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Evolving process maintenance through human-robot collaboration: An agent-based system performance analysis

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ABSTRACT

Periodic inspections of pressurized vessel systems are essential for maintaining safety through early fault detection. Traditional inspections often expose human operators to hazardous conditions within confined spaces. The advent of inspection robots has shifted the paradigm towards human-robot collaboration (HRC), which seeks to reduce risk while maintaining operational adaptability. This study compared the HRC and fully manual (FM) inspection processes, providing strategic insights for stakeholders. Historically, system performance evaluations have simplified or ignored dynamic human factors. To address this oversight, our research employs Agent-Based Models (ABMs) that encompass the evolving nature of human error, including the impact of fatigue and organizational factors, as well as the variability of human behavior and error recovery mechanisms. Our findings reveal that HRC significantly outperforms FM inspections, enhancing efficiency, accuracy, and safety. Notably, the study confirms that the miss rate of artificial intelligence (AI) for image identification within the HRC process is crucial for reliability and should not fall below the threshold of 0.04. This threshold is a benchmark for AI performance in HRC systems, ensuring that the balance between automated efficiency and human oversight is optimized. The research provides a comprehensive evaluation of HRC in pressurized vessel inspections. It offers a deeper understanding of the complex dynamics involved, advocating for integrating robust AI algorithms to support human operators in safety–critical tasks.

1. Introduction

Periodic inspection of pressurized vessels for early fault detection is crucial for safety management and cost savings. In China, it is required that the pressurized vessel equipment be inspected every six years to ensure it is in good condition. Conventionally, this involved qualified technicians manually magnetizing and inspecting this vessel—a task characterized by hazardous working conditions, including exposure to extreme temperatures, substandard air quality, and intense physical demand [11,12].

The rising adoption of robotic assistance in inspection tasks offers a beacon of transformation across various maintenance activities. Inspection robots are progressively introduced to improve the performance of conventional manual maintenance activities, such as power transmission line inspection[2], unmanned aircraft systems asset[27], building inspection[22], and the process industry[32]. This transition is particularly vital in the process industry, where manual inspections are laborious and fraught with risks, including human error—errors that can potentially escalate into full-blown disasters [40]. However, the need for human judgment and adaptability in these critical operations predicates a synergistic human-robot collaboration (HRC) model[20]. Understanding this paradigm shift is essential for informed decision-making regarding resource allocation, scheduling, and risk management.

System performance and reliability analysis could provide valuable decision-supporting information. However, these complex inspection processes comprise various nonlinear behavior components, have specialized functions, and involve many mutual influences, including human workers, automatic robots, and machines [26]. These systems can be classified as dynamic Phased Mission Systems (PMS) and Multi-Phase Systems (MPS)[21]. Researchers have undertaken significant efforts to develop methods for MSS-PMS analysis. Many performance and reliability modeling methods, such as Multistate Fault Tree (MFT) [18], Multistate Multivalued Decision Diagram (MMDD) [28], Bayesian Network (BN) [6], Markov Stochastic Process(MSP) [4], Petri nets (PN)

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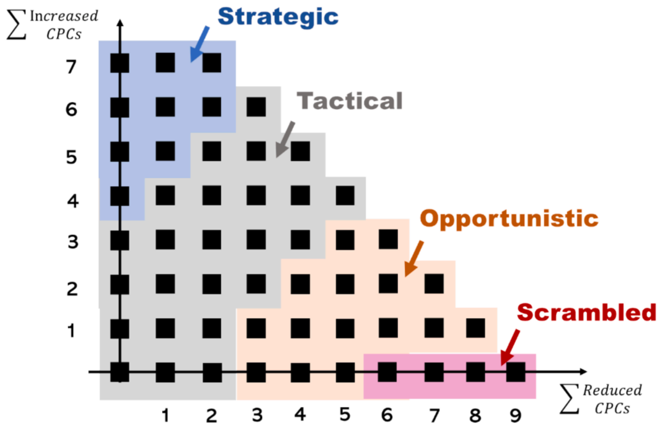

Fig. 1. Control modes [15].

Table 1
CREAM control modes [15].

Control modes	HEP interval	Control modes descriptions
Strategic	0.00005 < HEP < 0.01	Adequate time, practical, management, and organizational support are accessible to consider the actions
Tactical	0.001 < HEP < 0.1	Performance typically follows planned procedures, although some specified deviations are probable
Opportunistic	0.01 < HEP < 0.5	The next action is determined by shallow characteristics of the condition–Situation is characterized by a lack of planning
Scrambled	0.1 < HEP < 1.0	The choice of the next action is unexpected or disorganized

[29], Universal Generating Function (UGF) [36], and their combination have been adopted and updated[14].

However, these system performance modeling methods treat human reliability in a highly simplified and often implicit way. In addition, these methods have difficulties in incorporating social interactions maintenance operational scenarios. Agent-based model (ABM) is a modeling paradigm representing complex interactions and behaviors between components as autonomous agents in a system [23], which can be proposed to overcome this shortcoming. The contributions of this research are summarized as follows:

(1) An ABM modeling framework for a human-robot collaboration (HRC) system is introduced. This framework considers the dynamic human failure rate influenced by fatigue value and organizational factors. It also considers recovery factors, such as self-check, cross-team check, and maintenance of the robots' failure states.
(2) Three dimensions of system performance are defined and assessed. Efficiency is indicated by the total time to complete the inspection, the wrong result rate indicates accuracy, and safety is assessed through occupational accident risk.
(3) This research reveals performance differences between traditional full manual (FM) and HRC inspection systems support, which supports-making in operation designs and management.

The paper is organized as follows. Related works are as follows: Section 2 describes related work in the agent-based framework. Section 4 applies this framework to a case study. Section 5 shows the results and discussion. Section 6 concerns themes in this paper.

2. Related works

2.1. Human reliability analysis

Analyzing and modeling human error interacting with technical failures is essential when modeling a socio-technical system(Farzad [8]. Human reliability analysis (HRA) is a structured approach utilized to estimate the human error probability (HEP) using data, models, or expert judgment[35]. Since the first completed HRA method, The Technique for Human Error-rate Prediction(THERP), was officially proposed[34], the HRA methods have evolved from the simplified human inputs and outputs analysis to the context factors inclusive methods.

Within the second generation method, the Cognitive Reliability and Error Analysis Method (CREAM) proposed nine Common Performance Conditions(CPCs) and the four control modes(Fig. 1) to estimate the HEP (Table 1)[15]. The nine CPCs cover the most critical organizational, technician, and individual factors that can affect the operator behavior, including the adequacy of organization, working conditions, adequacy of human–machine interaction and operation support, availability of procedures, number of simulation goals, available time, time of the day, adequacy of training and preparation, and crew collaboration quality. However, when the context factors were fixed, the CREAM method treated HEP as a static value. An example of an application in the domain of process safety is Jie Geng et al. [17] and Geng et al. [10].

In the actual scenario, the HEP changes over time due to fatigue, stress, and decreased attention. Integrating dynamic models into HRA techniques can provide a better vision of human performance variability. Magoua et al. [24] extended the CREAM method with the Weibull distribution function to generate an increasing time-dependent unreliability curve. Givi et al. [13] proposed the fatigue-recovery and learning-forget human failure rate calculation model based on the learning curve theory and tested it in the assembly industry scenarios. To better consider the influence of fatigue recovery, this research combines CREAM with fatigue recovery factors to extend the CREAM to a dynamic method, as detailed in ABM in Section 3.

2.2. Agent-based models

ABM is a bottom-up method that captures emergent phenomena at the system level that results from the interactions of individual entities. It is recognized to correctly catch the individual behavior when nonlinear or exhibiting memory path-dependence and non-Markov behaviors [5].

Abdelkhalek and Zayed [1] developed an agent-based and discrete event simulation combined model to investigate the time and cost of the inspection process of the concrete bridge deck with non-destructive technologies. Their research considered details about selecting different machines and inspection technologies for some process plans. However, their research did not cover the accuracy of the inspection result and safety operation aspects. Janssen et al. [16] used an agent-based modeling and simulation approach to perform security risk analysis for airport operations, considering temporal and spatial aspects. This research moves from typical operational scenarios to security attack scenarios. However, no human–machine interaction or machine failure was considered. Guo et al. [14] developed a reliability modeling framework characterized by continuous system performance description, including a management agent and several system agents with various normal and failure-type states. This framework was applied in a case study of subsea oil-extracted infrastructure. However, the details of human factors were not included in their research.

Fruggiero et al. (2015) utilized the ABM to optimize the flow shop system performance in terms of production rate, flow time, when machine and worker as two types of limited resource. The model aims to explore task assignments and scheduling. Later, the same research group extended the model to human robotics collaboration scenarios.

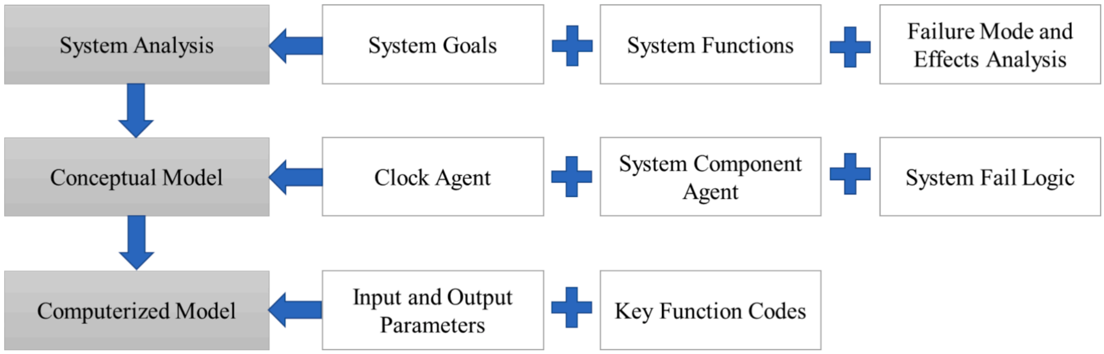

Fig. 2. The model developing stages.

Although their model considered fatigue and stress to influence factors to task time, they did not consider the human error mechanism (Fruggiero et al., 2020).[37] Developed an agent-based multi-fidelity modeling approach for the HRC process to investigate the impact of human-robot collaboration on construction productivity. A low-fidelity model was developed to extract the values of the parameters. Their high-fidelity model considered three human factors, forgetting, muscle fatigue, and behavior uncertainty, to differentiate human and robot agents. The findings of this study did not consider several factors that significantly influence the human-robot collaboration process, such as robot failure and regular maintenance. Ignoring this factor may overestimate the efficiency of the human-robot collaboration scenario.

The above studies prove the advantages of ABM theory applications in complex system analysis. The ABM in this research provides novel contributions in three main ways. First, extend from the regular operation to the failure scenarios considering human error, robot failure, and the maintenance process, Errors generated from human or robot, may change the workflow and introduce extract maintain process and recovery time. Therefore, understanding error dynamics is essential for system optimization and safety. When error mechanisms are explicitly modeled, it becomes easier to quantify uncertainty in the model's outputs. By accounting for the sources and patterns of errors, models can lead to more accurate predictions. Second, dynamic human failure reliability analysis methods are integrated. Finally, an in-depth comparison of the traditional full manual and HRC inspection system performance focused on efficiency, accuracy, and safety.

3. Methodology and model design

The agent-based simulation method could model the human operator and robot as independent agents with attributes expressed by different parameters. This method is chosen to model the total time duration and cost performance of the HRC system, for it has three key advantages:

- Using real-time data generated from probability distribution functions other than the fixed-point value. In this way, the difference between individuals can be represented, and then the uncertainty that comes from the different capacities of the individual, such as the moving velocity or operation velocity, can be simulated.
- Using the message-sending and receiving functions to simulate the process of human-robot or human–human communication and interaction.

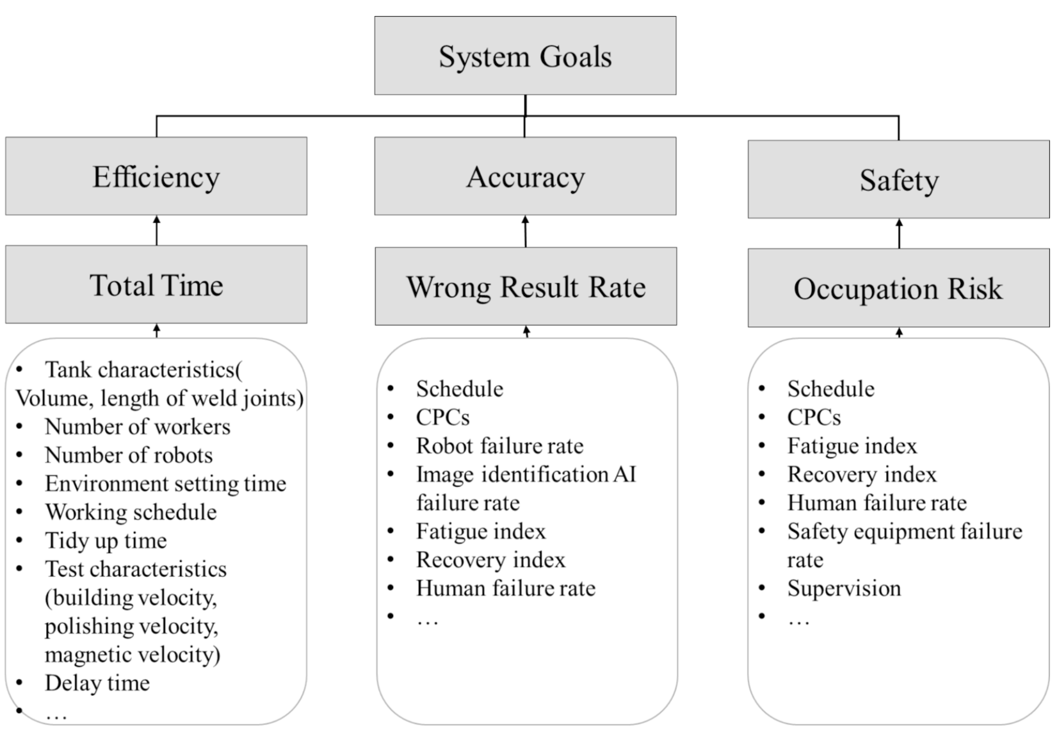

Fig. 3. Parameters influence system goals.

Table 2
FMEA analysis for the HRC operations.

Elements	Operational Mode	Function Requirement	Potential Failure Mode	Potential Cause/Mechanism	Current Process Controls
Polish Robot	Move/Polish	Move along joints	Loss direction	Laser sensor fails	monitoring
			Fall from surface	Move effector fail	monitoring
		Move at the setting speed	Stop	Move effector fail	monitoring
		Polish joints qualified	Low-quality polished joint	The grind brush is worn out	brush alarm
			Low-quality polished joint	Iron pieces cumulate	monitoring
	Control	Remote control	loss control	Communication system fail	monitoring
			loss control	Control system fail	monitoring
			loss control	Video sensors fail	monitoring
	Video	Video of the polishing process	no video	Video sensors fail	monitoring
Magnetic Robot	Move/Magnetic	Move along joints	Loss direction	Laser sensor fails	monitoring
			Fall from surface	move effector fail	monitoring
		Move at a set speed	Stop	move effector fail	monitoring
		Magnetic joints	low quality of magnetic joints	Magnetic effectors fail	alarm
	Control	Remote control	loss control	Communication system fail	monitoring
			loss control	Control system fail	monitoring
			loss control	Video sensors fail	monitoring
	Video	Video of the magnetic process	no video	Video sensors fail	monitoring
Technician	Work in Tank	Robot setting in time	delay setting	delay action	Repeat alarm
	Work in Tank	Robot maintenance on time	delay maintenance	delay action	Repeat alarm
	Work on Site	Robot monitoring	loss situation awareness	no detection	Repeat alarm

- Building the dynamic agent-based model simulates the agent attributes changing over time, such as the fatigue value and human failure rate.

The ABM was developed using AnyLogic© simulation software [3]. The main stages of developing the current model are shown in Fig. 2.

3.1. System analysis

System analysis is the first and foundation stage for model building. Explore the critical system goals and subgoals, define the model's scope, and identify essential system functions and agents.

A periodic non-destructive detection involving defects test of weld joints of a pressurized spherical storage tank is considered. The traditional process requires human operators to work for a long time inside the spherical storage tank, the confined space of a pressured vessel, which causes risks to the process, occupational health, and work delay. The procedure for non-destructive testing of the spherical vessels consists of many steps, all of which must be captured in the task analysis. The FM inspection process includes five stages: environment setting, scaffold building, polishing, magnetic, dismantling, and tidy-up. The HRC inspection process includes four phases: environment setting, polishing, magnetic, and tidy-up.

3.1.1. System goals

The main object of the spherical tank inspection activity is to detect the early fault correctly while considering occupational safety and time duration. Therefore, system goals could be summarized into time efficiency, accuracy, and safety. Examples of corresponding parameters are shown in Fig. 3.

For efficiency, the average total time is chosen as an indicator, influenced by the tank characteristics, resources allocated, working schedule, working speed, and delay. The formula for average total time is calculated as:

$$\overline{T} = \frac{\sum_{i=1}^{N_s}\left(T_{e_i} + T_{b_i} + T_{p_i} + T_{m_i} + T_{d_i} + T_{t_i}\right)}{N_s} \tag{1}$$

Where $\overline{T}$ is the average total project time duration, T_{e_i} is the environment setting work time duration in the ith experiment, T_{b_i} is the scaffold building work time in the ith experiment, T_{p_i} is the polishing work time in the ith experiment, T_{m_i} is the magnetic work time in the ith experiment, T_{d_i} is the dismantle time in the ith experiment, and T_{t_i} is the tidy-up time in the ith experiment. N_s is the number of simulation experiments.

The project's mean wrong result rate is chosen as the indicator for accuracy, influenced by schedule, human error probability (HEP), robot failure rate, and AI failure rate. The formula for the mean miss rate can be:

$$\overline{MR} = \sum_{i=1}^{N_s} \frac{\left(N_{m_i} + N_{f_i}\right)}{N_c{*}N_s} \tag{2}$$

Table 3
FMEA analysis for FM operations.

Agent	Operational Mode	Function Requirement	Potential Failure Mode	Potential Cause/Mechanism	Current Process Control
Construction Worker/Supervisor	Build	Build on high	Fall/Drop	miss execution	safety rope, helmet
		Build in tank	Suffocation	delay execution	check contact every 15 min
		Build stable	unstable	miss execution	self-check, cross-check
Construction Supervisor	Check	Recovery	Omission	omission	cross-check
Polish Worker/Supervisor	Polish	Polish on high	Fall/Drop	miss execution	safety rope, helmet
		Polish in tank	Suffocation	delay execution	check contact every 15 min
		Polish with tool	Get hurt	miss execution	wear gloves
		Polish qualified	Low quality	miss execution	self-check, cross-check
Polish Supervisor	Check	Recovery	Omission	omission	cross-check
Technician/Supervisor	Magnetic	Magnetic on high	Fall/Drop	miss execution	safety rope, helmet
		Magnetic in tank	Suffocation	delay execution	check contact every 15 min
		Magnetic with tool	Get hurt	miss execution	wear protect mask
		Magnetic qualified	Low quality	miss execution	cross-check
	Inspection	Find and mark the crack	Miss the crack	miss execution	cross-check
			False identify crack true	miss execution	cross-check
Technician Supervisor	Check	Recovery	Omission	omission	cross-check

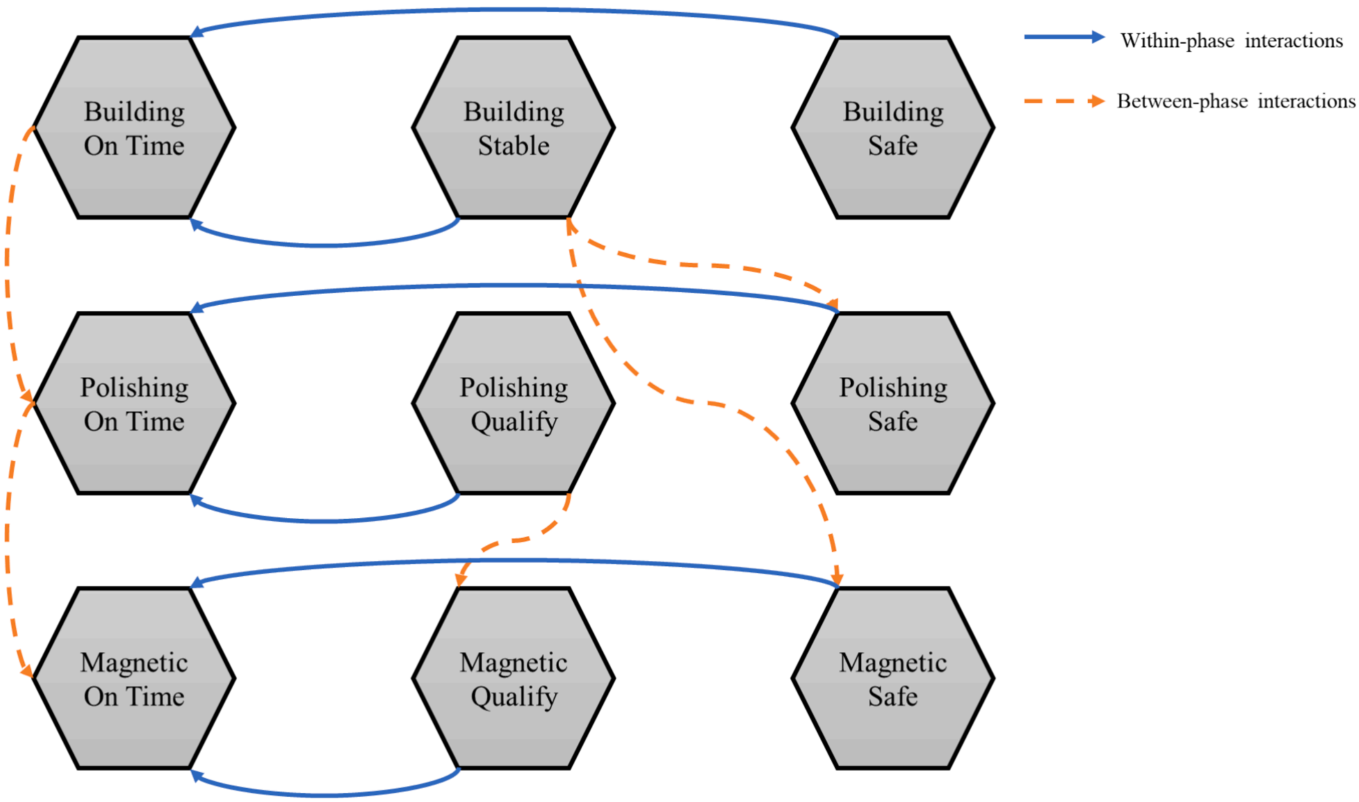

Fig. 4. Critical indicators of different stages and their interactions.

Where $\overline{MR}$ is the average project miss rate, N_{m_i} is the number of missed cracks in the i^{th} experiment, N_{f_i} is the number of false true cracks in the i^{th} experiment, N_c is the number of real cracks and N_s is the number of simulation experiments.

For safety, occupational safety risk is chosen as the indicator, and it is influenced by schedule and human error. The formula for the occupational safety risk can be:

$$\overline{OR} = \sum_{i=1}^{N_s} \frac{\sum_{j=1}^{N_o} N_{i,j} * C_{i,j}}{N_s} \tag{3}$$

Where $\overline{OR}$ is the average occupational safety risk, N_S is the times of simulation experiments, N_o and j is the number of occupation incident types, and $N_{i,j}$ is the number of incidents of type j in the i^{th} experiment. $C_{i,j}$ is the consequence level scores of incidents of type j in the i^{th} experiment.

3.1.2. *System functions*

3.1.2.1. System process phases. Human workers or robots move along the weld joints at the working speed to represent the critical phases. In addition, the robot's movement path and difference in velocity of movement and working will also be considered. Since the focus of the research is on polishing and magnetic inspection phases. The environment setting and tidy-up phases are simplified. They differ in terms of the time interval in the HRC and the FM systems. The scaffold-building process will be simulated by working speed and workload in terms of the volume of the spherical tank.

3.1.2.2. System functions failure and transition paths. The HRC operations include three element roles: polish robots, magnetic robots, and technicians. The detailed Failure Mode and Effects Analysis (FMEA) [33] for the HRC operations is shown in Table 2. The FM operations include six actors: construction workers, construction supervisors, polish workers, polish supervisors, technician workers, and technician supervisors. The detailed FMEA analysis is shown in Table 3.

3.2. *Conceptual model design*

3.2.1. *Agent model*

Bonabeau [5] defines each agent as independent, able to communicate with other agents, adapt to environmental changes, and influence the environmental states. An agent in the model has a unique index, can receive input variables from environment in form of message or other trigger conditions, has a set of attributes that could be express with its own parameters, a set of behaviors and the transition functions for its behaviors and results.

3.2.2. *Phases model*

The FM process has three primary phases: scaffold building, weld joints polishing, and weld joints magnetic. The three indicators described in 3.1.1 interact with each other (Fig. 4). The first phase, building on time, will be influenced by building stability and safety. The on-time completion of the second phase will be influenced by the timely completion of the first stage, polishing quality, and polishing safety. Polishing safety is also influenced by building stability. The first and second phases will influence the last phase on time, magnetic quality, and magnetic safety. In addition, the magnetic quality will be influenced by the polishing quality. Magnetic safety will be influenced by building stability. This phase's logic is likewise for the HRC process, excluding the building scaffold phase.

3.2.2.1. Total time model. In the FM inspection process, in normal operation as the total move distance and work amount is fixed, the total time will be influenced by workers' walking velocity, climbing velocity, and working velocity. If an accident happens, extra time will be needed to recover the situation. If a mistake happens in scaffolding or polishing operations and discovered by supervisor, more time will be delayed for

Table 4
The accident consequence scores in the FM scenarios.

Accident type	Accident description	Linguistic scale	Consequence scores
Accident 1	Hurt by a dangerous tool	Minor cuts, bruises, bumps	1
Accident 2	Suffocation, with rescue in time	Fatality	25
Accident 3	Suffocation, with no rescue in time	Multiple fatalities	50
Accident 4	Falls or hit by a fall-down object without protection	Fatality	25

the repeat of the previous operations.

In the HRC inspection process, in normal operation as the total move distance and work amount is fixed, the total time will be influenced by robots' walking velocity and working velocity. If an accident or maintenance event happens, extra time will be needed to recover the situation. If a mistake happens in polishing operations and discovered by monitoring workers, more time will be delayed for the repeat of the previous operations.

3.2.2.2. Wrong result rate model. In the FM inspection process, the polishing workers' errors may lead to low-quality polished weld joints. The two polishing supervisors will randomly choose four weld joints to check, and the technician supervisors will double-check four randomly chosen weld joints. Repolishing will start if any low-quality polished weld joint is found among these eight weld joints. Based on the previous work, the velocity of repolishing work will be three times the regular working speed. Moreover, the magnetic workers' errors in the spray and magnetic process may lead to low-quality magnetized joints in dynamic HEP. In the magnetic phase, three technicians cooperate as a group. The technician supervisors will check the inspection results and correct the falsely identified cracks. Finally, if the polished weld joints are of low quality, the magnetized joints will be of low quality, or the technician will make an error in recognizing the crack, and the number of missed or false true cracks will increase. Then, the wrong result could be calculated by Equation (2).

In the HRC inspection process, when a polishing robot is performing the polishing work, if it is in the polishing brush failure, too many iron pieces accumulate, or the automatic navigating laser sensor failure states and the alarms are not detected by technicians. The polished weld joints will be low-quality. Furthermore, the robot will keep on sending alarms when in failure states. If technicians detect the alarms and the control system works well, they will stop the robot and perform maintenance and recovery. Moreover, if the automatic navigating laser sensor fails when a magnetic robot performs magnetizing work, the magnetized weld joints will be low-quality. These failure modes also could be maintenance or recovery if the control system works. If there is a real crack, and the AI image identification algorithm fails to identify the crack, the missed crack number will increase. In addition, if the AI identifies a real or false true crack, it will alarm the technicians. If they miss this alarm in the dynamic HEP, the missed crack or false true crack numbers will increase.

3.2.2.3. Occupational risk model. For the FM process, the construction workers must work at height in a confined space with air quality detection equipment. Besides these risks, the polishing workers must also work with dangerous tools such as polishing sander. However, accidents could be prevented, or their consequences could be reduced by personal protective equipment (PPE). In contrast, the failure rate of not wearing a PPE is the initial failure rate of the worker and the supervisor. According to the literature [9], the consequence can be represented by scores. Then, the consequence scores for the corresponding accident type were assigned, as Table 4 shows.

3.3. Computerized model

3.3.1. Agent hierarchy

The FM model has three kinds of agents: the clock agent, the human agent, and the joint agent. The HRC model has five kinds of agents: the clock agent, the human agent, the robot agent, the joint agent, and the requirement agent. In this research, the hierarchical structure is described similarly to the study by Wu et al. [37] to express the agents' relationship, as shown in Fig. 5. Three layers are presented in this structure. The first layer is the simplified layout of the inside of the spherical tank and work site where technicians monitor the robots' work. The scaffold is simplified as a ladder to show the distance workers need to climb. In addition, this layer includes the system parameters as the model inputs and outputs.

The clock agent schedules the working and rest duration; the workers will shift every hour because of the low quality of air. For the HRC scenario, the clock is two hours a shift. The requirement agent is designed to record the arranged or randomly generated task or alarm for human workers in a requirement list to communicate them to a worker in the monitoring state and with attention (expressed as human reliability).

In the second layer, the internal states and transitions of the five agents are designed. The third layer includes the extended type of human agents, such as construction workers, polish workers, and

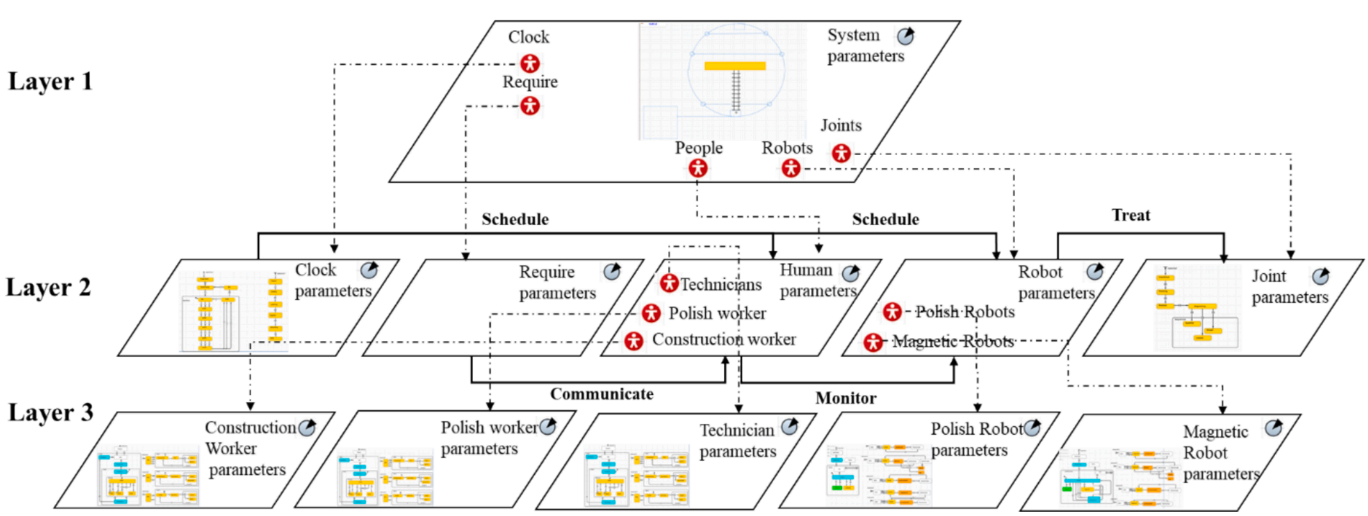

Fig. 5. Agent hierarchy structure.

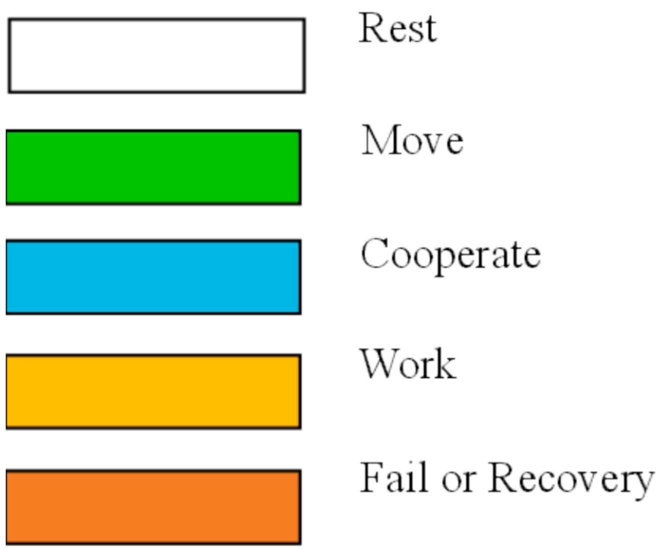

Fig. 6. Color response to different state type.

technicians. In addition, this layer includes the extended type of robot agents such as polish robots and magnetic robots.

3.3.2. *Modeling the work schedule*

As shown in Fig. 7, The state chart on the left simulates the daily work shift. Task analysis can support the development of this model, as in Yilmar Builes et al. [39] and Leva et al. [19]. While a function code is developed to get human worker states, if they have not finished the tasks or alarms in the requirement list, the work shift will be delayed, and the delayed time will be recorded. The state chart on the right simulates the project phase, shifting the work states of human workers. The clock agent in the HRC scenario is similar. Also, in the state charts for all agents, different colors are employed to represent different state types, as Fig. 6 shows.

3.3.3. *Modeling human workers*

3.3.3.1. The common factors of human workers. Three common factors are considered in the modeling of human operators.

(1) Dynamic human error probability.

As discussed above, the performance of humans reduces over time due to fatigue, stress, and loss of concentration accumulated over long, continuous working time. The contributors to fatigue are summarized in Fig. 8.

Givi et al. [13] proposed the fatigue-recovery and learning-forget human failure rate calculation model based on the learning curve theory and tested it in the assembly industry scenarios. According to their research the fatigue value could be calculated using the following formula:

$$F(t_i) = R(t_{i-1}) + (1 - R(t_{i-1}))(1 - \exp(-\lambda t_i)) \tag{4}$$

Where F (t_i) means the fatigue value after the ith period of work, R (t_{i-1}) represents the residual fatigue value after the (i-1)th period rest, and λ is the fatigue index.

$$R(t_i) = F(t_{i-1})\exp(-\mu t_i) \tag{5}$$

Where R (t_i) means the residual fatigue value after the ith period of rest, F (t_{i-1}) represents the fatigue value after the (i-1)th period of work, and μ is the recovery index.

Move to next step Givi et al. [13] developed the human error rate could be mapping with fatigue value and learning functions. In this research, the project is not repeated in a short time of internal work. Therefore, the learning-forget model is unsuitable. In addition, critical organizational factors such as working conditions, human–machine interface, training, and procedures must be considered. Therefore, the CREAM method is employed in this research to incorporate organizational factors. The base human error probability (HEP_{base}) is calculated by the CREAM control mode.

$$U(HEP_{base}, f) = HEP_{base} {}^* w_b + F^* w_f \tag{6}$$

Where HEP_{base} represents the primary human error probability value,

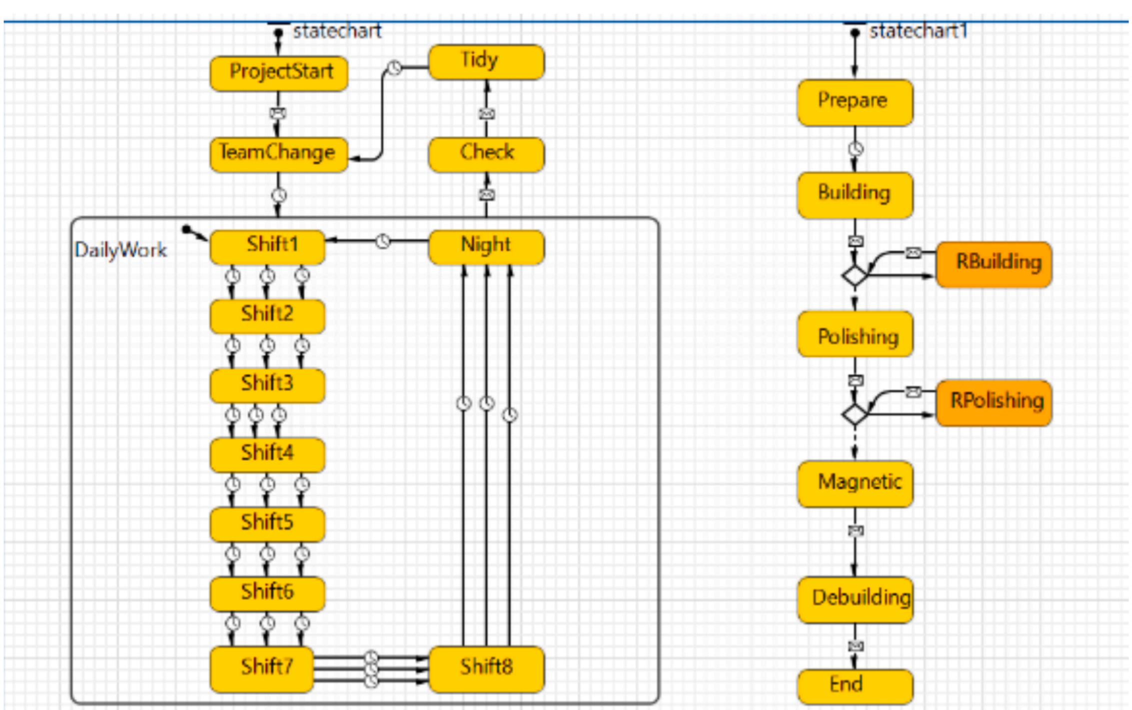

Fig. 7. The clock agent in the FM scenario.

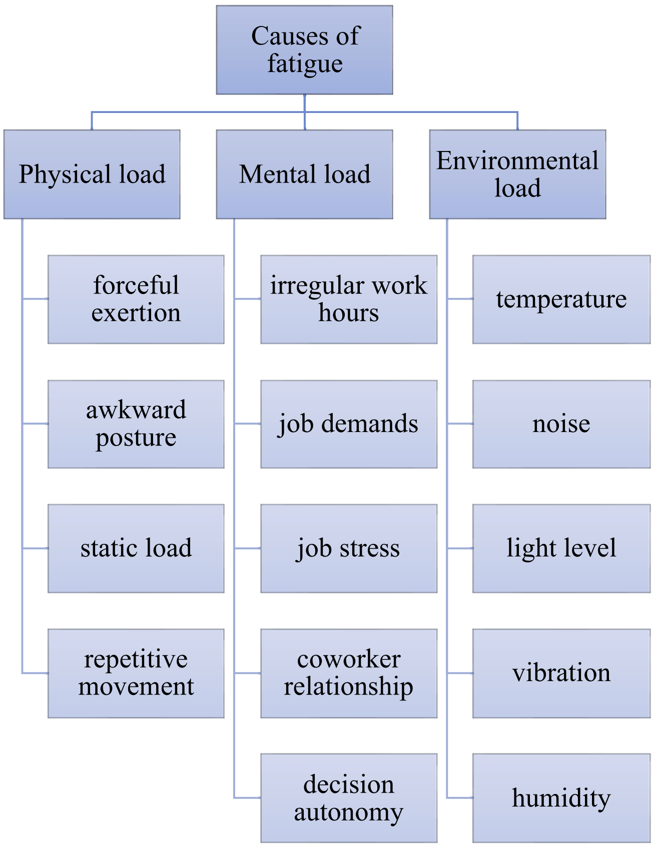

Fig. 8. Causes of fatigue []. adapted from 30

and f represents the fatigue value obtained from formulas (4) and (5), the w_b and the w_f are the weight for HEP_{base} and fatigue value, they are set as equal as an initial attempt.

$$\log(HEP) = 6 \times \log(U(HEP_{base}, f)) \tag{7}$$

Where HEP represents the human error probability value, and U (HEP_{base}, f) is obtained from Equation (6).

(2) human error recovery.

This research considers recovery factors, including self-check, supervisor double-check, and cross-team check.

(3) behavior uncertainty.

The most direct way to model the human workers' behavior uncertainty is to add distributions other than a point value to represent the random performance in the simulations (M. [37]. The triangular distributions with a 20 % variance are employed to represent human behavior uncertainty.

3.3.3.2. The human task and failure logic for the manual model. The

Table 5
The parameters of the human worker agent in the FM process.

Parameter	Meaning	Value
lambda_fatigue	Fatigue index	0.0192
um_recovery	Recovery index	0.0144
HEP_base	The primary human error probability from the CREAM control mode	[0.001,0.01]
Walking velocity	The moving velocity outside the tank	1.2 m/s
Climbing velocity	The moving velocity on the scaffold inside the tank.	0.3 m/s
Working velocity	The velocity to complete the workers' main task, e.g., for the construction worker, is the scaffold building velocity.	3.75 m3/h, 0.005 m/s, 0.008 m/s,

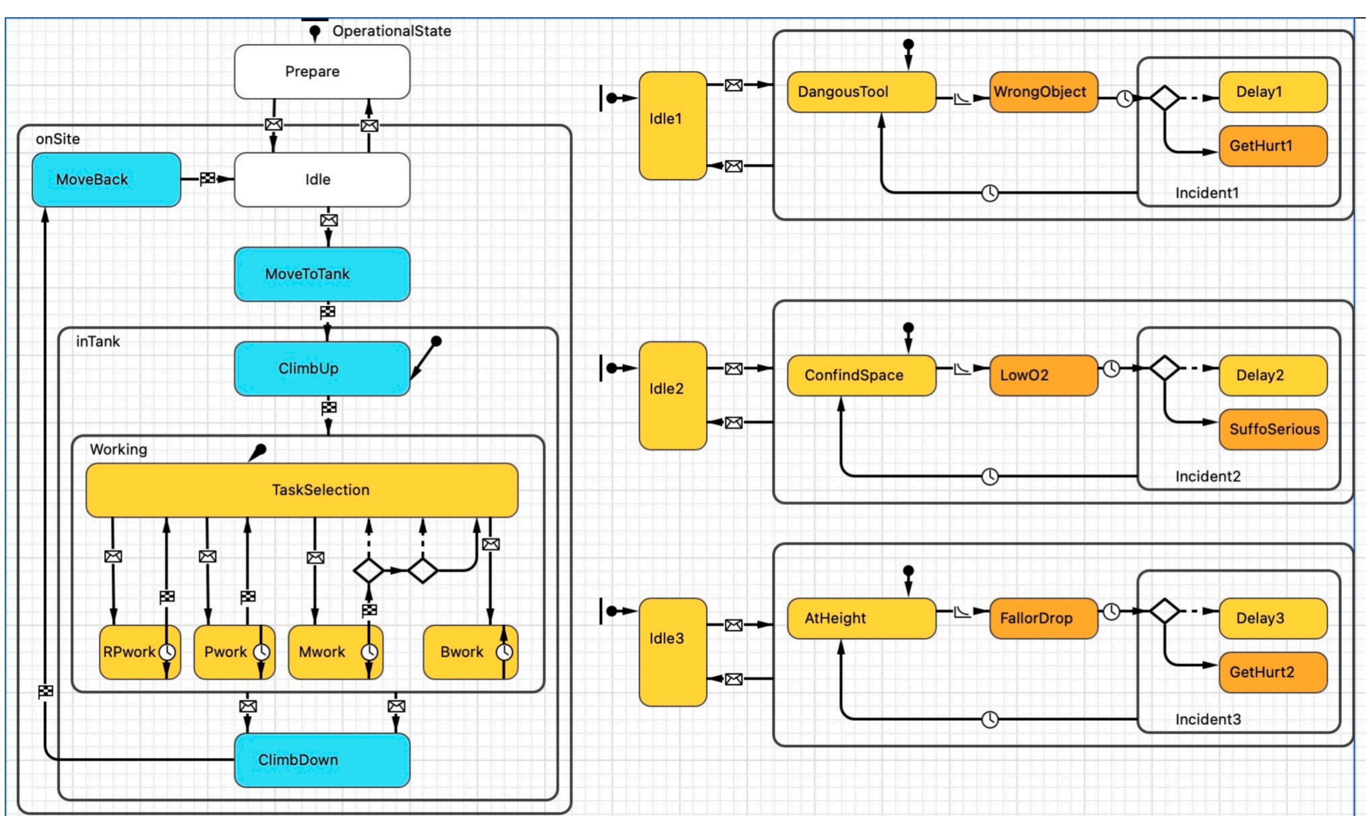

Fig. 9. Human workers' state chart in the FM scenarios.

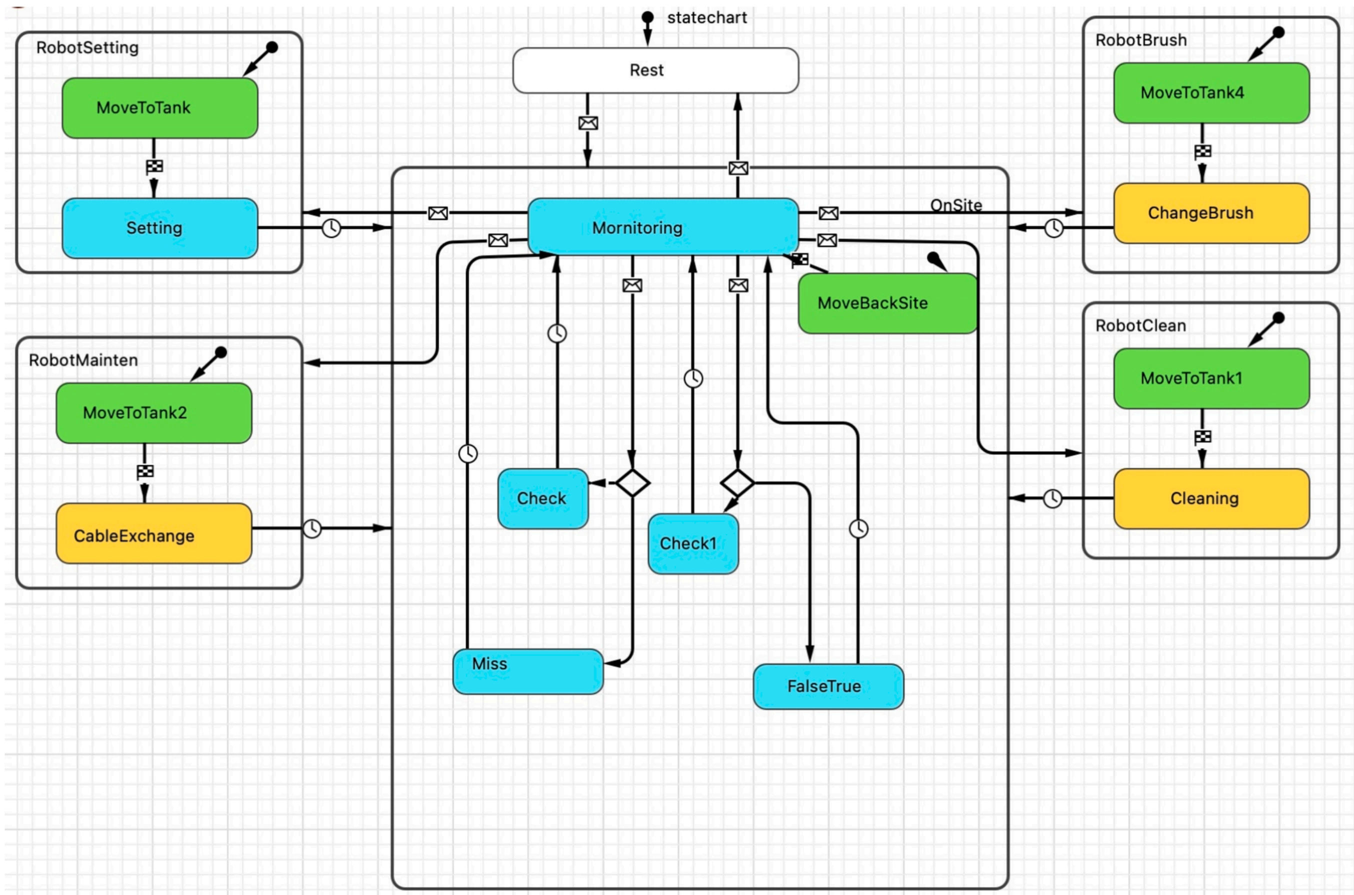

Fig. 10. Human workers' state chart in the hrc scenarios.

Table 6
The parameters of the human worker agent in the HRC process.

Parameter	Meaning	Value
lambda_fatigue	Fatigue index	0.0096
um_recovery	Recovery index	0.0144
HEP_{base}	The primary human error probability from the CREAM control mode	[0.001,0.01]
Mean human Walking velocity	The average moving velocity outside the tank	1.2 m/s
Mean Check duration	The average time for technicians to check the crack identified by a magnetic robot.	3 min
Mean Fix duration	The average time for technicians to repair a problem of the robot	15 min

construction worker needs to perform the scaffold building work. The polish worker needs to perform the polish job. Moreover, the technician needs to perform the magnetic work. Main hazards that lead to occupational accidents include working at height, working inside a confined space, and working with sharp edges and dangerous tools.

As shown in Fig. 9, human workers have one operation state chart on the left. In addition, they have three failure state transition charts on the right. The failure state will be triggered by rate, and personal protection equipment can be a barrier. Therefore, the result will be a delay or accident. Accidents will happen when a hazardous event happens, and humans fail to wear PPE, and the supervisor does not discover this. The parameter settings for human workers in the FM scenarios are shown in Table 5.

3.3.3.3. The human task for the HRC model. The technician in the HRC model needs to perform the robot setting, the robot monitoring, the robot regular maintenance, the robot response maintenance, and the magnetic crack check task. The task paths are shown on Fig. 10. The parameter settings for human workers in the HRC scenarios are shown in

Table 7
The parameters of a robot agent.

Parameter	Meaning	Value
$AI_{missrate}$	The rate of the crack image identification AI misses a crack	0.01
$AIf_{alsetruerate}$	The rate of the crack image identification AI judges a no crack as true	0.1
Up	If the robot responsible for the up area of the spherical tank	True or False
Robot Moving velocity	The moving velocity inside the tank	0.057 m/s
Robot Polish Working velocity	The velocity to perform the polish task.	0.008 m/s
Robot Magnetic Working velocity	The velocity to perform the magnetic task.	0.01 m/s
Mean Setting duration	The average time duration for the technician to set this robot.	3 min
Lambda_brush	The failure rate of the polish brush worn out	0.2/hour
Lambda_iron	The failure rate of the iron piece cumulated	0.1/hour
Lambda_effector	The failure rate of the effector of the robot	5.4E-7/hour
Lambda_LS	The failure rate of the laser sensor of the robot	1.2E-7/hour
Lambda_VS	The failure rate of the video sensor of the robot	1.2E-7/hour
Lambda_comm	The failure rate of the communication system of the robot	3.2E-7/hour
Lambda_control	The failure rate of the control system of the robot	6.4E-7/hour

Fig. 11. The FM and HRC operation scenarios.

Table 6.

3.3.4. Modeling the robot agent

The essential components of the robot include a mechanical part, control system, sensor, and actuator. According to China's regulation regarding industry robots, the MTBF is no less than 50,000 h. Then, the total robot failure rate can be estimated as 2×10^{-6}. According to empirical research results, the distribution of failure rate among different parts was the control system at 32 %, The effectors at 27 %, Communication at 16 %, Sensing at 12 %, and Power at 12 % [7]. Then, the following failure rates were estimated. The control system is at 6.4×10^{-7}, Effectors at 5.4×10^{-7}, the Communication system at 3.2×10^{-7}, the Sensor at 2.4×10^{-7}, Power at 2.4×10^{-7}, and Others at 2×10^{-8}. According to the field investigation and interview results. According to the inspection image AI algorithm training research literature(Q. [38], the relationships between Precision with $AI_{falsetruerate}$ and Recall with $AI_{missrate}$ are show in Equitation (8)(9). The parameter settings for robot agents in the HRC scenarios are shown in Table 7.

4. Case study

4.1. Case description

The cases analyzed come from the Special Equipment Inspection Institute in Zhejiang, China. The specific pressure vessel considered in this case study is a 5000 m^3 spherical, above-ground LPG storage tank; the total length of all weld joints is 710.4252 m. There are two polar zones and two temperate zones of weld joints.

4.2. Data collection

Three approaches were used to ensure the reliability of the study.

(1) Semi-structured interview. The information required to describe the inspection on the site was collected through semi-structured interviews. The interview script was designed to collect the following information: (a) the inspection for pressurized spherical tank phases and corresponding goals and subgoals. (b) teams involved in each phase and their respective goals and functions (c) critical task scenarios such as occupation risk and getting wrong results. Four field experts participated in the interview: one project manager, one inspection team technician, and two robot testing technicians. They all have 7–10 years of practical experience in pressurized equipment inspection. (d) the assessment for the weight of CPCs was collected by questionnaire; five experts with more than ten years of experience in chemical engineering participated in the assessment.

(2) Technical document collection. Relevant inspection documents were collected to provide details for implementing the method, including the inspection organization plan, scheme, technical standards and guidelines, risk and hazard list, and emergency response plan.

(3) Field investigation. A team of three scholars performed one work field investigation of a spherical tank inspection process in the FM and HRC scenarios, which were visited and recorded (Fig. 11).

4.3. Assumptions

(1) There is no more than one crack on one weld joint, the total number of no cracks is set as a fixed number of 24. While the real situations will be random number of cracks, this will not influence the indicator wrong result rate, therefore, this setting is for the convenience of simulation and comparison of the wrong result rate of the inspection process at the same starting baseline.

(2) The fatigue index for the HRC working conditions is set as 0.0096, which is calculated by Equation (4), which means that human workers will be exhausted after 12 h of work. The recovery index for the HRC working conditions is set as 0.0144, calculated by Equation (5), which means that human workers will recover after 8 h of work. At the same time, the fatigue index for the FM working conditions is 0.0192, calculated by Equation (4), which means that human workers will be exhausted faster after 6 h of work. The recovery index for the FM working conditions is also set as 0.0144. This setting is mostly a response to the real working conditions according to the labor law in China.

(3) In the FM systems, the shift schedule is set for one hour of work and rest for two groups, and in the HRC systems, the shift schedule is set

Table 8
The parameters setting for the sensitivity test.

Parameter	Min	Max	Step
HEP_{base}	0.001	0.01	0.001
HEP_{base} in the HRC scenario	0.1	0.5	0.05
Lambda_fatigue in the FM scenario	0.0144	0.028	0.002
Lambda_fatigue in the HRC scenario	0.0096	0.0144	0.002
$AI_{missrate}$	0.01	0.25	0.02
$AI_{falsetruerate}$	0.05	0.4	0.05

to two hours a shift. Each operator will work up to eight hours per day. This setting is mostly a response to the real working conditions according to the interview and field investigation.

4.4. Human reliability estimate

According to the expert judgment, the levels of CPCs for each group were graded, as Table A.1 shows. Then, the control modes of operators were set to be tactical, and the supervisors were set to strategic. Therefore, the basic HEP for operators was represented by a uniform distribution ranging from 0.001 to 0.1. The basic HEP for supervisors was calculated by the basic HEP for operators in the same group and multiplied by 0.5 coefficient, as they have more experience and knowledge.

4.5. Experiment setting

The primary settings for the HRC system model are two polish robots, two magnetic robots, and four technicians. At the same time, the FM system model resource settings are 18 construction workers, 12 polish workers, and 6 technicians.

ABMs are used as the Monte Carlo sampling object. All the human behavior parameters are randomly generated from the pre-set distributions. The Monte Carlo experiments for the FM and HRC operations were run 5000 times with random seeds and every 10 data as a group to calculate the mean value for total time and wrong result rate according to Equations (1) and (2). The mean occupational risk value was calculated based on extra data from Monte Carlo experiments in the FM scenario, including 200,000 data, and the bootstrapping method was employed for every 10,000 data in a group to run 1000 times to catch better the occurrence of an occupational accident.

For the sensitivity test, the experiment setting for each parameter is shown in Table 8. The sensitivity experiment for each step value of one parameter ran 500 times to catch the random behavior, and every 10 data as a group was used to calculate the mean results.

5. Results and discussion

Based on the ABMs and Monte Carlo methods, the modeling and simulations of the FM and HRC scenarios for the pressurized vessel inspection process were performed, and the results of the experiment data are as follows:

5.1. HRC operations performance assessment and comparison

After the Shapiro-Wilk test[31], the total time and wrong result rate results are not from a normal distribution with p-values smaller than 0.001. Their density distributions are shown in Fig. 12 A and B; the results demonstrated that the HRC system performance indicators had significantly lower variance in total time and wrong result rate, indicating the HRC had higher system reliability. The two-sample Wilcoxon rank-sum (Mann-Whitney) test [25] is selected to compare the FM and HRC operations' data. Results show that the HRC process could reduce the total time by more than half. The median value of mean total time changed from 432.25 to 181.60 (Fig. 12 (C)). As shown in Fig. 12 (D), the median value of the wrong result rate decreases from 0.04 to 0.01. This result is based on the image identification miss rate of 0.01 and the

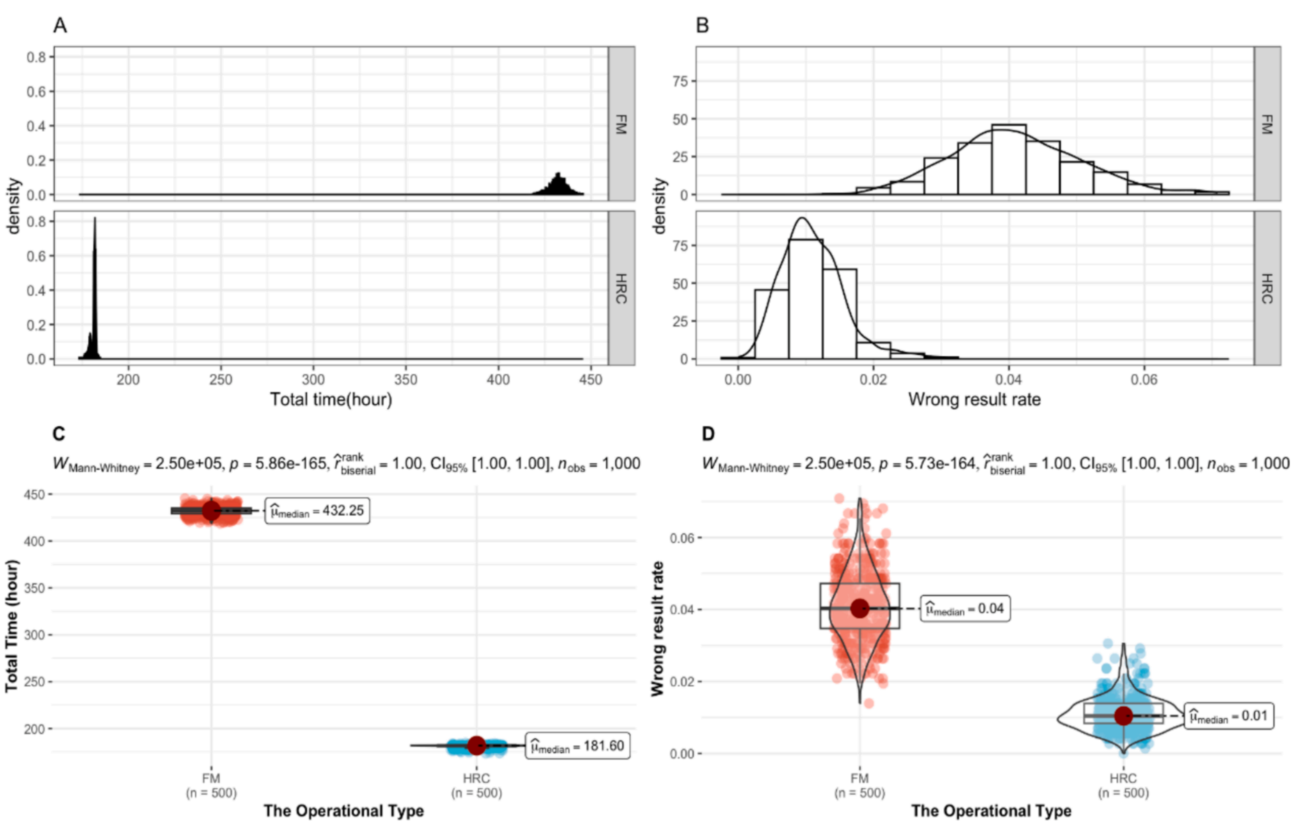

Fig. 12. System performance comparison between two operational types.

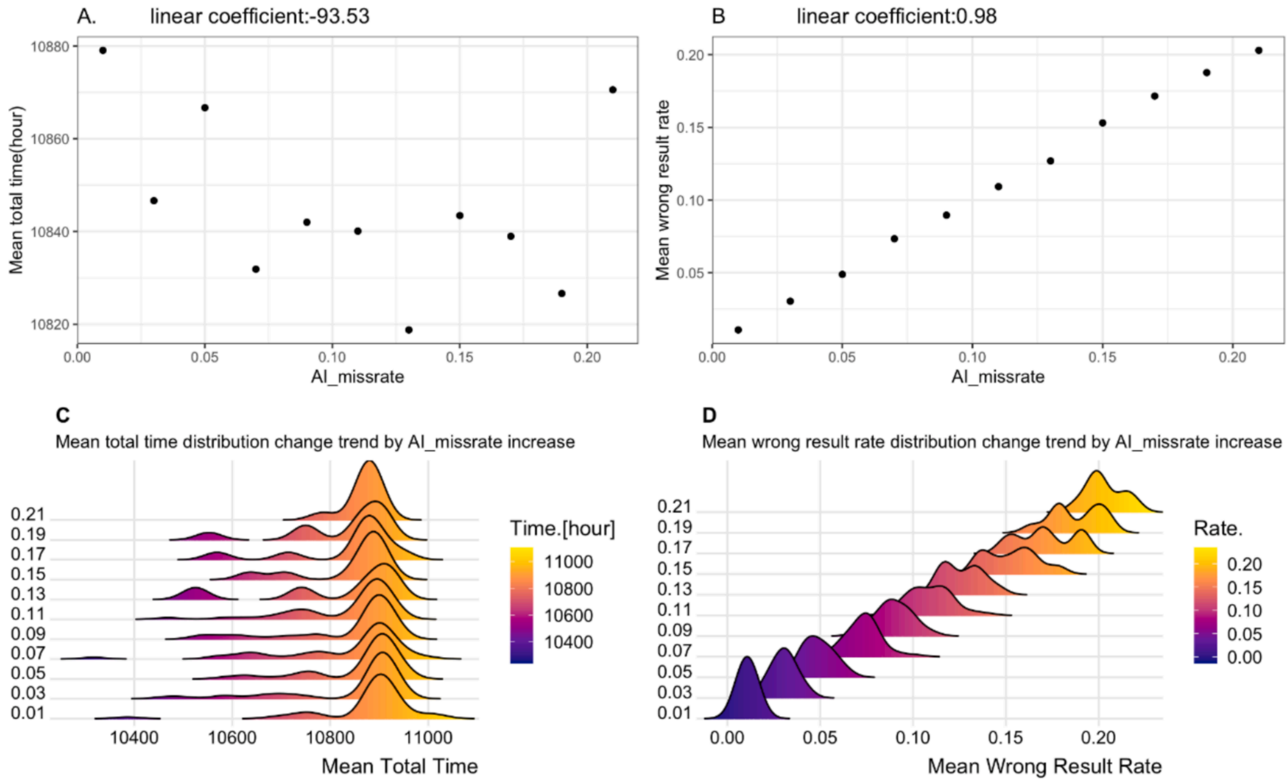

Fig. 13. System performance sensitivity to $AI_{missrate}$ in HRC operations.

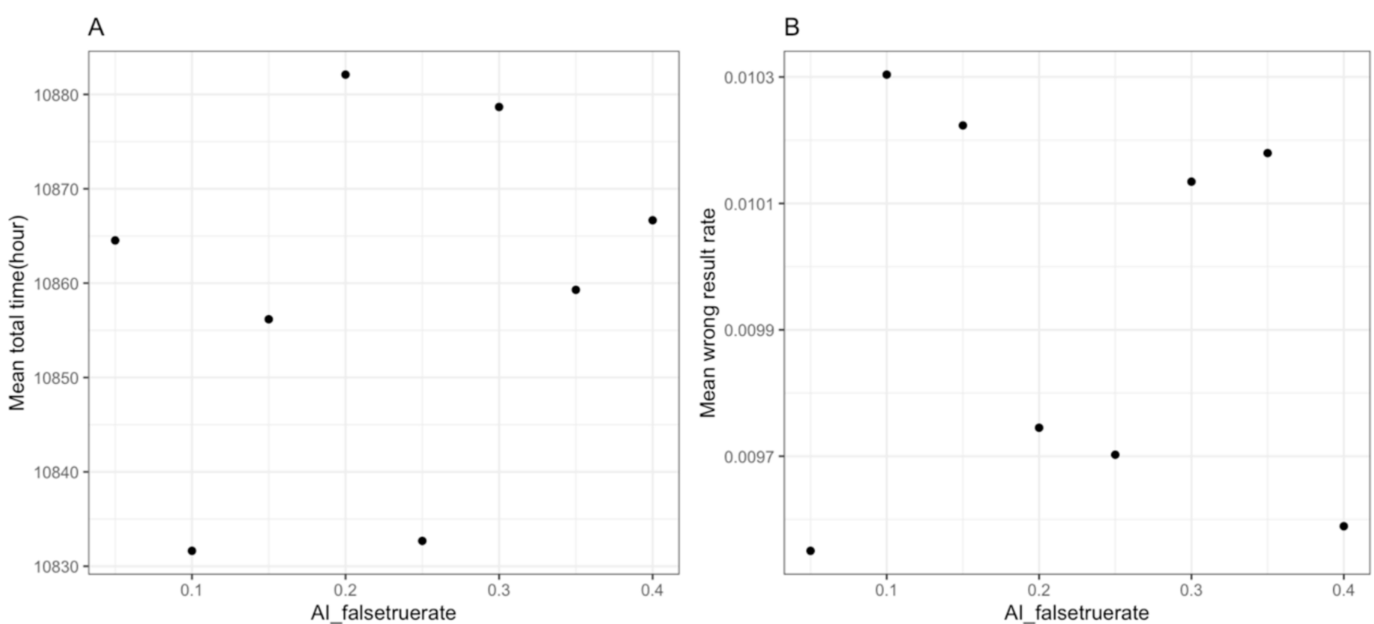

Fig. 14. System performance sensitivity to $AI_{falseturerate}$ in HRC operations.

false true rate of 0.1, which is an ideal value for the AI image identification algorithm.

For safety, the mean occupational safety risk in the FM process is 6.23×10^{-3} with a probability of 2.50×10^{-4} in the FM operations. In contrast, the value for the HRC process is nearly zero. In addition, the mean in-tank time of the construction workers is 55.74, the mean in-tank time of the polish workers is 42.11, and the mean in-tank time of the technicians is 47.32. In contrast, the in-tank time of technicians in the HRC system is less than one hour. In this way, the HRC process could reduce contact with occupation hazards by a great deal.

5.2. HRC scenario sensitivity analysis

The mean wrong result rate of the HRC process is significantly sensitive to the miss rate of image identification algorithms ($AI_{missrate}$). As the $AI_{missrate}$ increases, the mean value of the wrong result rate tends to increase as well and spread to a broader range, as shown in Fig. 13 B and D. While the mean total time is not sensitive to $AI_{missrate}$, this indicator

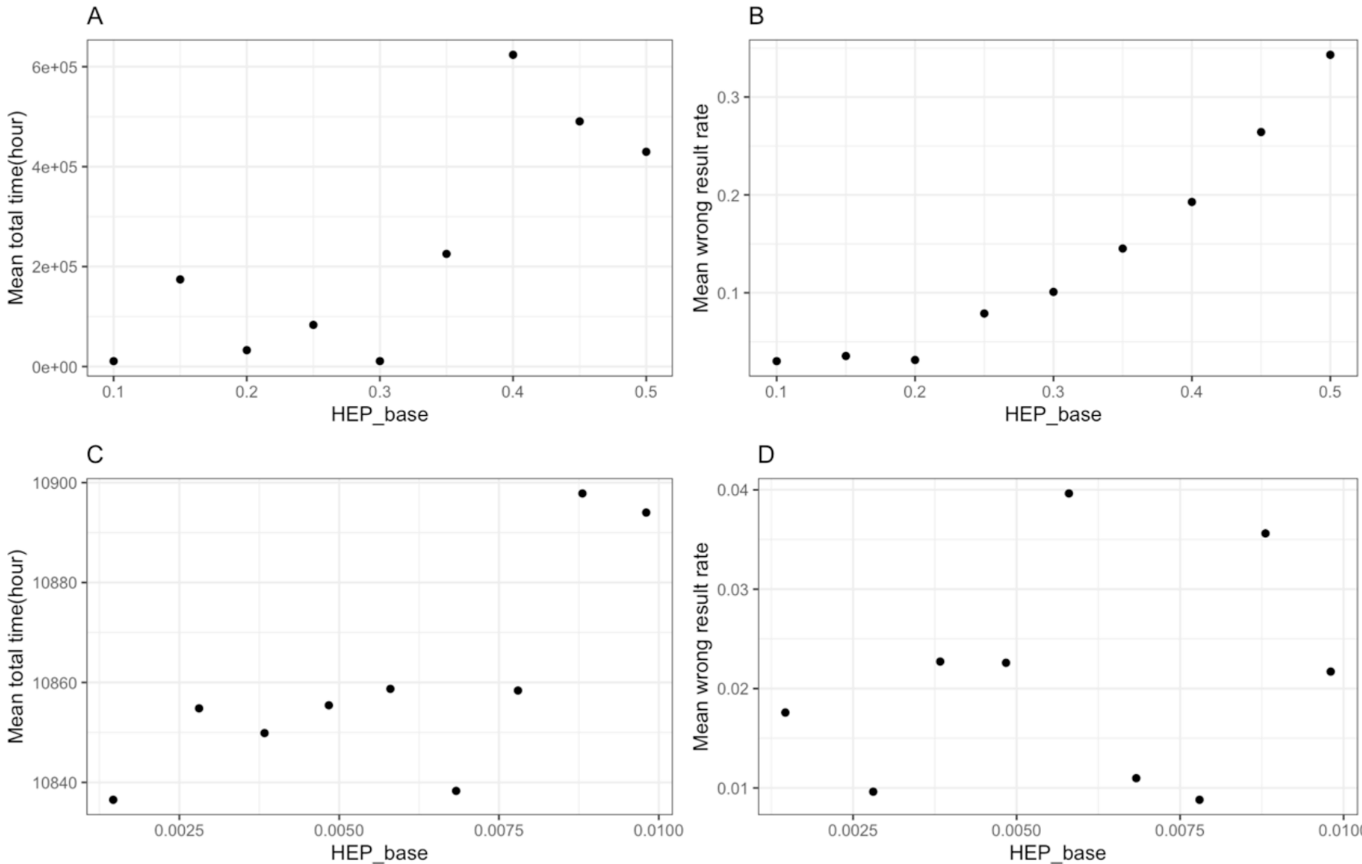

Fig. 15. System performance sensitivity to HEP_{base} in HRC operations.

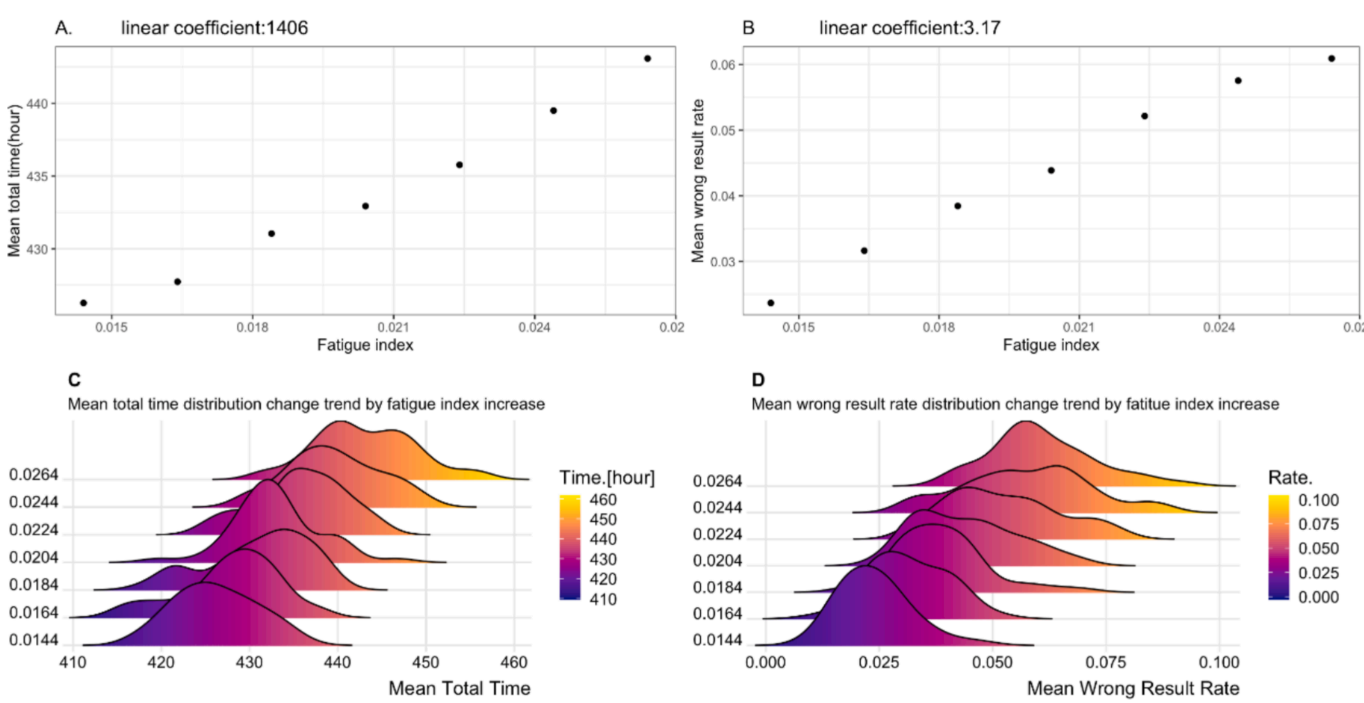

Fig. 16. The system performance change trend by Lambda_fatigue increase.

tends to decrease, as shown in Fig. 13 A. These results could be explained by the HRC procedures to identify the cracks. The magnetic robot performed the first step with AI image identification algorithms; if this step misses a crack, there is no way to recover this mistake. If this step gives a false true alarm, then the operator still has a chance to recover it with first and second checks.

Moreover, the directly missing a crack will save the check time. As discussed in 5.1, the median of the mean wrong result rate in the FM

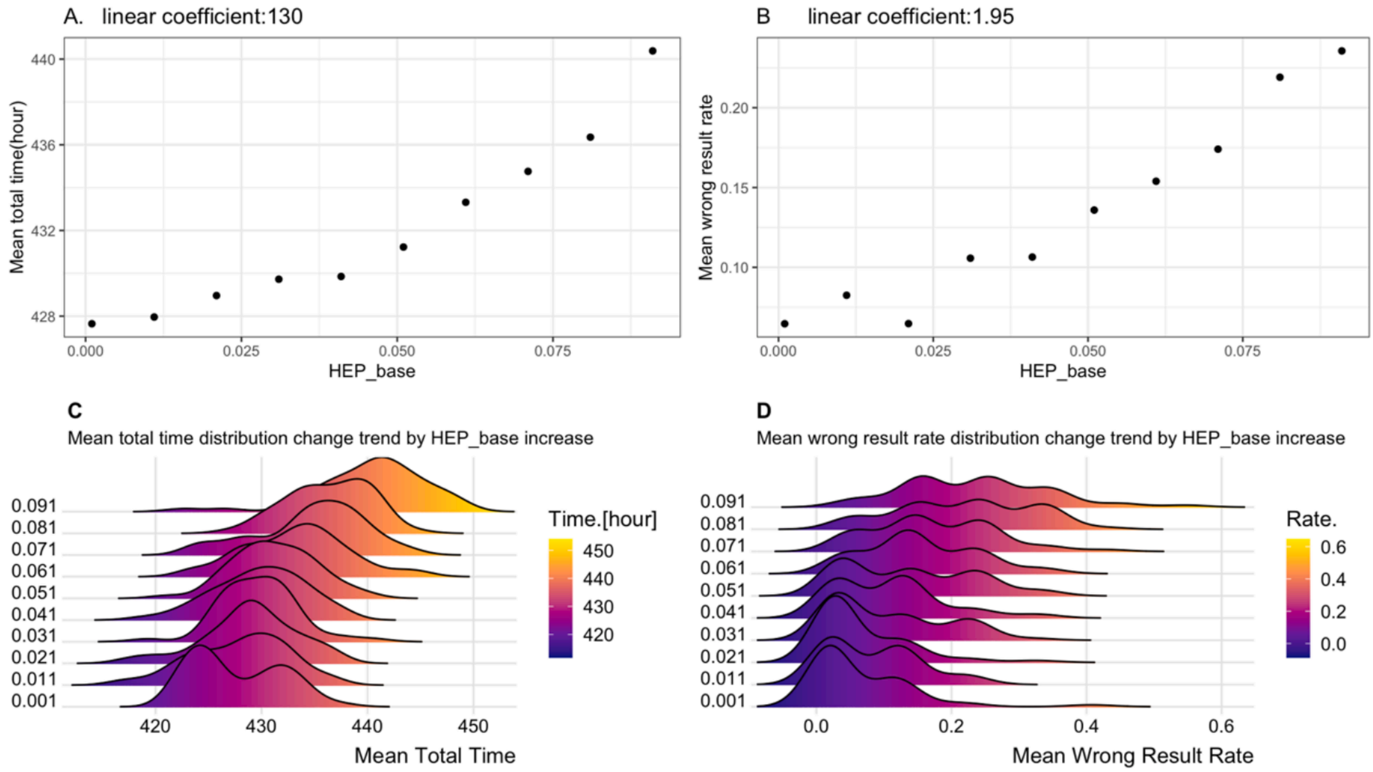

Fig. 17. The system performance change trend by HEP_{base} increase.

system is 0.04. Fig. 13 B shows the linear coefficient of $AI_{missrate}$, and the mean wrong result rate in the HRC system is 0.98. Therefore, only when the $AI_{missrate}$ is lower than 0.04 is employing an AI image identification algorithm meaningful.

As shown in Fig. 14 A and B, the HRC system performance is not sensitive to the $AI_{falsetruerate}$. This situation could be explained by the false true crack could be recovered by human technicians by first and cross check.

As shown in Fig. 15 C and D, when the HEP_{base} is lower than 0.1, the performance of the HRC process is not sensitive to the HEP_{base}, the same situation as the test of Lambda_fatigue sensitivity. However, as shown in Fig. 15 B, when the HEP_{base} is higher than 0.1, the mean wrong result rate of the HRC process is sensitive to the HEP_{base}. This change could be explained by the situations when the human technician wrongly changes the right decision from the AI algorithm with a more significant error probability than the $AI_{falsetruerate}$, being a major influencing factor to the wrong result rate.

5.3. *FM scenario sensitivity analysis*

As Fig. 16 and Fig. 17 are shown, the performance of the FM process is sensitive to the fatigue index and HEP_{base}. The mean values of performance indicators increase along with the Lambda_fatigue increase, as Fig. 16 and Fig. 17 A and B show. Also, the variance of wrong result rate increases, as shown in Fig. 16 and Fig. 17 D. This means the increase of HEP_{base} or Lambda_fatigue will introduce more difficulty in process quality control. This influence could be attributed to the FM process performed by human workers directly.

6. Conclusion

There is a trend in Industry 4.0 to employ a robot to assist human operators as a teammate. This transition also introduces new changes to system performance. Very few research studies have focused on the system performance comparison of FM and HRC operations. This research applies an agent-based simulation approach to address this question. The following conclusions can be drawn:

1. The proposed agent-based model novelty considers the dynamic human error change with fatigue and combines the organizational factors in the CREAM-based HEP as a base value. The models were tested in the pressurized vessel inspection operations in both FM and HRC scenarios. Results show that the models have advantages in reporting detailed quantitative system performance data and flexibility in parameter variance testing.
2. Results show that the fatigue index and HEP_{base} significantly influence FM system performance. The fatigue control measurement could be better arranged in the working schedule. At the same time, the $AI_{missrate}$ image is a critical influence factor to the HRC system reliability. Therefore, unless the $AI_{missrate}$ is achieved at a value lower than 0.04, it is not recommended to implement a magnetic robot with an automatic identification function. The alternative could start with a video of all the magnetic processes and then checks by human technicians. In addition, if the HEP_{base} is higher than 0.1, the HEP_{base} will increase the mean wrong result rate as it grows higher. Therefore, it is still essential in the HRC system to manage the organizational factors influencing human behavior, such as training and procedures.
3. A comparison of results from the two models shows that the HRC system is superior to the FM system in terms of efficiency, accuracy, and safety if the AI algorithm is mature enough.

Future research could be carried out in the following directions. First, the setting of robot reliability parameters in this research is mainly according to the policy requirements. More actual data could be integrated into the model with the inspection robot application in practice. Second, the proposed model is restricted to a small environment, such as the spherical tank and factory work field. Furthermore, the environment's random influences, such as the electricity shutdown and extreme weather, could be included in further research. In addition, the initial

Table A1
The weight of CPCs levels for four teams.

CPC name	Level	Team1	Team2	Team3	Team4
Adequacy of organization	Very efficient	0.26	0.22	0	0.25
	Efficient	1	0.78	1	0.75
	Inefficient	0	0	0	0
	Deficient	0	0	0	0
Working conditions	Advantageous	0	0	0	0
	Compatible	0.91	0.81	0.74	1
	Incompatible	0	0	0	0
Adequacy of MMI and operational support	Supportive	0	0	1	0
	Adequate	1	1	0	1
	Tolerable	0	0	0	0
	Inappropriate	0	0	0	0
Availability of procedures/plans	Appropriate	0	0	0	0
	Acceptable	1	0.09	1	0.69
	Inappropriate	0	0.91	0	0.31
Number of simultaneous goals	Fewer than capacity	0	0	0	0
	Matching current capacity	0.99	1	1	1
	More than capacity	0.01	0	0	0
Available time	Adequate	0.93	0.93	1	1
	Temporarily inadequate	0.07	0.07	0	0
	Continuously inadequate	0	0	0	0
Time of day	Daytime (adjusted)	1	1	1	1
	Night-time (unadjusted)	0	0	0	0
Adequacy of training and preparation	Adequate, high experience	1	1	1	0.73
	Adequate, low experience	0	0	0	0.27
	Inadequate	0	0	0	0
Crew collaboration quality	Very efficient	0	0	0	0
	Efficient	1	1	1	1
	Inefficient	0	0	0	0
	Deficient	0	0	0	0

Team 1 represents the construction team in the FM operation.
Team 2 represents the Polish team in the FM operation.
Team 3 represents the inspection technician team in the FM operation.
Team 4 represents the inspection technician team in the HRC operation.

attempt to set the weights of HEP_{base} and Fatigue value in Equation (7) is set equal in this research. Further work could explore optimal weights to balance the influential effect of the HEP_{base} and Fatigue value according to the dynamic HEP and corresponding data generated in the models. Moreover, other practical applications of the models could be extended with optimized algorithms for the human work schedule and robot work path.

CRediT authorship contribution statement

Shuo yang: Writing – original draft, Visualization, Conceptualization. **Micaela Demichela:** Writing – review & editing, Validation, Supervision, Project administration. **Zhangwei Ling:** Resources, Data curation. **Jie Geng:** Resources, Funding acquisition, Data curation.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Shuo yang reports financial support was provided by China Scholarship Council. Jie geng reports financial support was provided by the Natural Science Foundation of Zhejiang Province, China. Shuo yang reports a relationship with China Scholarship Council that includes: funding grants. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

See Table A1.

Data availability

Data will be made available on request.

References

[1] S. Abdelkhalek, T. Zayed, Simulation-based planning of concrete bridge deck inspection with non-destructive technologies, Autom. Constr. 119 (2020) 103337, https://doi.org/10.1016/j.autcon.2020.103337.
[2] A.B. Alhassan, X. Zhang, H. Shen, H. Xu, Power transmission line inspection robots: A review, trends and challenges for future research, Int. J. Electr. Power Energy Syst. 118 (2020) 105862, https://doi.org/10.1016/j.ijepes.2020.105862.
[3] AnyLogic (Version 8.8.4). (2024). [Computer software]. AnyLogic North America, LLC.
[4] Bielecki, T. R., Jakubowski, J., Vidozzi, A., & Vidozzi, L. (2008). Study of dependence for some stochastic processes. Stochastic Analysis and Applications, 26 (4), 903–924. Scopus. DOI: 10.1080/07362990802128958.
[5] Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. Proceedings of the National Academy of Sciences, 99 (suppl_3), 7280–7287. DOI: 10.1073/pnas.082080899.
[6] J.-E. Byun, J. Song, Generalized matrix-based Bayesian network for multi-state systems, Reliab. Eng. Syst. Saf. 211 (2021) 107468, https://doi.org/10.1016/j.ress.2021.107468.
[7] Carlson, J., Murphy, R. R., & Nelson, A. (2004). Follow-up analysis of mobile robot failures. IEEE International Conference on Robotics and Automation, 2004. Proceedings. ICRA '04. 2004, 4987-4994 Vol.5. DOI: 10.1109/ROBOT.2004.1302508.
[8] F. Naghdali, M.C. Leva, N. Balfe, S. Cromie, Human factors engineering at design stage: Is there a need for more structured guidelines and standards? Chem. Eng. Trans. 36 (2014) 577–582, https://doi.org/10.3303/CET1436097.
[9] W.T. Fine, Mathematical Evaluations for Controlling Hazards (AD0722011), Naval Ordnance Lab White OAK MD. (1970). https://apps.dtic.mil/sti/citations/AD0722011.
[10] J. Geng, S. Murè, M. Demichela, G. Baldissone, Atex-HOF methodology: Innovation driven by human and organizational factors (HOF) in explosive atmosphere risk assessment, Safety 6 (1) (2020). https://www.scopus.com/inward/record.uri?eid=2-s2.0-85079648560&doi=10.3390%2fsafety6010005&partnerID=40&md5=78f71e461bc0e8d3363d916105ca9b14.
[11] M. Gerbec, G. Baldissone, M. Demichela, Design of procedures for rare, new or complex processes: Part 2 – Comparative risk assessment and CEA of the case study, Saf. Sci. 100 (2017) 203–215, https://doi.org/10.1016/j.ssci.2016.10.015.
[12] M. Gerbec, N. Balfe, M.C. Leva, S. Prast, M. Demichela, Design of procedures for rare, new or complex processes: Part 1 – An iterative risk-based approach and case study, Saf. Sci. 100 (2017) 195–202, https://doi.org/10.1016/j.ssci.2016.08.015.
[13] Z.S. Givi, M.Y. Jaber, W.P. Neumann, Modelling worker reliability with learning and fatigue, App. Math. Model. 39 (17) (2015) 5186–5199, https://doi.org/10.1016/j.apm.2015.03.038.
[14] X. Guo, Q. Feng, D. Fan, Z. Wang, Y. Ren, B. Sun, D. Yang, An agent-based dynamic reliability modeling method for multistate systems considering fault propagation: A case study on subsea Christmas trees, Process Saf. Environ. Prot. 158 (2022) 20–33, https://doi.org/10.1016/j.psep.2021.11.047.
[15] E. Hollnagel, Cognitive reliability and error analysis method: CREAM (1st ed), Elsevier, 1998.
[16] S. Janssen, A. Sharpanskykh, R. Curran, AbSRiM: An Agent-Based Security Risk Management Approach for Airport Operations, Risk Anal. 39 (7) (2019) 1582–1596, https://doi.org/10.1111/risa:13278.
[17] J. Geng, S. Mure, G. Baldissone, G. Camuncoli, M. Demichela, Human error probability estimation in atex-hmi area classification: From therp to fuzzy cream, Chem. Eng. Trans. 43 (2015) 1243–1248, https://doi.org/10.3303/CET1543208.
[18] Y. Kai, Multistate fault-tree analysis, Reliab. Eng. Syst. Saf. 28 (1) (1990) 1–7, https://doi.org/10.1016/0951-8320(90)90039-P.
[19] Leva, M. C., Kay, A. M., Mattei, F., Kontogiannis, T., De Ambroggi, M., & Cromie, S. (2009). A Dynamic Task Representation Method for a Virtual Reality Application. In D. Harris (Ed.), Engineering Psychology and Cognitive Ergonomics (Vol. 5639, pp. 32–42). Springer Berlin Heidelberg. DOI: 10.1007/978-3-642-02728-4_4.

[20] S. Li, P. Zheng, S. Pang, X.V. Wang, L. Wang, Self-organising multiple human–robot collaboration: A temporal subgraph reasoning-based method, J. Manuf. Syst. 68 (2023) 304–312, https://doi.org/10.1016/j.jmsy.2023.03.013.
[21] A. Lisnianski, I. Frenkel, Y. Ding, Multi-state System Reliability Analysis and Optimization for Engineers and Industrial Managers, Springer London. (2010), https://doi.org/10.1007/978-1-84996-320-6.
[22] L. Ma, T. Hartmann, A proposed ontology to support the hardware design of building inspection robot systems, Adv. Eng. Inf. 55 (2023) 101851, https://doi.org/10.1016/j.aei.2022.101851.
[23] Macal, C. M., & North, M. J. (2005). Tutorial on agent-based modeling and simulation. Proceedings of the Winter Simulation Conference, 2005., 14 pp.-. DOI: 10.1109/WSC.2005.1574234.
[24] J.J. Magoua, F. Wang, N. Li, D. Fang, Incorporating the human factor in modeling the operational resilience of interdependent infrastructure systems, Autom. Constr. 149 (2023) 104789, https://doi.org/10.1016/j.autcon.2023.104789.
[25] H.B. Mann, D.R. Whitney, On a Test of Whether one of Two Random Variables is Stochastically Larger than the Other, Ann. Math. Stat. 18 (1) (1947) 50–60, https://doi.org/10.1214/aoms/1177730491.
[26] Martinetti, A., Braaksma, A. J. J., & Van Dongen, L. A. M. (2017). Beyond RAMS Design: Towards an Integral Asset and Process Approach. In L. Redding, R. Roy, & A. Shaw (Eds.), Advances in Through-life Engineering Services (pp. 417–428). Springer International Publishing. DOI: 10.1007/978-3-319-49938-3_25.
[27] A. Martinetti, E.J. Schakel, L.A.M. Van Dongen, Flying asset: Framework for developing scalable maintenance program for unmanned aircraft systems (UAS), J. Qual. Maint. Eng. 24 (2) (2018) 152–169, https://doi.org/10.1108/JQME-12-2016-0073.
[28] D.M. Miller, R. Drechsler, Implementing a Multiple-Valued Decision Diagram Package. 52–57 (1998) Scopus. https://www.scopus.com/inward/record.uri?eid=2-s2.0-0031633112&partnerID=40&md5=cab9d7ef262692035d63166b0c9131af.
[29] Petri, C. A. (1962). Kommunikation mit automaten.
[30] K. Sadeghniiat-Haghighi, Z. Yazdi, Fatigue management in the workplace, Ind. Psychiatry J. 24 (1) (2015) 12–17, https://doi.org/10.4103/0972-6748.160915.
[31] S.S. Shapiro, M.B. Wilk, An Analysis of Variance Test for Normality (Complete Samples), Biometrika 52 (3/4) (1965) 591, https://doi.org/10.2307/2333709.
[32] A. Shukla, H. Karki, Application of robotics in onshore oil and gas industry—A review Part I, Rob. Auton. Syst. 75 (2016) 490–507, https://doi.org/10.1016/j.robot.2015.09.012.
[33] Stamatis, D. H., 1947-. (1995). Failure mode and effect analysis: FMEA from theory to execution. Milwaukee, Wisc. : ASQC Quality Press, [1995] ©1995. https://search.library.wisc.edu/catalog/999755655202121.
[34] Swain, A. D., & Guttmann, H. E. (1983). Handbook of human-reliability analysis with emphasis on nuclear power plant applications. Final report (NUREG/CR-1278, SAND-80-0200, 5752058; p. NUREG/CR-1278, SAND-80-0200, 5752058). DOI: 10.2172/5752058.
[35] K.-P. Timpe, H.-G. Giesa, K. Seifert, Engineering Psychology, in: C.D. Spielberger (Ed.), Encyclopedia of Applied Psychology, Elsevier, 2004, pp. 777–786, https://doi.org/10.1016/B0-12-657410-3/00338-X.
[36] I.A. Ushakov, A universal generating function, Sov. J. Comput. Syst. Sci. 24 (5) (1986) 118–129.
[37] M. Wu, J.-R. Lin, X.-H. Zhang, How human-robot collaboration impacts construction productivity: An agent-based multi-fidelity modeling approach, Adv. Eng. Inf. 52 (2022) 101589, https://doi.org/10.1016/j.aei.2022.101589.
[38] Q. Wu, X. Qin, K. Dong, A. Shi, Z. Hu, A learning-based crack defect detection and 3D localization framework for automated fluorescent magnetic particle inspection, Expert Syst. Appl. 214 (2023) 118966, https://doi.org/10.1016/j.eswa.2022.118966.
[39] Yilmar Builes, Balfe, N., Leva, C., & Douglas, E. (2014). Inclusive Task analysis and risk assessment in high-risk industrial cleaning: a case study using scope softwaRE. DOI: 10.13140/RG.2.1.5000.4008.
[40] E. Zarei, F. Khan, R. Abbassi, Importance of human reliability in process operation: A critical analysis, Reliab. Eng. Syst. Saf. 211 (2021) 107607, https://doi.org/10.1016/j.ress.2021.107607.