecks, system utilization, due date, etc, and decide when to issue an order to the inventory. After that, the user is supported for the execution of the activity by the related work instructions.

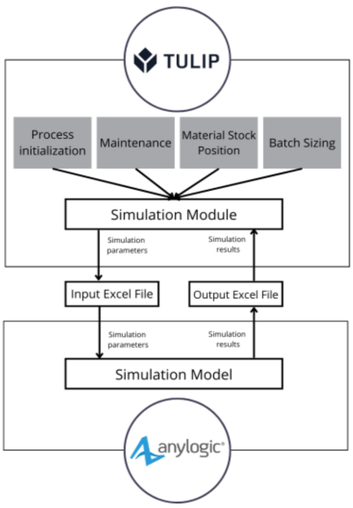


Figure 5: Interaction among the different parts of the proposed system

3.5 AHP

Since not all production activities can involve a line operator on both decisional and operational levels, the AHP is used for determining which approach between HITL and HI/OTL can be applied, based on the specific activity in analysis, in particular the picking planning. The optimal alternative is determined as the best-rated alternative. Four, relevant criteria for the case study are gathered from the literature (Table 2):

- Task execution attention: level of concentration and focus required by an operator to accurately perform a specific task without errors or lapses.
- Decision cognitive demand: mental effort and complexity involved in making decisions related to a task, including information processing, problem-solving, and judgment.
- Operators' experience: accumulated knowledge, skills, and proficiency an operator has gained through practical engagement in similar tasks over time.
- Safety: extent to which a task is performed in a manner that minimizes risks to the operator's health and well-being, as well as ensuring the integrity of the equipment and the environment.

For the determination of the criteria's weights, Saaty's method (Saaty, 1980) has been chosen. In particular, each pair of criteria i and j are rated as shown in Figure 6.

$$(s_{ij}) = \begin{cases} 1 - i \text{ and } j \text{ are equivalent} \\ 3 - i \text{ is mildly preferred to } j \\ 5 - i \text{ is strongly preferred to } j \\ 7 - i \text{ is very strongly preferred to } j \\ 9 - i \text{ is absolutely preferred to } j \end{cases}$$

Figure 6: Criteria evaluation scale

This method compares each pair of criteria i and j. Four experts and practitioners of the sector evaluated the criteria according to their experience. They were equally experts on the subject, which implies that their weight is 1/4. The evaluations are written into Saaty's matrix (Saaty, 1980). The total value per each criterion is calculated and then the standardized priority vector (PV) is determined as the mean value of the experts' rates. The individual alternatives are then rated among each other, per each criterion, by an additional expert in the process, and the PV is calculated. In the end, the final rate of each alternative is obtained as the weighted sum of the related PV per the criteria's PV.

Table 2: Criteria and alternatives considered for the AHP

ID	Criteria	Source
C1	Task execution attention	Biondi et al., (2023)
C2	Decision cognitive demand	Sgarbossa et al., (2020)
C3	Operators' experience	Mabrok et al., (2020); Philips-Wren et al., (2009);
C4	Safety	Dapari et al., (2023)

ID	Alternatives	Source
A1	HITL	Authors
A2	HI/OTL	Authors

4. Results

4.1 System prototype

The system prototype is composed of three main components: the simulation model, the user interface, and interaction and integration settings.

4.1.1 Simulation

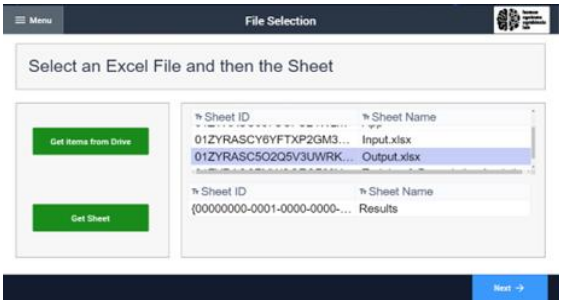
The generation of the simulation model through the SFMT is based on a list of all the system's entities, which are stored in the databases and are used as input. Before the simulation runs, it updates the parameter, creates the machines' network, sets their processing time based on the chosen inputs, and simulates the process. The inputs are i) the number of operators and the path they will follow to move the material from one machine to another, ii) the number and position of machines, and their cycle time, which is dependent on the recipe to simulate (Figure 7). After the simulation ends, it automatically fills an Excel file with the useful information for the operator that will be displayed on TULIP.

	id	name	pos_x	pos_y	cycle_time_mins
1	0	Milling_machine	100	300	12
2	1	Heater_machine	250	500	5
3	2	Brewing_allin1_m...	500	600	5
4	3	Brewing_allin1_m...	500	100	7
5	4	Chiller_machine	600	600	3
6	5	Fermentator_mac...	600	300	13
7	6	Filling_machine	700	600	2
8	7	Filling_machine2	700	100	12
9	8	Capper_machine	800	300	4

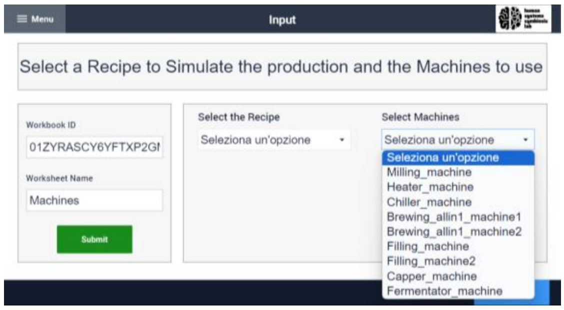
Figure 7: Database used in the use case to set machines' parameters

4.1.2 Interface features

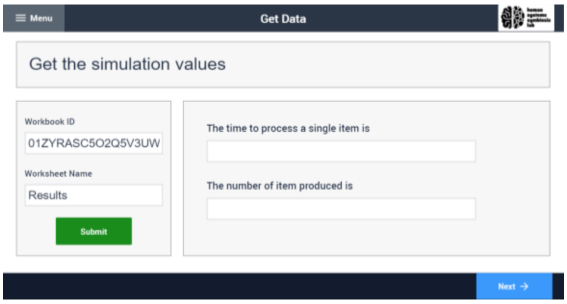
Within the simulation model, the operator must choose which file needs to be accessed (Figure 8a), between the input file (Figure 8b) or the output file (Figure 8c). To prevent typing errors or comprehension difficulties, the input visualization guides the operator through the parameter's settings. The input data can be selected from a drop-down menu where the recipes and machines' lists are available, autonomously filling the table that will be used as input for AnyLogic (Figure 7). By presenting results in a clear, graphical format, operators can quickly grasp the necessary information. This approach can improve interpretability and facilitate more accurate and timely decision-making, enabling operators to easily compare different scenarios and their potential impacts on the production process.



(a)



(b)



(c)

Figure 8: HMI visualization for (a) file decision (b) simulation parameter input (c) simulation results display

4.1.3 Integration and interaction

This system is triggered by the operator through the functionality "Run Simulation" (Figure 9) integrated into the digital work instruction of an uncertain step, the HMI is then redirected to the simulation (Figure 8). The simulation model is built modularly, allowing it to be used in different parts of the process where a variability aspect is introduced (e.g. maintenance, material stock position, batch sizing). The inputs for each activity are already defined, so that the operator is guided through the settings. Data generated by the simulation model will be first displayed to the operator for decision-making and later stored in TULIP tables to be retrieved when needed and displayed in the adaptive digital work instruction that will support the operator in the task execution.

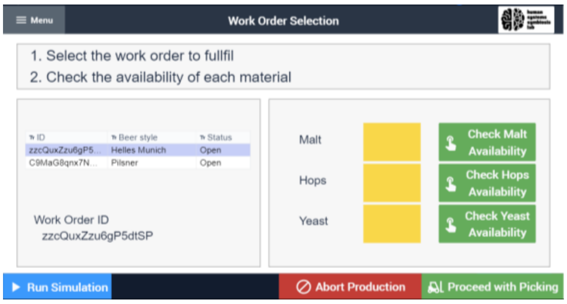


Figure 9: Example of how the simulation can be accessed during normal operations

4.2 AHP for alternatives evaluation

The standardized experts’ evaluation and final mean value are available in Table 3, while in Table 4 are reported the ranking of the alternatives with respect to each criteria and the final rate.

Table 3: Experts' criteria relative evaluation

Criteria	Exp1	Exp2	Exp3	Exp4	PV Mean Value
C1	0,21	0,26	0,22	0,62	**0,33**
C2	0,33	0,49	0,08	0,22	**0,28**
C3	0,37	0,19	0,27	0,11	**0,23**
C4	0,09	0,07	0,43	0,05	**0,16**

Table 4: PV of alternatives' relative ranking per each criterion

Alternative	C1	C2	C3	C4	Final Rate
A1	0,1	0,17	0,75	0,1	**0,27**
A2	0,9	0,83	0,25	0,9	**0,73**

The evaluation shows that regarding the picking activity, a combined approach HI/OTL is suitable for the task execution attention, the decision to be taken, safety, and the low skills of the operators that characterize our use case. By changing the activity in analysis, these results might change, and the line operator would be involved just in operational activities, following a HITL approach.

5. Discussion

This research highlights several important points. Firstly, the decision-making capacity of low-skilled operators at the shop floor level is constrained by their experience. Therefore, the type of decision that they can make is limited and must be carefully evaluated to reduce risks. This constraint can be addressed by applying the AHP at a managerial level, to assess whether an operator can handle both operational and decisional tasks, considering the relevant criteria. In particular, this approach is generalizable and applicable to every activity involved in the production process.

However, since operators can still make errors during the process, the DSS is used to enable the HI/OTL approach. As described above, the system can be applied to any process by adapting the list of defined machines or products that feed the simulation model to the different use cases. This flexibility enhances the system's utility across diverse manufacturing contexts, making it a robust tool for managing dynamic and unpredictable production environments.

From a human-centric perspective, this approach ensures that even low-skilled operators can effectively interact with complex simulation models through a user-friendly interface, democratizing access to technological empowerment. The intuitive design of human-system interaction solutions reduces stress and cognitive load, enhancing operator well-being. Furthermore, the integration of these tools ensures data transparency and interpretability, enabling clear and informed decision-making. Ethical technology use is supported through transparent and justifiable decisions, with active human participation mitigating potential biases in automated processes.

6. Conclusion

The system developed will promote human empowerment, and in particular low-skilled employees, by supporting both decisional and operational tasks. The scientific contribution of this paper lies in the proposed HI/OTL approach, supported by the AHP for an applicability analysis, for SMEs’ line operators, aiming to empower low-skilled operators with decision-making capabilities through a simulation-based DSS.

The next steps of this work will be to test the system with potential users, in order to verify the usability of the interface and the effective advantage of using such a supporting system. Also, the effect of the responsibility shift deserves further study. Both high-skilled and low-skilled operators are affected when using this approach, and their role within the company might change, as well as their cognitive load and satisfaction.

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