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An Agent-Based Reliability and Performance Modeling Approach for Multistate Complex Human-Machine Systems With Dynamic Behavior

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ABSTRACT A complex human-machine system (CHMS) consists of heterogeneous components with extensive human-machine interactions. CHMSs are typical multistate systems with the ability to adapt to disturbances such as machine failures. These characteristics must be considered comprehensively to accurately evaluate the reliability and performance of a CHMS. However, the existing literature scarcely considers both the reliability and performance simultaneously. In this paper, we propose an agent-based approach to model and evaluate a CHMS. First, a general agent-based modeling framework for a CHMS is generated by analyzing the structure and operations of a CHMS. Then, a dual-clock mechanism is introduced to describe the behaviors of the machine failures and human errors. Two environmental disturbance modeling methods are proposed based on the state transitions of the agent and random events. The methods to model the repair and reconfiguration behaviors are presented based on the contract network. A Monte Carlo-based method is developed to evaluate the reliability and performance of the CHMS simultaneously. Finally, a deck scheduling process for an aircraft carrier is used as a case study to verify the approach. The results show that the reliability and performance of a CHMS can be effectively evaluated.

INDEX TERMS Complex human-machine system, agent-based model, reliability model, performance evaluation.

I. INTRODUCTION

Complex human-machine systems (CHMSs) have been extensively studied in different applications such as airport dispatching systems [1], intelligent transportation networks [2], and aircraft carriers [3]. The stable and efficient operation of a CHMS is of great significance; therefore, the reliability and system performance of CHMSs should be a focus of study.

CHMSs consist of a large number of heterogeneous elements[4], [5], and there are many human-machine interactions during its operation[6], [7]. There are multiple normal working states and abnormal states for both humans and machines in a CHMS. Furthermore, disturbances to the system are occasionally produced by the external environment. In addition, CHMSs have the ability to adapt to the system faults and disturbances [8], [9]. Thus, an accurate assessment of the reliability and performance of a CHMS is very difficult [10].

There are many performance evaluation methods for complex systems [11], [12]. The most representative method is agent-based modeling (ABM) [13]–[16]. ABM can describe the interactions between humans and machines and various nonlinear behaviors of the system through the interactions between agents [17], [18]. Many agent-based modeling methods can well describe the multistate of functions for objects or systems, but the current literature has not explored multistate faults [19], [20], so the evaluation results are not accurate.

Models for evaluating the reliability of complex systems can be divided into two categories, fault logic models and reliability evaluation models based on performance [21]. There is abundant research on reliability models based on fault logic, such as the fault tree (FT) and reliability block diagram (RBD). This paper compares various fault logic models through the CHMS features, as shown in TABLE 1. Although

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TABLE 1. Differences among fault logic models.

Categorization criteria	Applicable system		Human factor		System behavior		Faulty state		Related to performance	
Approach	Normal system	CHMS	Human error	Human-machine Interaction	Static	Dynamic	Two-state	Multi state	Yes	No
Universal generating function[23][25]	√		√		√		√	√		√
RBD model[26][27]	√				√		√			√
Fault tree[28][29]	√		√		√	√	√	√		√
Dynamic fault tree[30][31]	√		√			√	√			√
Bayesian network[32][33]	√		√		√		√			√
Dynamic Bayesian network[34]	√		√		√	√	√			√
Petri net model[35]	√		√			√		√		√
GO methodology[36]	√				√	√	√		√	

most methods can evaluate the reliability of complex systems that match their characteristics, the table shows that none of the methods can reflect the human-machine interaction. Additionally, most methods cannot evaluate the reliability with multiple fault states and performance.

Some studies use reliability models based on system performance, such as that of Chiacchio *et al.* [22], in which the performance of an energy supply was used as the starting point to evaluate the reliability of the system with the Monte Carlo method. Others used an agent-based approach to build performance-based reliability models [24]. However, the models in these studies lack the ability to handle machine faults, human error, environmental disturbances, maintenance, and reconstruction information.

In this paper, we propose an agent-based approach to model and evaluate the performance and reliability of the CHMS simultaneously. Note that reliability is one of the system performance measures in our work since it is described as the probability of failure-free performance over a specified timeframe, under specified environmental and duty-cycle conditions. Compared to the related work on the reliability and performance of CHMSs, the main contributions of this work are as follows. First, this paper proposes a general comprehensive modeling framework that considers features such as multiple states, dynamics, and human-computer interaction. Second, the framework establishes a modeling method for machine faults, human error and environmental disturbances considering a multistate feature. Third, the system reconstruction and repair behavior modeling methods of the preferred participants are proposed. Finally, this paper presents a flexible definition of the system fault criteria that can be used to synchronize the performance and reliability evaluation with Monte Carlo-based evaluation methods.

The remainder of this paper is organized as follows. In Section II, a general description of a complex human-machine system is presented. In Section III, we propose a general modeling framework based on an agent. In Section IV, a reliability and performance evaluation algorithm based on a Monte Carlo approach is proposed. A case study of an aircraft carrier, the results and discussion, are presented in Section V. Finally, Section VI concludes the study.

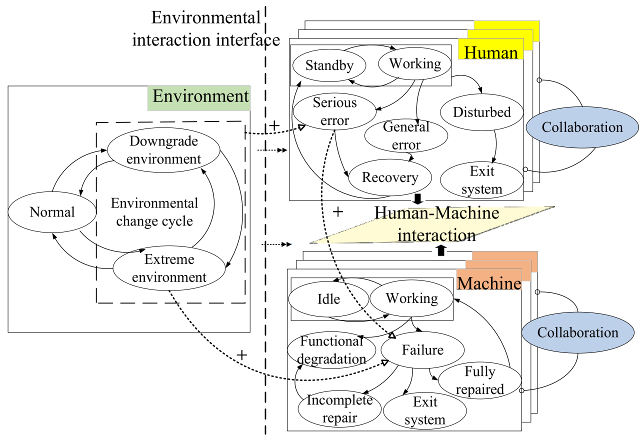

FIGURE 1. Systematic state changes and interactions.

II. PROBLEM DESCRIPTION

A. CHMS PROCESSES

The state change process of a basic CHMS configuration and the interactions of each component are shown in FIG 1. The figure shows that the state of each system component dynamically changes and the components continuously interact with each other during the CHMS operating process.

The CHMS machines handle the system tasks. The states primarily include the standby state, working states (1-0), fault state(1-p) and maintenance state(1-q). After the machine is repaired, the machine state can be assessed as the unrecoverable state, the partial recovery state, and the full recovery state according to the maintenance condition.

The environment is the comprehensive expression of the spatial state of the CHMS. Many factors affect the environment. They can be divided into three main states according to the impact of the environment on the system: the normal environmental state, the degraded system performance state, and the extreme environmental state. In general, the system will not operate in the extreme environmental state.

The completion of tasks by the CHMS is based on the interactions of the CHMS components with each other, and the performance of the system is reflected by the interactions. The interaction categories include environment-entity, human-machine, human-human, and machine-machine interactions. During faults, disturbances and system recovery, the interaction relationship is more complex, which increases the difficulty of modeling and evaluating the performance and reliability of the CHMS. Therefore, through an analysis of the composition and operational characteristics of a CHMS, this paper uses an agent-based method to establish a comprehensive evaluation model of a CHMS performance and reliability, which can effectively evaluate the reliability and performance.

B. BASIC ASSUMPTIONS

Several assumptions are made for the modeling process:

(i) In modeling the CHMS, only the typical states of each component are described.

(ii) A person of the same type is assumed to be responsible for only one job.

(iii) The state logic of the same type of machine or person is assumed to be the same.

C. REQUIRED DEFINITIONS

(i) The purpose in this study is to give a general agent-based modeling framework for a CHMS. The description of the typical states of each component is highly representative so that the essential characteristic can be grasped.

(ii) In fact, a single human task facilitates the definition of the interaction protocols more accurately. Meanwhile, it is in line with a real implementation.

(iii) In an agent-based model, this is the way to simplify the work.

III. AGENT-BASED MODELING FRAMEWORK OF CHMS

A. DESCRIPTION OF THE FRAMEWORK

In our work, an agent-based model is proposed for a CHMS consisting of interconnected agents. The model consists of four types of agents: the task management agent (TMA), the machine agent (MA), the human agent (HA) and the environmental agent (EA). According to the state of each component in the real system, the logic change of an agent is expressed using the state diagram method. The agent-based modeling framework adopted in this paper is shown in FIG 2. To realize the interactions among various types of agents, the implementation of the system task is distributed, but the conflicts between different agents are ignored.

Most existing agent-based modeling frameworks can describe complex systems and the functional multistate features. The framework proposed in this paper highlights the agent-oriented fault and disturbance design, agent-based recovery modeling and agent-based model evaluation algorithms.

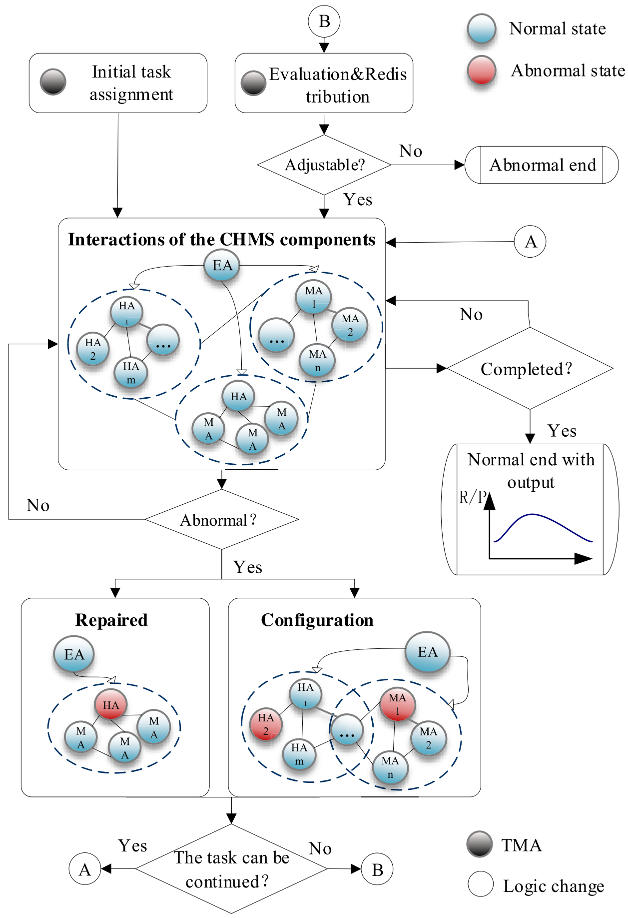

FIGURE 2. Universal framework for agent-based modeling.

For the MA, HA, and EA, the agent states are divided into the normal and abnormal states, and the agent moves between these states according to the conditions. The state change of an agent can be represented in a quantified form.

The ABM for a CHMS includes 1 TMA,m MAs, n HAs, and 1 EA.

If the ith MA has the$l$ typical state, the state can be represented by $\varepsilon_{ij}(j = 1, 2, \ldots, l)$ ranging from [0,1], where $\varepsilon_{i1} = 1$ represents the standby state and $\varepsilon_{il} = 0$ represents the fault state. The remaining l-2 different working states ranging from (0,1) represent functional degradation. When MA_i is in a certain normal state which the corresponding work cannot be completed, the state of MA_i will transition to the abnormal state, ε_{il}, if $\varepsilon_{ij} = 0$. In particular, if MA_i is in the standby state, it can be triggered by TMA and move to the working state according to the results of task assignment. As the states change, the MA_i interacts with the TMA, the HA, the EA and itself based on information, enery, etc.

Similar to an MA, $\varepsilon_{ij}(j = 1, 2, \ldots, l)$ can also be used to represent the state of HA_i, where $\varepsilon_{i1} = 1$ represents the idle state, $\varepsilon_{il} = 0$ indicates that HA_i cannot perform the system function and $-1 \leq \varepsilon_{ik} < 0 (1 < k < l)$ represents an error state. The remaining l-3 states ranging from (0,1) represent the degraded function state in a working status. During the operation, an HA cannot continue to work after being disturbed and the current state will change from $\varepsilon_{ij} = 0$ to ε_{il}. When an error occurs in HA$_i$, it enters the error state and the value of ε_{ik} is determined according to the error condition. When in the idle state, HA$_i$ can transition to every working state according to the task requirement. If HA$_i$ is in a working state and $\varepsilon_{ij} = 1$, it can transition to other working states.

The state of the EA affects the state of the HA and the MA. Similarly, $\varepsilon_{ej}(1 \le j \le l)$ is used to represent the l state of the EA and $0 \le \varepsilon_{ej} \le 1$. ε_{el} represents the extreme environmental state and $\varepsilon_{el} = 0$. The remaining l-1 states represent the typical states of the EA. $\varepsilon_{el} = 1$ indicates that the environmental state is good and does not affect the operations of the MA and HA; when $0 < \varepsilon_{el} < 1$, the state affects the system performance.

In this paper, we define an environmental coefficient k_e, which indicates the impact of the EA on the HA and MA, and $0 \le k_e \le 1$. The value of k_e is determined according to the environmental state, ε_{el}. $k_e = 1$ indicates that the environment does not affect the operating status of the HA and MA, and $k_e = 0$ indicates that the MA and HA cannot be normal. For an HA or MA numbered i, their state, ε_{ij}, can be expressed as Eq. (1) after an environmental correction.

$$\vec{\varepsilon}_{ij} = k_e \times \varepsilon \tag{1}$$

B. MODELING FAULTS AND DISTURBANCES

1) MODELING MACHINE FAULTS

MA$_i$ consists of q functional units, and the jth unit is denoted as $U_{ij}(1 \le j \le q)$. We consider that the functional units have two-state faults and that MAs have multistate faults and the different fault modes correspond to different processing methods. The life of U_{ij} is TTF_{ij} and the life of MA$_i$ is TTF_i.

The occurrence of a fault is a discrete event[37]. According to the simulation logic, when the simulation clock advances to $t = TTF_i$, MA$_i$ should enter the fault state. However, the fault event cannot be directly input into the normal simulation clock of MA$_i$. Therefore, this paper proposes a dual-clock mechanism for the fault clock to realize the fault.

The basis of the fault clock mechanism is the dynamic consumption mechanism. The fault clock stock corresponding to MA$_i$ is recorded as $S_i(t)$, $0 \le S_i(t) \le 1$ and the dynamic consumption rate is v_i. If $v_i = 1/TTF_i$, the system dynamics stock is:

$$S_i(t) = 1 - v_i \cdot t = 1 - t/TTF_i \tag{2}$$

Thus, when $S_i(t) = 0$, MA$_i$ fails. According to Hypothesis 6, when MA$_i$ enters the standby state, the consumption rate can be adjusted to 0.

Determining the lifetime of MA$_i$ is a critical step of the fault clock advancement mechanism. The life of MA$_i$ can be determined based on the life of each unitTTF_{ij} and the fault logic of MA$_i$. The determination steps are shown in Steps 1 to 3.

Step 1: Determine the life of the functional units

In general, the functional unit life of a machine is a random variable that follows a certain distribution. In this paper, the continuous random variable sampling method [38] is used to determine the TTF_{ij} of each functional unit. The basic sampling process is expressed as follows.

TTF_{ij} is a continuous random variable that follows the distribution function $Z = F(x)$, where $0 \le Z \le 1$. Then, the kth sample value is:

$$TTF_{ij}(k) = F^{-1}(Z) \tag{3}$$

If the functional unit life follows the exponential distribution, the sampling formula for TTF_{ij} is:

$$TTF_{ij} = F^{-1}(\eta) = -\ln(\eta)/\lambda_{ij} \tag{4}$$

where η is a random number from [0,1] and λ_{ij} is the failure rate of the functional unit.

Step 2: Determine the fault logic of MA$_i$

According to the structure of the MA, the RBD (reliability block diagram) can be established with the functional units. Based on the RBD, the structural function, $\phi(X_{i1}, X_{i2}, \ldots, X_{iq})$, of MA$_i$ can be obtained. The objective of the structure function is to determine the system state based on the state of the functional unit[39]. The state value of U_{ij} is X_{ij}, and the value of X_{ij} is:

$$X_{ij} = \begin{cases} 1 & normal \\ 0 & failure \end{cases} \tag{5}$$

$X_{ij} = 1$ indicates that the state of U_{ij} is normal, and $X_{ij} = 0$ indicates that U_{ij} is faulty. The value of the structure function is either 1 or 0. If $\phi(X_{i1}, X_{i2}, \ldots, X_{iq}) = 1$, MA$_i$ is normal; if $\phi(X_{i1}, X_{i2}, \ldots, X_{iq}) = 0$, MA$_i$ is faulty.

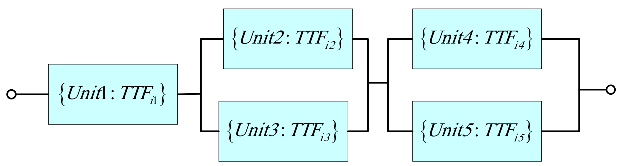

FIGURE 3. Reliability block diagram of an MA.

If there is an MA, the RBD structure is as shown in FIG 3. The structural function can be expressed as follows.

$$\begin{aligned} \phi(X_{i1}, X_{i2}, \cdots, X_{i9}) = {} & [1 - (1 - X_{i1})] \\ & \times [1 - (1 - X_{i2})(1 - X_{i3})] \\ & \times [1 - (1 - X_{i4})(1 - X_{i5})] \end{aligned}$$

Step 3: Determine the TTF_i of MA$_i$

According to the RBD of MA$_i$, MA$_i$ does not fail after the unit fails, so the lifetime, TTF_i, of MA$_i$ must be determined based on the life of the units. According to the simulation time advancement, when $t = TTF_{ij}$, the unit is faulty and its state value is $X_{ij} = 0$. If $X_{ik} = 0(1 \le k \le q)$, $\phi(X_{i1}, X_{i2}, \ldots, X_{iq}) = 0$ and $TTF_i = TTF_{ik}$. If the RBD of MA$_i$ is a series model, $TTF_i = \min\{TTF_{ij}\}$; if the RBD of MA$_i$ is a parallel model, $TTF_i = \max\{TTF_{ij}\}$.

The faults of different units make the fault mode of the agent different, so the behavior and state of the agent in different fault modes must be designed in the modeling process.

An MA will enter the fault detection state when a unit's fault occurs. First, the system detects whether the failed unit is in the standby state. If the unit is on standby, it will trigger the failure until the unit transitions to the work state. If the unit is already working, different consequences and corresponding state transitions need to be designed according to different fault modes. For example, if the aircraft agent fails on the ground, it will enter the maintenance state directly. When the plane agent fails in the air, the aircraft mission will be negatively impacted.

2) MODELING HUMAN ERROR

Human behavior is complex and people make mistakes. The *TTM* (time to mistake) is defined as the time that a person makes a mistake at work, which obeys the distribution $Z = F(x)$. The dual-clock mechanism is also used in this paper to model human error.

The human error time sampling is at the individual level, which is different from that of the machine. The working state of the HA is cyclic, and when HA_h enters the working state, the TTM_h. must be sampled again.

The method of sampling TTM_h is the same as the machine fault clock sampling method. The TTM_h of HA_h can be expressed as follows.

$$TTM_h = F^{-1}(Z) \tag{6}$$

In general, the time of human error follows a lognormal distribution[40]. The sample value of TTM_h is:

$$TTM_h = F^{-1}(\eta) = \exp(\sigma\sqrt{-2\ln\eta}\sin 2\pi\eta + \mu) \tag{7}$$

where η is a random number from [0,1], μ is the mean error time and σ is the root mean square of the error time.

According to the dual-clock mechanism, the clock inventory $S_h(t)$ of HA_h at any time can be expressed as follows:

$$S_h(t) = 1 - v_h \cdot t = 1 - t/TTM_h \tag{8}$$

where $v_h = 1/TTM_h$ is the consumption rate. When $S_h(t) = 0$, HA_h has made a mistake.

3) MODELING OF ENVIRONMENTAL DISTURBANCE

There are two types of environmental disturbances in a CHMS. The first type is caused by changes in the normal environmental conditions under the given environmental profile. This type of environmental disturbance can degrade the performance of the CHMS or have no effect. When the state of EA transitions, k_e, changes, the states of HA and MA are affected during the interaction with the EA.

The second type of disturbance is caused by random extreme environmental changes. This type of disturbance usually significantly influences the performance of the CHMS, so random events are necessary to simulate extreme environments. The number of disturbances can be expressed by the nonhomogeneous Poisson process [42]. If there are k extreme environmental events, the probability can be calculated as follows:

$$P\{N(t) = k\} = [\lambda(t)]^k \cdot e^{-\lambda(t)}/k! \tag{9}$$

where $\lambda(t)$ is the average number of occurrences of the event over the time period (0,t]. Under special circumstances, an homogeneous Poisson distribution can also be used to describe extreme environmental events, and $\lambda(t)$ is a constant.

The state of the MA and HA can be corrected by k_e as described in section III.A. In addition, the environment has a greater impact on human error than on machine failure. After correcting k_e, the human error clock can be expressed as follows:

$$S_h(t) = 1 - (v_h/k_e) \cdot t = 1 - t/k_e \cdot \mathrm{TTM}_h \tag{10}$$

C. MODELING RECOVERY

Reasonable recovery behavior can effectively reduce the impacts of faults and disturbances. The system controls the impact of a disturbance on the system through maintenance and reconfiguration to restore the system to a normal or steady state.

The essence of the maintenance recovery process and the reconstruction recovery processed is that multiple agents interact with each other. This paper uses the contract network mechanism to model the maintenance and reconstruction of a CHMS.

1) MODELING MAINTENANCE

C_f represents the target agent that needs to be repaired, primarily referring to an MA. C_a represents the service provider of the repair process. C_o represents the manager of the maintenance process agent, which is responsible for controlling the management and maintenance recovery process. The maintenance process mechanism is shown in FIG 4.

The maintenance coordination mechanism in the figure applies to all maintenance behaviors in the CHMS. The basic steps are shown in Steps 1 to 3.

Step 1: C_f issues the specific tender

C_f needs to be repaired after entering the fault state, and it sends out the information requesting repair. C_o receives the information and begins to manage the coordinated maintenance activities, and C_f simultaneously issues the tender, PR_i, to lC_as.

$$PR_i = (\Delta T | R_T, R_M) \tag{11}$$

where ΔT is the deadline for the service agent- C_a to respond to the tender, R_T represents the time constraint, and R_M represents the replacement parts requirement.

$$R_T = T_M + T_{DL} \tag{12}$$

T_M is the time to complete the maintenance task, and T_{DL} is the guarantee resource delay time.

There may be multiple maintenance activities during the CHMS operation, so one C_a will receive information for

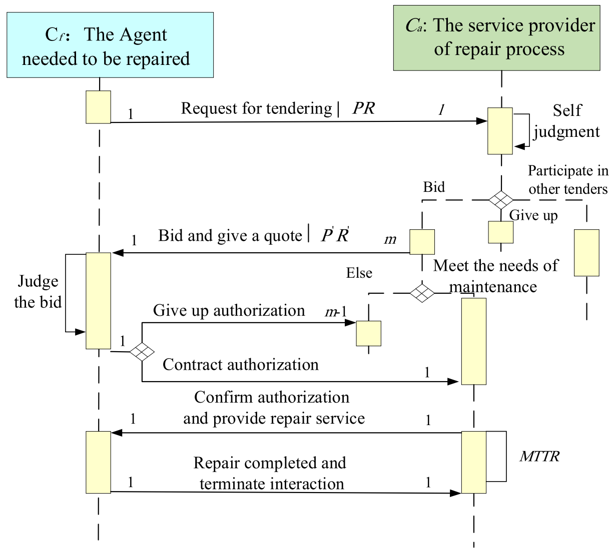

FIGURE 4. Basic maintenance process.

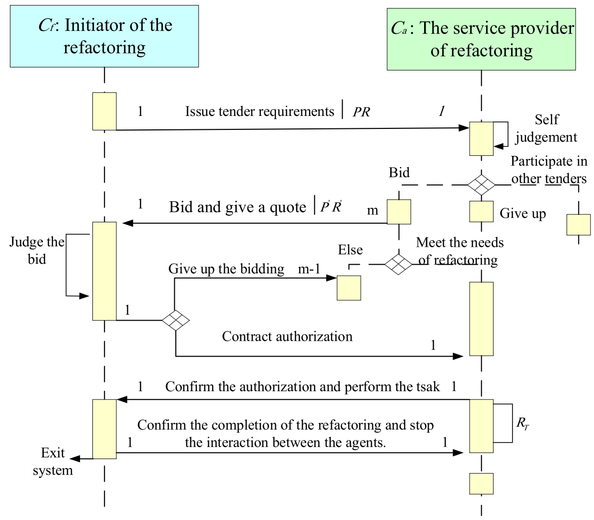

FIGURE 5. Basic reconstruction process.

multiple bids. After receiving the bidding information, C_a will first evaluate its status. If the status of C_a cannot bear any bidding requirements, it will abandon the bidding. If the status is available, it will choose the bidding that best matches its conditions. In addition, in the end C_f will receive m bids and $m \leq l$.

$$PR'_{\mathrm{i}} = \left(R^{i}_{Ti}, R'_{Mi}\right), \quad i = 1, 2, \ldots, m \tag{13}$$

C_f only accepts the reverse quote returned by ΔT. The remaining l-m service providers no longer participate in the tender

Step 2: C_f selects the appropriate server to authorize.

$\mathrm{C_f}$ determines if $R'_{M\mathrm{i}}$ meets the requirements and selected the smallest $R'_{T\mathrm{i}}$ of C_a to authorize, and does not authorize any of the remaining m-1 C_as.

Step 3: Perform the maintenance process.

When the selected bidder C_{ap} is authorized, C_{ap} undertakes the maintenance task and enters the working state. After T_{DL}, C_{ap} enters the maintenance state, and then after T_M, the maintenance task is completed, and the C_f transfers to the full recovery or partial recovery state. Then, C_f evaluates the completion of the maintenance, and the interaction is terminated, C_{ap} again enters the idle state.

2) MODELING REFACTORING

C_f represents an agent that cannot continue to undertake a system task and triggers system reconstruction. C_o represents the management agent in the reconstruction process, and C_a represents the refactoring server. The reconstruction mechanism of the CHMS is shown in FIG 5.

The refactoring mechanism shown in the figure is applicable to all the refactoring processes in the CHMS. The basic steps are shown in Steps 1 to 3.

Step 1: C_f issues a specific tender

When C_f is unable to undertake a system task due to interference, it needs other agents to cooperate in the system reconfiguration, and issues the tender, PR_i, to lC_as.

$$PR_i = (\Delta T | R_T, R_S) \tag{14}$$

where ΔT is the response time, R_T is the time to enter refactoring and complete the refactoring process. R_S is the state capability constraint of the server.

Similar to the maintenance recovery process, one C_a will receive the information for multiple bids. After receiving the bidding information, C_a will first evaluate its status. If the status of C_a cannot bear any bidding requirements, it will abandon the bidding. If the status is available, it will choose the bidding that best matches its conditions. In addition, C_f will finally receive m bids and $m \leq l$.

$$PR'_i = \left(R'_{Ti}, R'_{Si}\right), \quad i = 1, 2, \ldots, m \tag{15}$$

C_f only accepts the reverse quote returned by ΔT. The remaining l-m service providers no longer participate in the tender.

Step 2: C_f selects the appropriate server for authorization.

C_f determines if R'_{Mi} meets the requirements and selects the smallest R'_{Ti} of C_a for authorization, and does not authorize the remaining m-1 C_as.

Step 3: Perform the refactoring process

The authorized C_{ap} transitions to the working state. After time R_T, the reconstruction process is completed and C_{ap} transitions to the idle state and C_f exits system.

The proposed repair and reconstruction models in this section are most basic models for a CHMS. When the system functioning is disturbed, the maintenance and reconstruction processes of the system will be more complex for a certain CHMS.

IV. SYSTEM SIMULATION EVALUATION ALGORITHM

Many parameters that affect the reliability and performance of a CHMS cannot be expressed analytically. The Monte

Carlo algorithm based on ABM is used in this paper to evaluate the reliability and performance of the CHMS.

In this paper, the reliability of the CHMS is evaluated from the system performance perspective. For different types of CHMSs, the metrics are different. Therefore, the detailed performance features will not be discussed in the proposed framework.

ABM is used as the Monte Carlo sampling object and the sampling number is n. Suppose the number of input parameters of the ABM model is m and the performance number of the model is k. Then, the output matrix corresponding to the ith sample is recorded as:

$$[y_{i1}, y_{i2}, \ldots, y_{ik}](1 \leq i \leq n).$$

P_j represents the performance of the j-th term of the CHMS. After Monte Carlo sampling, the simulated result matrix of the j-th performance is $[y_{1j}, y_{2j}, \ldots, y_{nj}]$. This paper uses the average method to calculate the performance of the CHMS. Therefore, the j-th performance calculation result is:

$$P_j = \sum\nolimits_{i=1}^{n} y_{ij}/n \tag{16}$$

The reliability evaluation relies on the system performance results, and it is necessary to determine whether the ABM model operation succeeds according to the performance of every sampling simulation.

$[\overline{\overline{y}}_1, \overline{\overline{y}}_2, \ldots, \overline{\overline{y}}_k]$ is the standard matrix for the success of a sampling simulation. If the simulation result of the i-th sampling reaches the standard, $y_{i1} \geq \overline{\overline{y}}_1, \overline{\overline{y}}_{i2} \geq \overline{\overline{y}}_2, \ldots, y_{ik} \geq \overline{\overline{y}}_k$, the sampling simulation is considered successful. The performance of the CHMS dynamically changes, which makes the CHMS exhibit multistate features. The criteria for a single simulation vary for different assessment requirements, so the value and dimension of the standard matrix can be corrected based on the state requirements of the system.

According to the success criterion matrix, the number of successful simulations is l, so the reliability level, R, of the CHMS can expressed as follows:

$$R = l/n \tag{17}$$

V. CASE STUDY

A. INPUT DATA

The basic layout of the aircraft carrier and some data are adopted from existing literature [43], [44]. The basic layout of the aircraft maintenance system is shown in FIG 6. In this paper, the Anylogic software is used to build the ABM model for the aircraft carrier system to realize a visual simulation.

After the ABM model is built according to the previous modeling framework, a series of parameters must be generated to determine the data statistics. Some parameter and data settings are shown in TABLE 2. In the table, F_R represents the *failure rate*, *MTTR* is the mean time to repair, P_c represents the *completion probability*, F_I represents the *fault isolation rate*, F_D represents the *fault detection rate*. The lifetime of all the devices are assumed to follow an exponential distribution.

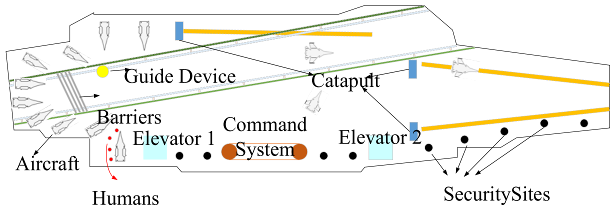

FIGURE 6. Basic layout of the aircraft carrier.

TABLE 2. Quality parameters of some system objects.

	FR	MTTR(min)	Pc	FI	FD
Aircraft	7.33E-02	120	0.95	0.95	0.95
Barrier	3.24E-04	100	0.95	0.92	0.96
Elevator	9.38E-04	150	0.95	0.97	0.97
Catapult	4.79E-04	90	0.99	0.95	0.94
Guide device	7.78E-04	120	0.92	0.92	0.99
Command system	9.48E-04	110	0.93	0.96	0.97
Security site	5.99E-05	100	0.94	0.96	0.95

TABLE 3. Parameter settings of aircraft subsystem.

Subsystem	FR	Pc	FI	FD	Maintenance classification
Engine system	2.24E-03	0.95	0.95	0.98	Mechanical group
Electromechanical system	5.38E-03	0.95	0.95	0.97	Armament group
Flight control system	4.79E-03	0.99	0.95	0.94	Avionics group
Power supply system	1.78E-03	0.97	0.92	0.93	Mechanical group
Fuel System	3.41E-03	0.92	0.97	0.96	Mechanical group
Lifesaving system	2.59E-03	0.96	0.96	0.97	Special group

TABLE 4. Mean time and variance of human error.

Interaction type	Time mean	Time variance
Field Human-machine Interaction	120 minutes	12 minutes
Infield Human-machine Interaction	150 minutes	10 minutes

The equipment structure of the equipment of the system is complex. For example, the aircraft contains 24 subsystems, and the impact of each subsystem on the failure of the aircraft is different. The parameters of some key subsystems of the aircraft are shown in the TABLE 3. These parameters were obtained by a reasonable modification of the practical data.

According to the characteristics of the system, the human-machine interactions are divided into infield and field types. The mean time and time variance of human error under different interactions are shown in TABLE 4.

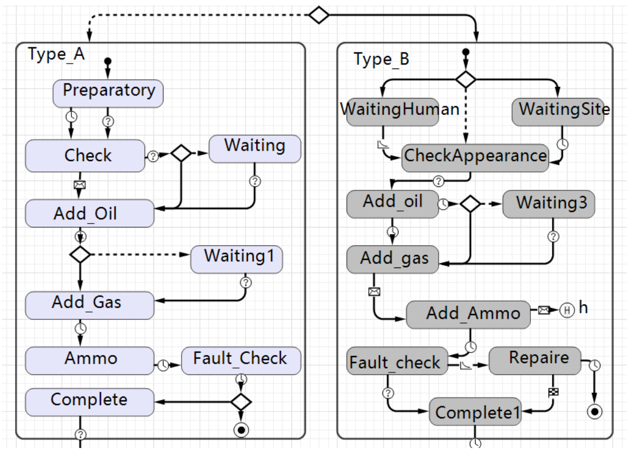

FIGURE 7. State design of the guarantee process.

In this paper, the number of Monte Carlo simulation samples is 5,000. Considering that a fleet consists of 26 aircraft on an aircraft carrier. The fleet is divided into three formations, and both formations A and B have 10 aircraft. In addition, the remaining 6 aircrafts are spare aircraft, which are denoted by formation C. The spare aircraft will be used when there is a problem with one of the formation A or B aircraft. The aircraft carrier will perform a 7-days day mission, and $k_e = 1$ during the day. The fleet will dispatch 8 waves per day, and every formation will perform a mission in turn.

In this case, the criteria for the failure of the mission are:

(i) During the dispatch of the aircraft formation, the assembly time of the aircraft formation exceeded 20% of the specified time.

(ii) During the return flight of the aircraft formation, the landing time of the aircraft formation exceeded 10% of the specified time.

When the number of assembled aircraft is insufficient, it can be handled by criterion (1).

B. MODELING OF SIMULATION RESULTS

In the modeling process, whether the aircrafts or various support facilities and humans have multiple states and a large number of dynamic behaviors (i.e., states change with time), so it is necessary to establish their complex life cycle state diagrams. Also we have to design their own state transition rules and interaction messages between agents. The state transition of an agent is complex, for example, in the Anylogic software, the partial design of the aircraft support process is shown in the FIG 7.

The Monte Carlo simulation can start when the modeling is completed. According to the simulation result, the number of successful simulations is $l = 4253$. According to the success degree of the task, the task reliability of the CHMS is:

$$R = 4253/5000 = 0.8506 \tag{18}$$

After the Monte Carlo simulation, the average number of successful dispatching tasks per 7 days and per day were

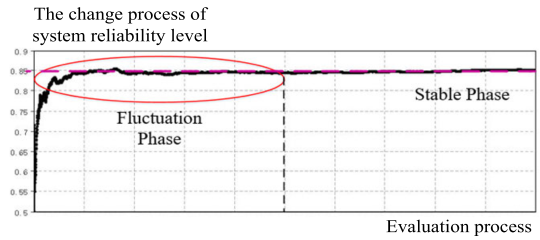

FIGURE 8. System reliability changes due to sampling.

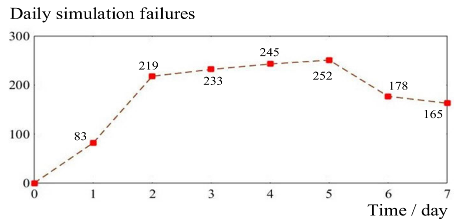

FIGURE 9. Average daily simulation failures.

406 and 57, respectively. The average support time per dispatching wave was 27.6 minutes, and the utilization level of the support facilities was 42.9%.

The reliability curve of the system during the simulation is shown in FIG 8. The system reliability values are all 5000 times simulation results. Although there are a large number of uncertain parameter inputs in the simulation model, the curve in FIG 8 is maintained at a stable value after a certain number of simulations. Clearly, the reliability level tends to be stable when the number of samples reaches 2,500, and 0.85 is used as the boundary line.

The system will not meet the simulation success criteria for various reasons. After Monte Carlo sampling, an approximate failure probability for the scheduling system is shown in FIG 9. In the simulation, the number of cumulative failures was 1747 times, and the number of daily mission failures from the first day to the seventh day was 83, 219, 233, 245, 252, 178, and 165. For example, the approximate probability of failure on the first day is $83/5000 = 0.0163$.

As the system operates, the performance changes over time. The ability to dispatch the aircraft is the most important performance parameter of the aircraft carrier. We take the average task dispatch time of aircraft per day to describe the performance. An aircraft carrier can only carry a limited amount resources when fighting at sea. When the aircraft and the various facilities fail, they may not be recovered in time due to insufficient resources. Therefore, with the advancement of combat time, the ability to dispatch the aircraft will decrease from the first day to the seventh day in the repeatedly simulation cycle. The average value of 5000 simulations is thus consistent with the actual situation, which is shown in FIG 10.

The average flying time of the aircraft in each wave is also an important performance parameter, its value can be obtained through 5000 times simulation experiments in every

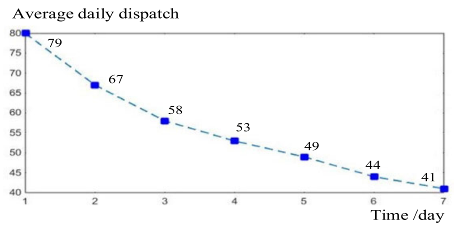

FIGURE 10. Average daily output of the aircraft.

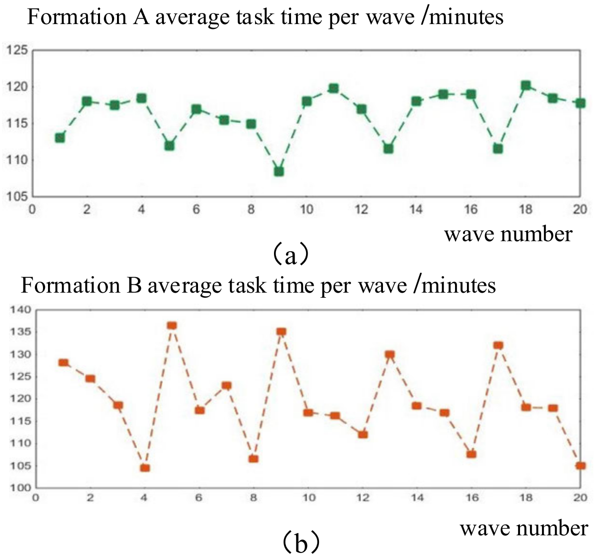

FIGURE 11. Average flying time for each formation.

single day. For the formation A and B aircraft, the average flying time of each wave is shown as FIG 11(a) and FIG 11(b).

C. DISCUSSION

The composition of a CHMS is very complex. If one parameter of the CHMS is changed, there will be an obvious effect on the reliability and performance. The effects of different factors on the system are discussed separately in this section. During the analysis, we only change the target parameters.

We analyzed the system reliability trend after environmental disturbances. To determine the impact of normal environmental disturbances, we set the ke = 0.85. As the number of environmental disturbances increases, the reliability decreases, as shown in FIG 12.

In this paper, nonhomogeneous Poisson distributions are used to describe the extreme environmental disturbance events, and in special cases, homogeneous Poisson distributions can also be used. When we increase the intensity of the parameters with the homogeneous Poisson distributions, the reliability of the system will also decrease as shown in FIG 13.

This system contains a large amount of important equipment. The failure rate level of this equipment will directly affect the system performance and system reliability. Therefore, analyzing the important equipment is of great

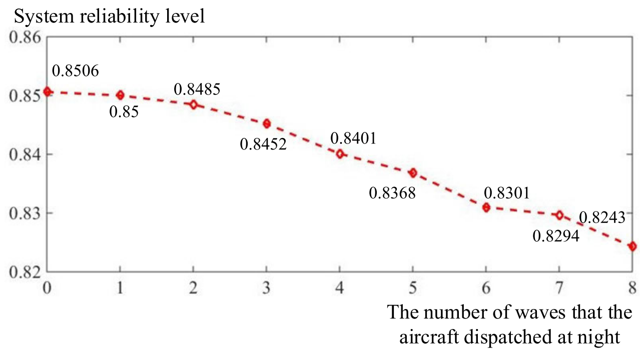

FIGURE 12. Impact of environmental changes on the system reliability level.

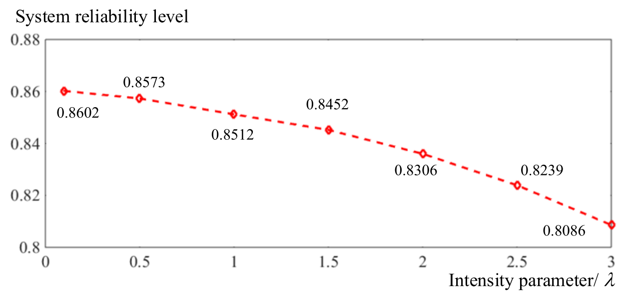

FIGURE 13. The system reliability variance due to the intensity of extreme environmental events.

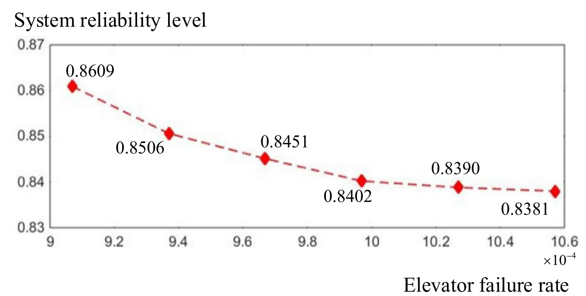

FIGURE 14. Impact of the elevator failure rate on the system reliability.

significance to control the system performance and reliability. We take the elevator as an example, the relationship between the system reliability and the elevator failure rate is shown in FIG 14.

With an increase in the total number of aircraft, the reliability and performance of the system will change. In this section, we will gradually increase the number of spare aircrafts, but the number of formation A and B aircraft is still 10. The ability to dispatch the aircraft is also affected by the number of aircraft available and the reliability of the support facility. When the impact of the reliability of the support facility exceeds, the number of available aircraft, the positive incentive effect of the number of spare aircraft becomes weak. The average number of aircraft dispatched per 7 days varies with the number of spare aircraft as shown in FIG 15(a).When the number of spare aircraft increases to a certain extent, the number of dispatches increases very little.

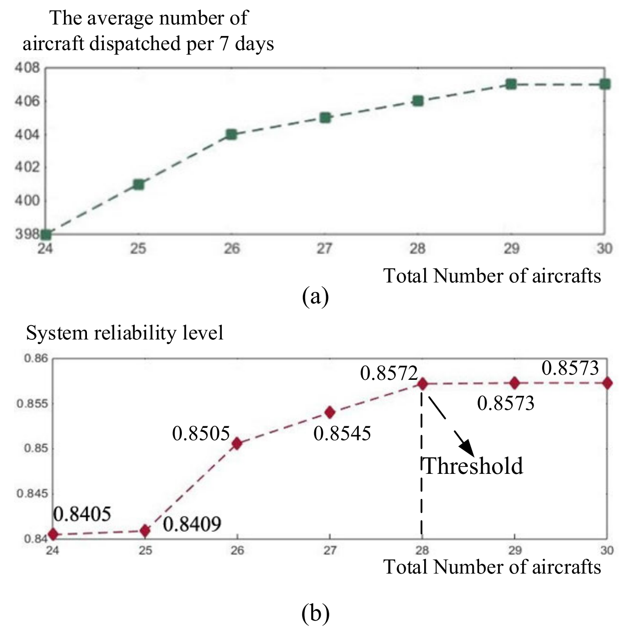

FIGURE 15. Impact of the number of aircraft on the system performance.

Similarly, the reliability of the system varies with the number of spare aircraft as shown in FIG 15(b). When it is increased to a certain extent, the reliability increases very little.

VI. CONCLUSION

In this paper, an agent-based modeling framework and method are proposed to evaluate the reliability and performance of a CHMS with multistate systems and dynamic behaviors. The effectiveness of the proposed approach is verified in a case study of deck scheduling on an aircraft carrier as an example. The main innovations and advantages are as follows.

(i) The proposed method can describe the multistate functions, multistate disturbances and the adaptive behaviors of the CHMS.
(ii) A dual-clock for mechanism faults and human errors is used to accurately describe the occurrences of machine failures and human errors.
(iii) The state transition of the environment agent and random events are used to describe the environmental disturbances and extreme environmental conditions for the CHMS.
(iv) The contract-based approach can automatically select the most suitable participants for the maintenance and reconfiguration processes of the CHMS to achieve proper control of the system disturbances.
(v) The system failure criteria in the model can be defined by combining the performance values of multiple degraded parameters, which can more effectively determine the correct state of the multistate fault and simultaneously evaluate the reliability and performance of the CHMS.

The agent-based approach in this paper can be directly applied to analyze the reliability and performance of various CHMSs. However, some parameters in the agent-based model are stochastic. In addition, although the multistate analysis is dominant at the system level in our work, a two-state analysis still applies to the minimum modeling components such as for machine failures and human errors. In the future, the research could be extended by optimizing the parameters in the CHMSs based on the agent and using a more fine-grained behavior modeling method for machine failures, human errors, maintenance and reconfiguration in the CHMS.

REFERENCES

[1] W. Wattanacharoensil, M. Schuckert, A. Graham, and A. Dean, "An analysis of the airport experience from an air traveler perspective," *J. Hospitality Tourism Manage.*, vol. 32, pp. 124–135, Sep. 2017.
[2] W. Ni, W. Wu, and K. Li, "A message efficient intersection control algorithm for intelligent transportation in smart cities," *Future Gener. Comput. Syst.*, vol. 76, pp. 339–349, Nov. 2017.
[3] C. Chen, W.-Q. Tan, X.-J. Qu, and H.-X. Li, "A fuzzy human pilot model of longitudinal control for a carrier landing task," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 54, no. 1, pp. 453–466, Feb. 2018.
[4] W. Fan, P. Yang, A. H.-S. Ang, and Z. Li, "Analysis of complex system reliability with correlated random vectors," *Probabilistic Eng. Mech.*, vol. 45, pp. 61–69, Jul. 2016.
[5] J. Boes and F. Migeon, "Self-organizing multi-agent systems for the control of complex systems," *J. Syst. Softw.*, vol. 134, pp. 12–28, Dec. 2017.
[6] Y. Cui, R. M. Voyles, J. T. Lane, A. Krishnamoorthy, and M. H. Mahoor, "A mechanism for real-time decision making and system maintenance for resource constrained robotic systems through ReFrESH," *Auton. Robots*, vol. 39, no. 4, pp. 487–502, 2015.
[7] K. A. Ouedraogo, S. Enjalbert, and F. Vanderhaegen, "How to learn from the resilience of human-machine systems?" *Eng. Appl. Artif. Intell.*, vol. 26, no. 1, pp. 24–34, 2013.
[8] X.-J. Li and G.-H. Yang, "Fuzzy approximation-based global pinning synchronization control of uncertain complex dynamical networks," *IEEE Trans. Cybern.*, vol. 47, no. 4, pp. 873–883, Apr. 2017.
[9] J. Mi, Y.-F. Li, W. Peng, H.-Z. Huang, "Reliability analysis of complex multi-state system with common cause failure based on evidential networks," *Rel. Eng. Syst. Saf.*, vol. 174, pp. 71–81, Jun. 2018.
[10] X.-S. Si, C.-H. Hu, Q. Zhang, and T. Li, "An integrated reliability estimation approach with stochastic filtering and degradation modeling for phased-mission systems," *IEEE Trans. Cybern.*, vol. 47, no. 1, pp. 67–80, Jan. 2017.
[11] X. Yuan, B. Cai, Y. Ma, J. Zhang, K. Mulenga, Y. Liu, and G. Chen, "Reliability evaluation methodology of complex systems based on dynamic object-oriented Bayesian networks," *IEEE Access*, vol. 6, pp. 11289–11300, 2018.
[12] R. De Andrade, K. N. Hodel, J. F. Justo, A. M. Lagana, M. M. Santos, and Z. Gu, "Analytical and experimental performance evaluations of CAN-FD bus," *IEEE Access*, vol. 6, pp. 21287–21295, 2018.
[13] P. Ghadimi, F. G. Toosi, and C. Heavey, "A multi-agent systems approach for sustainable supplier selection and order allocation in a partnership supply chain," *Eur. J. Oper. Res.*, vol. 269, no. 1, pp. 286–301, 2018.
[14] C. Sahin, M. Demirtas, R. Erol, A. Baykasoğlu, and V. Kaplanoğlu, "A multi-agent based approach to dynamic scheduling with flexible processing capabilities," *J. Intell. Manuf.*, vol. 28, no. 8, pp. 1827–1845, 2017.
[15] K. Singh and C.-W. Ahn, "An agent based model approach for perusal of social dynamics," *IEEE Access*, vol. 6, pp. 36948–36965, 2018.
[16] F. Qiang, L. Songjie, and S. Bo, "A multi-agent based intelligent configuration method for aircraft fleet maintenance personnel," *Chin. J. Aeronaut.*, vol. 27, no. 2, pp. 280–290, 2014.
[17] V. N. Coelho, M. W. Cohen, I. M. Coelho, N. Liu, and F. G. Guimarães, "Multi-agent systems applied for energy systems integration: State-of-the-art applications and trends in microgrids," *Appl. Energy*, vol. 187, pp. 820–832, Feb. 2017.

[18] R. A. Williams, ''Lessons learned on development and application of agent-based models of complex dynamical systems,'' *Simul. Model. Pract. Theory*, vol. 83, pp. 201–212, Apr. 2018.

[19] Y. Ren, D. Fan, Q. Feng, Z. Wang, B. Sun, and D. Yang, ''Agent-based restoration approach for reliability with load balancing on smart grids,'' *Appl. Energy*, vol. 249, pp. 46–57, Sep. 2019.

[20] F. Ye, W. Zhang, L. Ou, and G. Zhang, ''Optimal disturbance rejection controllers design for synchronised output regulation of time-delayed multi-agent systems,'' *IET Control Theory Appl.*, vol. 11, no. 7, pp. 1053–1062, 2017.

[21] Y. Shi, Z. Lu, S. Chen, and L. Xu, ''A reliability analysis method based on analytical expressions of the first four moments of the surrogate model of the performance function,'' *Mech. Syst. Signal Process.*, vol. 111, pp. 47–67, Oct. 2018.

[22] F. Chiacchio, D. D'Urso, F. Famoso, S. Brusca, J. I. Aizpurua, and V. M. Catterson, ''On the use of dynamic reliability for an accurate modelling of renewable power plants,'' *Energy*, vol. 151, pp. 605–621, May 2018.

[23] Q. Feng, X. Zhao, D. Fan, B. Cai, Y. Liu, and Y. Ren, ''Resilience design method based on meta-structure: A case study of offshore wind farm,'' *Rel. Eng. Syst. Saf.*, vol. 186, pp. 232–244, Jun. 2019.

[24] G. Levitin, L. Xing, and Y. Dai, ''Optimizing dynamic performance of multistate systems with heterogeneous 1-out-of-*N* Warm standby components,'' *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 48, no. 6, pp. 920–929, Jun. 2018.

[25] P. Gao, L. Xie, W. Hu, C. Liu, and J. Feng, ''Dynamic fuzzy reliability analysis of multistate systems based on universal generating function,'' *Math. Problems Eng.*, vol. 2018, May 2018, Art. no. 6524629.

[26] M. Catelani, L. Ciani, and M. Venzi, ''Component reliability importance assessment on complex systems using credible improvement potential,'' *Microelectron. Rel.*, vol. 64, pp. 113–119, Sep. 2016.

[27] S. Babu, P. Hilber, E. Shayesteh, and L. Enarsson, ''Reliability evaluation of distribution structures considering the presence of false trips,'' *IEEE Trans. Smart Grid*, vol. 9, no. 3, pp. 2268–2275, May 2018.

[28] S. Getir, L. Grunske, A. van Hoorn, T. Kehrer, Y. Noller, and M. Tichy, ''Supporting semi-automatic co-evolution of architecture and fault tree models,'' *J. Syst. Softw.*, vol. 142, pp. 115–135, Aug. 2018.

[29] S. Li and D. Guo, ''Cache coherence scheme for HCS-based CMP and its system reliability analysis,'' *IEEE Access*, vol. 5, pp. 7205–7215, 2017.

[30] F. Chiacchio, D. D'Urso, L. Compagno, M. Pennisi, F. Pappalardo, and G. Manno, ''SHyFTA, a stochastic hybrid fault tree automaton for the modelling and simulation of dynamic reliability problems,'' *Expert Syst. With Appl.*, vol. 47, pp. 42–57, Apr. 2016.

[31] S. Kabir, ''An overview of fault tree analysis and its application in model based dependability analysis,'' *Expert Syst. Appl.*, vol. 77, pp. 114–135, Jul. 2017.

[32] P. Gehl, F. Cavalieri, and P. Franchin, ''Approximate Bayesian network formulation for the rapid loss assessment of real-world infrastructure systems,'' *Rel. Eng. Syst. Saf.*, vol. 177, pp. 80–93, Sep. 2018.

[33] S. Kabir, M. Walker, and Y. Papadopoulos, ''Dynamic system safety analysis in HiP-HOPS with Petri nets and Bayesian networks,'' *Saf. Sci.*, vol. 105, pp. 55–70, Jun. 2018.

[34] Z. Li, T. Xu, J. Gu, Q. Dong, and L. Fu, ''Reliability modelling and analysis of a multi-state element based on a dynamic Bayesian network,'' *Roy. Soc. open Sci.*, vol. 5, no. 4, 2018, Art. no. 171438.

[35] L. Yu, Z. Zhou, Y. Fan, M. E. Papka, and Z. Lan, ''System-wide trade-off modeling of performance, power, and resilience on petascale systems,'' *J. Supercomput.*, vol. 74, no. 7, pp. 3168–3192, 2018.

[36] Y. Ren, D. Fan, X. Ma, Z. Wang, Q. Feng, and D. Yang, ''A GO-FLOW and dynamic Bayesian network combination approach for reliability evaluation with uncertainty: A case study on a nuclear power plant,'' *IEEE Access*, vol. 6, pp. 7177–7189, 2018.

[37] L. Yin, Z. Li, N. Wu, S. Wang, and T. Qu, ''Fault diagnosis in partially observed Petri nets using redundancies,'' *IEEE Access*, vol. 6, pp. 7541–7556, 2018.

[38] Y. Liu, B. Liu, X. Zhao, and M. Xie, ''Development of RVM-based multiple-output soft sensors with serial and parallel stacking strategies,'' *IEEE Trans. Control Syst. Technol.*, to be published.

[39] P. Wei, F. Liu, and C. Tang, ''Reliability and reliability-based importance analysis of structural systems using multiple response Gaussian process model,'' *Rel. Eng. Syst. Saf.*, vol. 175, pp. 183–195, Jul. 2018.

[40] Y. Shang-wen and H. Ming-hua, ''Estimation of air traffic longitudinal conflict probability based on the reaction time of controllers,'' *Saf. Sci.*, vol. 48, no. 7, pp. 926–930, 2010.

[41] W. J. Matthews, E. Marsh-Matthews, R. C. Cashner, and F. Gelwick, ''Disturbance and trajectory of change in a stream fish community over four decades,'' *Oecologia*, vol. 173, no. 3, pp. 955–969, 2013.

[42] F. Cadini, G. L. Agliardi, and E. Zio, ''A modeling and simulation framework for the reliability/availability assessment of a power transmission grid subject to cascading failures under extreme weather conditions,'' *Appl. Energy*, vol. 185, pp. 267–279, Jan. 2017.

[43] X.-C. Su, W. Han, Y. Wu, Y. Zhang, and J.-Y. Song, ''A robust scheduling optimization method for flight deck operations of aircraft carrier with ternary interval durations,'' *IEEE Access*, vol. 6, pp. 66918–66936, 2018.

[44] Y. Wu and X. Qu, ''Path planning for taxi of carrier aircraft launching,'' *Sci. China Technol. Sci.*, vol. 56, no. 6, pp. 1561–1570, 2013.

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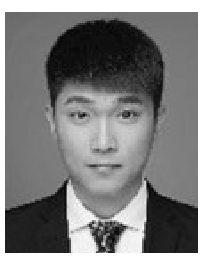

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