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An Agent-based Model to Evaluate Influences on Structural Reliability by Human and Organizational Factors

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Human and Organizational Factors (HOFs) are considered to have significant impacts on structural reliability. Yet how structural reliability is affected by these factors and how large this impact is remains inadequately studied. A model that is designed to reveal such relationships is proposed in this paper. First, a review of problem related studies from three different methodological viewpoints is presented. The proposed model integrates the reviewed methods under an Agent-Based Modeling (ABM) framework that is capable of capturing the dynamics and nonlinear influences of HOFs on the structural reliability. Subsequently, preliminary results of the structural failure probability frequency distribution from a case study of a simple floor slab structure are presented to illustrate the possibilities of the model. It is found out that the failure probability distribution changes significantly due to the influence by HOFs and checking for errors.

Keywords: Human and organizational factors, Structural reliability, Agent-based Modeling, Performance Shaping Factors, Simulation-based HRA, Dynamic HRA, Monte-Carlo simulation.

1. Introduction

Structural reliability refers to the ability of a structure or a structural member to fulfil the specified requirements (CEN, 2002). It is and has always been an essential issue in the Building Industry. Adverse events like structural failures can lead to economic, social and environmental loss, and even human injury and fatality. Thus attention should be paid to prevent structural failures and enhance structural reliability in practice. It is widely acknowledged by numerous researches in the structural safety field that the majority of structural failures are caused by human errors or flaws that are embedded in the project organization during the structural design and construction phase (De Haan, 2012; Terwel, 2014). An approximation of $70 - 90\%$ of the structural failures are estimated to result from human errors, among which $40 - 50\%$ are due to structural design and construction errors (Melchers, 1984; Ellingwood, 1987). Therefore, HOFs, other than rare extreme loads or deterioration, are considered as major contributors to structural failure (Stewart, 1992a; Terwel, 2014). Hence, investigating structural reliability from a non-technical perspective (i.e. HOFs) may lead to significant improvements with regard to structural safety.

The purpose of this research is to provide a model that is capable of measuring the dynamic influence of HOFs on structural reliability during the structural design and construction process. Therefore in this paper, the problem at hand is addressed by first reviewing previously published related works, then by presenting a preliminary model that evaluates the influence of HOFs on structural reliability. In addition, a simple case study is presented to illustrate the potential of the proposed model. In the end, contributions and remarks of this model, as well as recommendations for future work, are discussed.

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2. Related Works

2.1. *Human error and structural reliability*

Since structural reliability is significantly influenced by HOFs, many researchers have investigated the effects of human error on structural reliability. Melchers (1984) proposed a model with linear dependency of the structural failure probability on the human error probability and a control factor. Frangopol (1986) presented mathematical models to combine human errors to probabilistic models for structural risk assessment by treating human errors as conservative (positive) or unconservative (negative) changes to the probability distributions of load and resistance. Human errors in Frangopol's research were treated in general while a review of statistical surveys of failure data and structural safety studies by Ellingwood (1987) identified the human error proneness of different building processes as well as different error causes. Furthermore, El-Shahhat et al. (1995) presented three approaches to deal with human errors in design and construction.

According to Reason's Swiss Cheese Model (Reason, 2000), unsafe acts can be interpreted as the extreme load acts on the structure, whereas human errors can be viewed as preconditions for unsafe acts. Unsafe supervision refers to the missing or misconducted checks and inspections during the design and construction process. In this paper, human performance and organizational influences are both considered as HOFs, and subsequently modelled as Performance Shaping Factors (PSFs) in the proposed model.

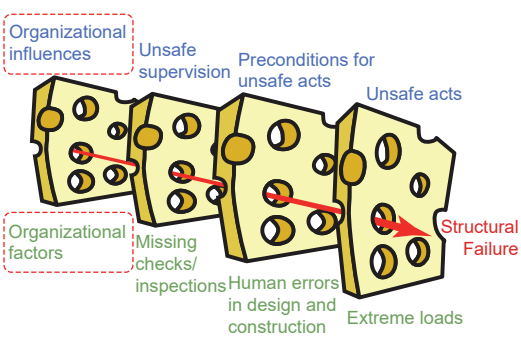

Fig. 1. The Swiss Cheese Model (adapted from (Reason, 2000))

2.2. *Human Reliability Analysis*

Human Reliability Analysis is a set of methods to evaluate human contributions to system reliability by estimating Human Error Probability (HEP) and assessing system degradation caused by human errors (Swain and Guttmann, 1983). HRA aims to identify, model, and quantify human error. An important component of HRA is the PSFs, which represent task, personal and environmental characteristics in the system that will potentially affect human performance in a positive or negative manner (Di Pasquale et al., 2013). The identified and quantified PSFs are utilised to modify the nominal HEP value to acquire a better estimation.

Many HRA methods have been developed and applied in various domains such as nuclear, aviation and chemical processing. In the structural safety field, a series of works by Stewart (1992a,b, 1993a,b) developed an HRA method to evaluate the human error effects during the structural design and construction phase. A micro-task human performance model was proposed within these studies, consisting of two important parameters namely the human error rate and the error magnitude. Moreover, De Haan (2012) proposed an HRA model for evaluating the human error consequence for structural design engineering. A simplified Cognitive Reliability and Error Analysis Method (CREAM) (Hollnagel, 1998) was first developed for assessing HEP in design tasks, then this simplified CREAM model was combined with Stewart's HRA method to evaluate structural failure probability affected by human errors in structural design.

The simulation-based dynamic HRA can enhance the accuracy in modeling human performance and is thus promising with respect to the research aim of this paper.

2.3. *Agent-based Modeling*

Along the design and construction process, the reliability status of a structure evolves as a result of a constant influence by HOFs. Besides, human and organizational performance in one task does not only affect the task result, but also interacts and influences the performance in the next task. Therefore, a structural design and construction process that concern HOFs and structural reliability, as well as their interactions between each other, can be viewed as a socio-technical system. This socio-technical system consists of a social network of project actors and performed tasks, and technical entities of structural parameters that follow the natural laws of physics. Such a socio-technical system can be adequately modelled using ABM, making it a promising method to model the influence of HOFs on structural reliability.

ABM is a bottom-up approach within which the system properties emerge from diverse behaviours of distributed autonomous agents and their interactions. In ABM a system is modelled by describing each individual agent and their interactions with other agents and the system environment. Agent behaviours are captured in the ABM model to map all the possible system states and param-

eter range by repeated simulation runs (Van Dam et al., 2012).

A few studies have modelled the construction project risk management and construction safety with ABM. Palaniappan et al. (2007) present a conceptual framework that consists of key components for agent-based model development in modeling a construction safety system. Furthermore, an agent-based model for risk management in construction projects was proposed by Zhang et al. (2012) using coloured Petri nets. Given the fact that the risk management should be treated as a dynamic process throughout the project life cycle, Taillandier et al. (2015) developed a multi-agent model to study the complexity of risk management in construction projects.

Given the studies mentioned above, it is concluded that agent-based models have been developed for risk management of construction projects in the building industry. The risk studied in these cases are occupational risks and financial losses of the project. However, no agent-based model is found concerning the structural reliability assessment from a HOF perspective. Therefore, to fill in this gap, an agent-based model to evaluate the influence of HOFs on structural reliability is developed in this paper, as presented in the following section.

3. Methodology

The main research goal, to which this work contributes, is to develop a model that can dynamically evaluate the structural reliability influenced by HOFs during the structural design and construction process in the building industry. In this model, HOFs are modelled as PSFs, which is common to represent and quantify human and organizational performance in HRA methods (Alvarenga et al., 2014). In the proposed model, a dynamic Standardized Plant Analysis Risk-Human Reliability Analysis (SPAR-H) method is applied to obtain the HEP value. The SPAR-H method is chosen due to the fact that as a second generation HRA method, it takes human cognition into consideration. Also, it acknowledges that PSFs not only contribute to human error, but also enhance human performance. Most importantly, it makes use of PSFs in HEP assessment in a clear and simple structure, which provides foundations to define agents behaviour in the proposed agent-based model.

3.1. *Model framework*

In the proposed model, several methods are integrated into an agent-based model, following the model framework in figure 2.

Firstly, a task analysis of the structural design and construction process is conducted to break down the process into detailed micro-tasks in order to acquire information for developing the agent-based model. After the task analysis, each individual task's content, performing actor, type, and affected parameters are identified. Secondly, a dynamic SPAR-H method is applied within each task to stochastically simulate the PSF level. Subsequently, the multiplier given by the PSF level is applied to the basic HEP to calculate the HEP value of a task. Thirdly, Stewart's HRA method is adopted to evaluate whether human error is included in the task, and subsequently, to analyse the changes of the affected parameters. This is achieved by generating a random number within $[0, 1]$ and comparing it with the previously obtained HEP value. If the random number is bigger than the HEP value, then the current task is deemed as "error free", thus the design value is kept as is; however, if the random number is smaller than or equal to the HEP value, then the current task is "error included", therefore the design value of the affected parameter is attached with an error magnitude. Later, a check procedure is activated to detect the human error that is included in the micro-task. If the error is spotted and corrected, then the error magnitudes will be erased from the affected parameters; otherwise the error magnitudes stay with the affected parameters and pass to the next micro-task. Finally, if the error still exists after the check, a level III reliability method to evaluate the structural reliability is performed. This method applies a Monte Carlo simulation to estimate the structural failure probability based on the input from load parameter distributions in the probabilistic model code by the JCSS (2001) and the modified resistance parameter distributions from the previous simulation process. Whereas if the task is error free after the check, no Monte Carlo simulation will be performed. The structural failure probability is updated after the check for each task, thus the accumulated influence of HOFs on structural reliability can be obtained after the completion of the final task. Moreover, after repeating this process

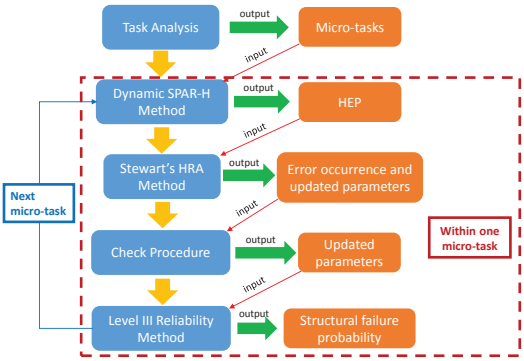

Fig. 2. The model framework

for a large number of times, the distribution of structural failure probabilities that is affected by HOFs is acquired.

3.2. *Agent-based model*

All the methods used in the model are integrated into an agent-based model. The problem that is addressed within this agent-based model is how HOFs' influence structural reliability. Furthermore, the system under study is the structural design and construction process of a simple building structure.

3.2.1. *Agents and agent behaviour*

There are four main types of agent in the system, namely actor, task, check, and structure. While actor, task and check are autonomous agents that take actions according to their encoded rules, the structure agent is an object that responds to requests from other agents. The actor agents represent the stakeholders that participate in the structural design and construction phase. Since the HOFs in the model are represented by the eight PSFs in the SPAR-H method, the evaluation of the HOFs' influence is thus translated to assessing the influence of the PSFs. Whereas, in the agent-based model, the PSFs of "stress and stressors", "experience and training", "work processes", and "fitness for duty" are associated with the actor agent and the PSFs of "available time", "complexity", "procedures", and "ergonomics and human-machine interaction" are associated with the task agent. The actor agents and the task agents autonomously decide (by chance, user setting, or system variables) on their PSF level. Thus these two agent breeds together determine the task HEP in a stochastic manner. Besides this, the task agents also contain other properties like task type, affected parameters, occurrence of error, HEP, actual cost, and actual duration. Hence, the task agent can decide if a task is "error free" or "error included", and subsequently send a request to the structure agent to update the affected parameters. The structure agent contains all the true design values for structural parameters as well as structural failure mechanisms known from mechanical engineering. It can store and update parameters in response to requests from the task agent. If a task is "error free", then the affected parameters of said task remain the same in the structure agent, otherwise, the task agent requests the structure agent to modify the affected parameters by attaching the corresponding error magnitude to them and record this update. Moreover, the structure agent can perform a Monte Carlo simulation to obtain the structural failure probability if a task is error included. The check agent will perform a check after each micro-task is finished, then decide whether to take correction actions according to the check result and its own stochastic behaviour rules.

3.2.2. *Dynamics in PSFs evaluation*

This agent-based model provides a dynamic simulation-based approach to assess the human and organizational performance during the structural design and construction process. Following the static SPAR-H method, PSF levels are evaluated by domain experts, then the evaluation results are used to calculate a HEP for each task. Whereas in the agent-based model, PSFs are assigned as properties of the actor agents and the task agents. Therefore, these agents can determine the PSF level autonomously in a stochastic manner. Thus the aim of this model is not to evaluate HEP according to PSF evaluating judgements, but to provide a map of all possible human and organizational performance scenarios, and to then investigate on the affected structural reliability under different scenarios. In the end, critical paths that lead towards structural failures with a high probability can be identified, and such a map can be adopted for better structural safety management support.

For the study at hand, two types of HOF influences are considered. Firstly, structural reliability is affected directly by HOFs when a task is being performed during the design and construction process. This direct influence is termed as the first-order influence, which is evaluated by different PSF levels. Secondly, the time and monetary costs can affect the HOF influences. From the project management perspective, time and cost constraints can significantly affect human and organizational performance. Therefore, the task time and monetary costs will affect relevant PSF levels, and thus indirectly also the structural reliability. This indirect influence is termed the second-order influence.

The second-order influence consists of the effects of task duration and cost on the PSF level of "available time" and "stress and stressors". The current task performance regarding time consumption will decide the PSF level of "available time" for the next task, whereas "stress and stressors" of the coming task is determined by both time and cost consumptions of the current task. This impact is determined by two basic variables from the task agent, namely actual cost (C_a) and actual time (T_a), and four variables of the structure agent, namely planned cost (C_P), planned time (T_P), total cost (C_{to}) and total time (T_{to}). The total cost and total time is the summation of the planned cost and planned time. The actual cost and actual time follow normal distributions that have the planned cost and planned time as their mean value and estimated standard deviations from practice. The values of the actual cost and actual time for a task are random draws from their distributions. Then four variables termed time left (T_l), time delay (T_d), cost left (C_l) and cost delay (C_d) are defined as follows:

$$T_l = T_{to} - T_a \quad (1)$$

$$T_d = T_p - T_a \quad (2)$$

$$C_l = C_{to} - C_a \quad (3)$$

$$C_d = C_p - C_a \quad (4)$$

If $T_l < 0$ or $C_l < 0$, then the PSF level of "stress and stressors" for the next task is "extreme"; if $T_d < 0$ or $C_d < 0$, then the "stress and stressors" level for the next task is "high"; otherwise the "stress and stressors" level for the next task is "nominal".

If $T_l \leq 0$, then the PSF level of "available time" for the next task is "inadequate"; if $T_l > 0$ and $T_d < 0$, then the "available time" level for the next task is "barely adequate"; if $T_l > 0$ and $T_d > 0$, then the "available time" level for the next task is "extra"; otherwise the "available time" level for the next task is "nominal".

The first-order and second-order influence present the HOF influence in a stochastic and interactive way, which enhances the dynamics of PSFs evaluation in the agent-based model.

3.2.3. *Checks*

The check agent will be activated to perform a check on each micro-task after the completion of that task. In the structural design phase, a micro-task will be performed by the structural engineer, then it is checked by his supervisor. Whereas in the construction phase, the micro-tasks will be conducted by the prefabricate concrete component factory, the material transportation company, or the contractor according to the task contents. Then the client (project owner) will perform an inspection after each task.

When a micro-task is "error free", then the check agent finds no error in the task, and hence takes no action in the check procedure. When a micro-task is "error included", then the check agent is assumed to have an 80% chance to detect this error and a 20% chance that it fails to find the error. Following this, if the check agent fails to find the error, then no action will be taken. Whereas if the error is spotted by the agent, there is an assumed 90% chance that it corrects the error right, and a 10% chance that it ignores the error and takes no action to correct it. The scenario that the error is corrected wrongly by the check agent is not considered in this study. The check agent corrects the identified error by sending a request to the structure agent to erase the error magnitude that attached to the affected parameters within this micro-task. Afterwards, the structure agent will update and store the parameters again.

The check procedure represents real practice in the building industry. It indicates the fact that human and organizational influence on the structure is not a linear accumulation, but a dynamic process that requires more nonlinear modeling considerations.

3.3. *Error magnitude*

Error magnitude is an important parameter in this model. It implies the deviation of structural parameters from the correct design value, influenced by HOFs in each micro-task. According to (Stewart, 1992a), the error magnitude follows a lognormal distribution. In addition, De Haan (2012) pointed out that the standard deviation of the error magnitude is related to the task complexity. Whereas in the agent-based model, task complexity is modelled as a PSF that belongs to the task agent. Thus for every task that is error included, the corresponding error magnitudes are determined by the generated "complexity" level of the task agent. Since the task agent can stochastically decide on the "complexity" level, the error magnitude distributions are therefore dynamic.

For the error magnitude, the μ of the lognormal distribution is assumed to be 0. Thus the error magnitude can be obtained based on the σ listed in table 1 (De Haan, 2012).

Table 1. σ of error magnitude by task complexity.

Task complexity	σ
High	0.6688
Moderate	0.5409
Nominal	0.4219
Obvious	0.2980

When a task is error included, the affected parameters in this task are multiplied by the corresponding error magnitudes. Since the values of a lognormal distribution are always above 0, and can be smaller or bigger than 1, thus the error magnitude can decrease or increase the design parameter value in a stochastic manner. The product of these two distributions is calculated by taking random draws from each distribution and then multiply these two values. This calculation is carried out within the Monte Carlo simulation when evaluating the structural reliability.

3.4. *The simulation process*

The simulation process of this agent-based model follows the basic steps of the model framework that elaborated in subsection 3.1. If error remains after the whole process, a level III reliability analysis is performed to calculate the structural failure probability after this task based on the modified parameters. This is achieved by a Monte Carlo simulation to generate random values from the distributions of load and resistance parameters, then calculate the limit state value Z.

$$Z = f(R, S) \tag{5}$$

In this formula, R represents resistance variables and S represents load variables. If the limit state Z is smaller than 0, then structural failure occurs; otherwise no structural failure happens. Afterwards, the structural failure probability is calculated by dividing the number of Monte Carlo simulation runs within which structural failure occurs (n) by the total number of runs (N).

$$P_f = n/N \tag{6}$$

This Monte Carlo simulation is carried out after every check when error is included in the task. Due to the fact that the influences of HOFs are successive across tasks, the structural failure probability updates with input from every Monte Carlo simulation throughout the design and construction process. Thus the final structural failure probability that influenced by HOFs can be obtained after the final task.

The above process is denoted as one simulation run. By repeating the simulation run for a large number of times, the structural failure probability distribution can be obtained. This is elaborated with a simple case study and some preliminary simulation results in the coming section.

4. Case Study

4.1. *Case description*

A simple case study of the design and construction of a prefabricated reinforced concrete slab is presented. The slab span is designed to be $5\mathrm{m}$, and other parameters are from Eurocode (CEN, 2002) and the probabilistic model code by the JCSS (2001), see Table 2. This slab is represented by the structure agent, and the ultimate limit state bending moment (Eq. 7) is the failure mechanism evaluated in this case.

$$Z = \theta_R A_s f_{yd} \left(h - c - \frac{\varnothing}{2} - \left(\frac{A_s f_{yd}}{2 f_{cd}} \right) \right) - \frac{\theta_E (p_G + p_d) L^2}{8} \tag{7}$$

Besides, only the process of design, prefabrication, transportation, and installation of the slab element is studied. The task agent breed consists of individual tasks within this process. Apart from this, the actor involved in the slab structural design phase is the structural engineer, and actors in the construction phase are the contractor, the prefabricated concrete component factory, and the material transportation team. Each actor is modelled as an actor agent and performs corresponding tasks in the process. Checks are conducted by the supervisory structural engineer in design, and by the client in construction. A check is carried out right after the completion of a task by the check agent.

4.2. *Simulation results*

The proposed agent-based model is implemented in NetLogo, using the Python extension. Within each simulation run, $1.0\mathrm{e}5$ Monte Carlo iterations are performed to calculate the structural failure probability before the first task and after each micro-task, if error exists after checking. In total, $1.0\mathrm{e}5$ simulation runs are conducted. The above experiment is also conducted to calculate the structural failure probability for the situation without HOFs' influence and the scenario without checks. The results of this preliminary study are presented in Figure 3. In figure 3, the top figure shows the normalized frequency distribution of the structural failure probability with checks and HOFs' influence. The figure to the bottom left shows the result of failure probability frequency distribution without HOFs' influence. For this figure, checks have no influence on the distribution since all the tasks are deemed error free in the simulations. The figure to the bottom right indicates the failure probability frequency distribution with HOFs' influence, but without checks.

It can be concluded from the bottom left figure that the failure probability distribution is approximate to a normal distribution with a $\mu = 9.826\mathrm{e}{-3}$, and $\sigma = 3.12\mathrm{e}{-4}$. When compared with the above figure, it can be observed that the failure probability distribution is scattered over a wider range of probabilities from almost 0 to around 0.4. Additionally, from the zoomed in segments of the top figure, it can be deducted that the top figure does not follow one typical distribution, but rather multiple individual (overlapping) normal distributions within the range. The bottom left distribution can also be seen in the top figure, as shown in the top left zoomed in figure. Thus the structural failure probability has the highest chance to be free from HOFs' influence, while a lower frequency to be affected by HOFs, but with a higher failure probability.

When comparing the bottom two figures in which checks are not considered in the simulation process, it can be observed that the distribution with HOFs' influence skew toward higher failure probabilities over a wider probability range compared to that without HOFs' influence. Besides, the mean value of the distribution with HOFs' influence shifts to around 0.38, which is significantly higher than the distribution without HOFs' influence. Therefore, it can be concluded that without checks, the HOFs' influence can significantly increase the structural failure probability.

The checking effects on structural failure probability can be concluded via comparing the top

Table 2. Parameter distributions of the slab.

Parameter	Symbol	Unit	Distribution	μ	σ
Design load	p_d	$\mathrm{N\,mm^{-2}}$	normal	5.00e−3	1.00e−3
Slab span	l	mm	normal	5.00e+3	50.00
Slab width	b	mm	normal	1.00e+3	0.10
Compression strength concrete	f_{cd}	$\mathrm{N\,mm^{-2}}$	lognormal	2.976	0.198
Yield strength	f_{yd}	$\mathrm{N\,mm^{-2}}$	lognormal	6.213	0.060
Shape factor concr. compr. zone	α	-	N/A	0.25	0.00
Shape factor concr. compr. zone	β	-	N/A	0.389	0.00
Slab depth	h	mm	normal	250.00	5.00
Self weight	p_G	$\mathrm{N\,mm^{-2}}$	normal	6.25e−3	1.00e−3
Concrete cover	c	mm	gamma	20.00	5.00
Reinforcement diameter	$\varnothing$	mm	normal	10.00	0.10
Reinforcement area	A_s	$\mathrm{mm^2\,m^{-1}}$	normal	524.00	20.00
Uncertainty of resistance	θ_R	-	lognormal	0.093	0.070
Uncertainty of load effect	θ_R	-	lognormal	−0.020	0.198

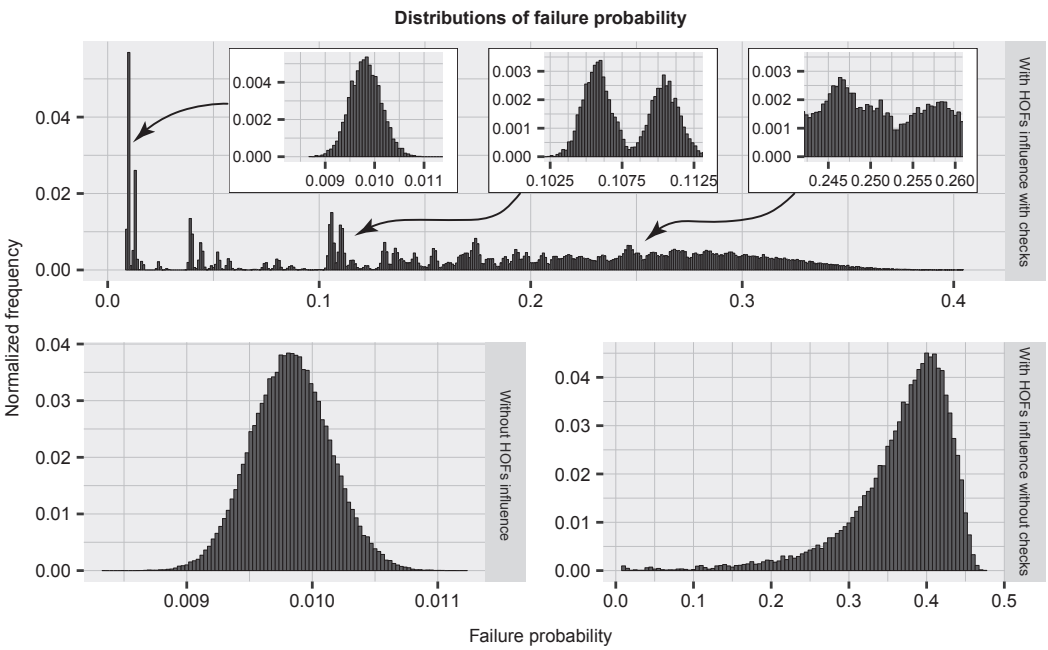

Fig. 3. The normalized frequency distributions of structural failure probabilities.

figure with the bottom right figure. It can be seen that checks decrease the frequency of high failure probabilities dramatically, and increase the frequency of low failure probabilities. Thus checking can be considered as an efficient barrier for structural reliability under HOFs' influences.

The emerged result is created by all the autonomous stochastic choices of PSF levels and random draws of parameter values from all agents, as well as the defined interactions between them. In the preliminary implementation of the model, it cannot yet be determined which tasks and which PSFs contribute most to this result. Therefore, future work will aim at data analysis to obtain that information from the simulations.

5. Conclusions and Future Work

The proposed agent-based model is an innovative method that integrates several modeling methods into an ABM approach. This model incorporates a dynamic SPAR-H method for HEP estimation, Stewart's HRA method to determine task outcome, and a level III reliability analysis to obtain the structural failure probability. Within the model framework, different agents follow their own be-

havioural rules and interact with each other in the simulation process to map the final results. In contrast with the static HEP assessment methods, this model provides a dynamic basis for evaluating HEP and the HOF influence on structural reliability due to the autonomous behaviour of agents and agent interactions. Moreover, this agent-based model can simulate the whole structural design and construction process by considering the accumulated HOF influence across tasks. In addition, two managerial variables of time and monetary cost are taken into account in evaluating the HOFs' influence, modelled as the second order influences. In the end, the frequency distribution of structural failure probabilities can be obtained.

Although the model is promising, some critical remarks exist and recommended future work is needed. First of all, the used SPAR-H method is adopted directly from the nuclear industry, the PSFs and the attached multipliers are not defined for the construction industry. Thus future adjustments are needed to adapt this method to be suitable for the presented model which aims at the building industry. Secondly, typical human errors are not described in this model. Therefore, future work will include possible task outcome scenarios. Finally, with ABM it is possible to trace back to all the tasks and different PSFs level combination scenarios that lead to the emerging result. Therefore, an extensive data analysis needs to be performed to identify the critical tasks and HOFs in the structural design and construction process in order to create critical reliability paths for structural safety management support.

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