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Sensitivity analysis based on Morris method of passive system performance under ocean conditions

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ABSTRACT

Passive safety systems, which do not require external input to operate, are widely used to enhance the inherent safety in new generation nuclear power plants. A challenging issue still to be resolved is the quantification of the functional failure probability of passive safety systems. The evaluation of functional failure relies on repeated thermal-hydraulics simulations which is usually time-consuming in practice. Response surface method has been proposed to tackle this issue. However, the number of input parameter limits its efficiency to a great extent. Therefore, it is necessary to identify the uncertain input parameters that have an important impact on the system performance, which helps reduce the dimension of the input parameters. Especially in marine nuclear power plants, the complex ocean motions will introduce more uncertainties in the passive system behavior. It's of great significance to screen key parameters for passive safety systems under ocean conditions. In this paper, the Morris method is used to perform an efficient sensitivity analysis to identify key parameters for a passive residual heat removal system in IPWR200. Twenty-four parameters related to passive system behavior are screened and ranked for their sensitivity. The results demonstrated that four of the twenty-four parameters have a more significant influence on the passive system performance.

1. Introduction

In recent years, there has been an increasing interest in passive safety features in new generation nuclear reactors (Liu et al., 2019). More and more innovative reactors introduce passive systems as a complement to the active ones. Passive safety systems, which rely on gravity or natural circulation to perform system functions, not only enhance the inherent safety of the reactors but also increase the economic competitiveness due to the elimination of equipment such as pumps and valves (Zhou and Treleaven, 2015). However, the uncertainty associated with passive systems is usually larger. These uncertainties mainly stem from the lack of understanding of the underlying phenomena as well as the lack of operating or experimental data. Especially when the marine nuclear power plants are considered, the complex ocean motions will lead to more uncertainties in thermal-hydraulics (T-H) characteristics, in a further step, impact the passive system behavior (Yan, 2017). The quantification of uncertainty is the key to evaluate the functional failure probability, which is the major contributor to passive system failure.

Monte-Carlo method has been proposed to evaluate the functional failure associated with passive systems. Unfortunately, it typically relies on repeated (e.g., many hundreds or thousands) evaluations of the simulation code for different combinations of system inputs (Zio et al., 2003). With the development of numerical technique, for most conditions the thermal-hydraulics codes require several hours or more to run one single simulation, so it becomes computationally prohibitive in practice. To overcome this issue, fast-running surrogate models (also known as response surfaces or metamodels) can be applied to surrogate the complicated T-H codes. With the maturity of the response surface techniques, it has been increasingly applied to passive systems reliability assessment. Mathews et al. (2009) built a first-order linear response surface, and regression coefficients were estimated by the method of least squares. Zio and Pedroni (2011) used the artificial neural network to replace T-H models so as to improve efficiency. However, there are many input parameters during the construction of the metamodels, which determine how many simulations are needed. The computational efficiency is directly limited by the number of input parameters, so it is significant to exclude those negligible parameters. From this point of view, screening key parameters is of great importance for the reliability assessment of passive systems.

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To effectively reduce dimensions of input parameters, several techniques have been proposed. Ma et al. (2015) employed improved Analytical Hierarchy Process (AHP) to analyze the influence of the parameters on the passive containment cooling system in AP1000. Four key parameters are selected from 49 inputs based on experts' judgments. The major advantages of using the AHP method for determining the important parameters affecting the top goal proved to be simplicity, flexibility, and transparency. However, the scoring process relies too much on the experience of experts, which usually involves too much subjectivity. Additionally, it requires one round after another of scoring till the results are consistent, thus it's a very time-consuming process in practice. Global sensitivity indices can be also used in screening parameters. Liu and Homma (2012) applied the variance-based method to decay heat removal system in a gas-cooled fast reactor for identifying the significant input variables. The variance-based method is a technique that the variance of the output decomposes into fractions that can be attributed to input parameters (Zhao et al., 2019). The Sobol' method, as a variance-based sensitivity analysis method, usually need a large number of model evaluations to calculate sensitivity indices. Another common sensitivity analysis method is the local sensitivity analysis, which typically provides the partial derivatives of the output to the input parameters. Although it has a significant advantage in terms of computational cost, the local sensitivity index only studies the impact of small input perturbations around the nominal values and ignores the interaction effects. Yu et al. (2015) used correlation analysis to screen the key parameters of a passive containment cooling system. However, the correlation coefficient such as Pearson coefficient or Spearman coefficient can only characterize the linear correlation between parameters. For highly nonlinear models like passive systems operational characteristics, correlation analysis cannot reflect the importance of the input parameters.

To solve the issues mentioned above, in this paper we adopt the Morris method to screening the key input parameters. Morris method, as a global sensitivity technique, can measure the contribution of an input to the variability of the output over the entire range. Morris method is capable of screening inputs that have negligible effects with acceptable runs of thermal–hydraulic codes. And then the sensitivity analysis was carried out based on the modified RELAP5 code, which simulates the system behavior under ocean conditions well. The results of Morris provide a systematical guideline to select relevant input parameters for the passive system reliability assessment.

2. Morris method

Instead of deep exploration of the system behavior, this work aims to provide a fast screening method that only a small number of thermal-hydraulics code calls are required. As a global sensitivity analysis method, the Morris method (Morris, 1991) has the advantages of better applicability and easy operation, so it well-suited when the number of input is high. Morris method can identify non-important input parameters effectively because it does not rely on a strong prior assumption about the model (Pujol, 2009). The Morris method was proven to achieve a good compromise between the accuracy and efficiency, especially for sensitivity analysis of computationally expensive models (Jiang et al., 2017).

The Morris method is a specialized One-At-a-Time (OAT) design that can handle a large number of inputs with a low computational cost. Morris method screens parameters based on the concept called elementary effect. For a given $\boldsymbol{x} = \{x_1, \cdots x_i \cdots x_j\}$, the elementary effect was calculated by the formula below:

$$EE_i = \frac{F(x_1, \cdots x_i + \Delta \cdots x_j) - F(x_1, \cdots x_i \cdots x_j)}{\Delta} \tag{1}$$

where $F(\boldsymbol{x})$ is the output of the simulation; Δ is the magnitude of the step between 0 and 1–1/($p-1$), which is a multiple of 1/(p-1); p is the number of levels.

2.1. Trajectory-based sampling strategy

Two model simulations are required to obtain the elementary effect of each variable, thus, the pivotal idea of Morris method is sharing simulation points in a trajectory. In that way, only one new model simulation needs to be added for each variable after the starting point. An example to illustrate the trajectory-based sampling strategy is given in Fig. 1. As we can see, four simulations are required for this three variables model in Morris trajectory, while six simulations are generally necessary for individual elementary effects. For j-dimensional problem, the region of experimentation is thus partitioned to a j-dimensional p-level grid. The minimum number of simulations needed is given as follow:

$$N_s = p \cdot (k+1) \tag{2}$$

where N_s is the number of the simulations needed and k is the number of input parameters. For the Sobol and FAST methods, the number of model simulations needed depends on the number of variables and the sampling method used. The smallest sample size for the Sobol method is $n \times (2k+2)$, n is the minimum model simulations for estimating each individual effect; it usually takes the value of 16, 32 or 64. At the same time, the smallest sample size for the FAST method is 65 k (Nguyen and Reiter, 2015). The Morris method has an obvious advantage in the number of model evaluations required.

Morris (1991) defines the trajectory matrix, which is a $k \times (k+1)$ matrix starting from a random point x^*. First of all, a base matrix containing ones in its strict lower triangular part and zeros on the rest is constructed. The matrix $J_{k+1,1}$ denotes a matrix with dimension $(k+1) \times 1$, of which the elements are all ones. The matrix B' can provide successive trajectory points by sequentially increasing one of its coordinate by Δ.

$$B' = \left(J_{k+1,1}(x^*)^T + \Delta B\right)^T \tag{3}$$

However, B' does not meet the requirements of random design. It's a deterministic trajectory except for the random starting point x^*. The modifications have been made for a properly randomized matrix in the below formula:

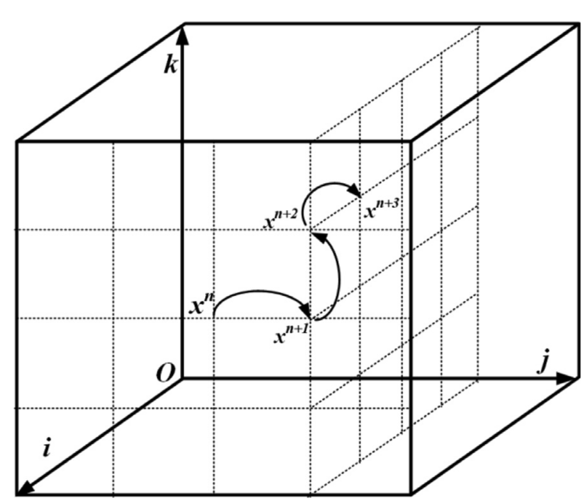


Fig. 1. Diagram of Morris method sampling strategy.

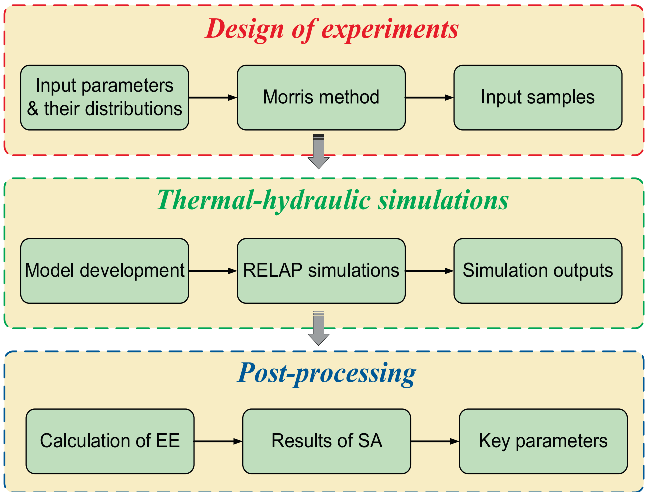


Fig. 2. Flow chart of screening parameters based on Morris method.

$$B^* = \left[\left(J_{k+1,1}(x^*)^T + \frac{\Delta}{2}\left[(2B - J_{k+1,k})D^* + J_{k+1,1} \right] \right) P \right]^T \tag{4}$$

A k-dimension diagonal matrix D^* that contains -1 or 1 on its diagonal randomly introduced randomness in the modified version. Additionally, P is a $k \times k$ random permutation matrix.

2.2. Morris method indices

Each input parameter will be computed for several times to obtain the mean value, μ_i and standard deviation,σ_i. The mean value assesses the overall influence of the input parameter and the standard deviation is used to estimate the totality of the higher-order effects. A high value for the mean indicates this input parameter is important while a low value indicates an unimportant parameter. A high value of σ_i means a nonlinear effect on the output or/and interactions with other parameters. They are calculated using Eqs. (5) and (6):

$$\mu_i = \frac{\sum_{i=1}^{r} EE_n}{r} \tag{5}$$

$$\sigma_i = \sqrt{\frac{1}{r}\sum_{i=1}^{r}(EE_n - \mu_i)^2} \tag{6}$$

However, the mean value fails to consider the effect that elementary effects with opposite signs cancel each other. To overcome this drawback, Campolongo et al. (2007) introduce a new index μ_i^*, the mean of the absolute value of EE_n, as given in Eq. (7).

$$\mu_i^* = \frac{\sum_{i=1}^{r} |EE_n|}{r} \tag{7}$$

The index μ_i^* can provide more complete information about sensitivity combined with μ and σ.

3. Sensitivity analysis of passive residual heat removal system in IPWR200

3.1. Sensitivity analysis framework based on Morris

Sensitivity analysis is the study of how sensitive a system is concerning the variation of the input parameters. It helps identify the crucial parameters for system performance and reduce the dimension of input parameters. The framework for screening parameters based on the Morris method was given in Fig. 2.

In general, it requires three main steps: design of experiments, thermal–hydraulic simulations, and post-processing.

(1) Design of experiments: the parameter screening process starts with the identification of input parameters. First of all, uncertainty parameters which may influence the system performance are determined based on expert judgment or engineering experience. The distribution characteristics, that

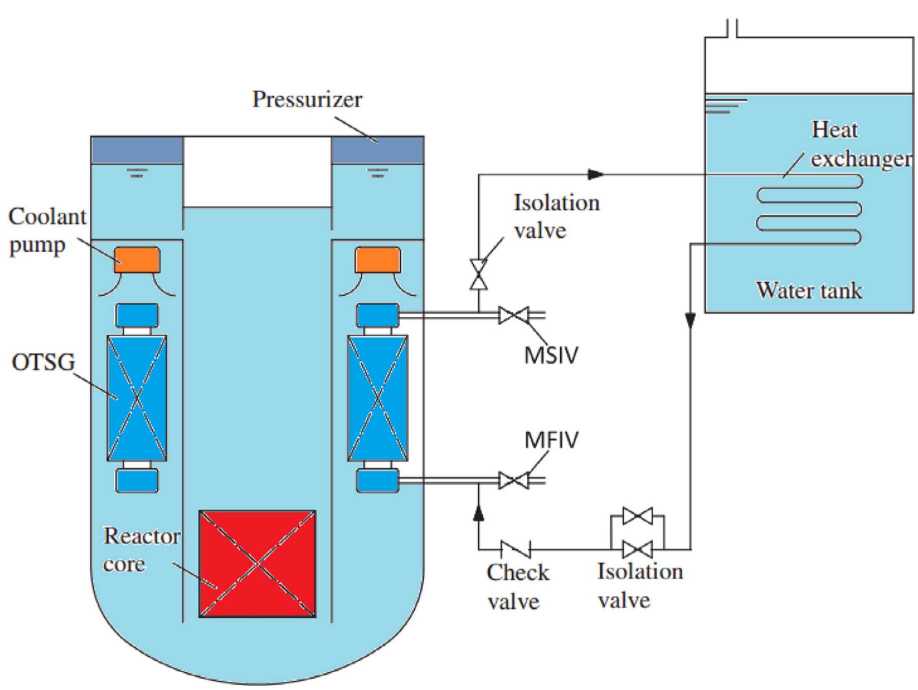


Fig. 3. The schematic diagram of IPWR200.

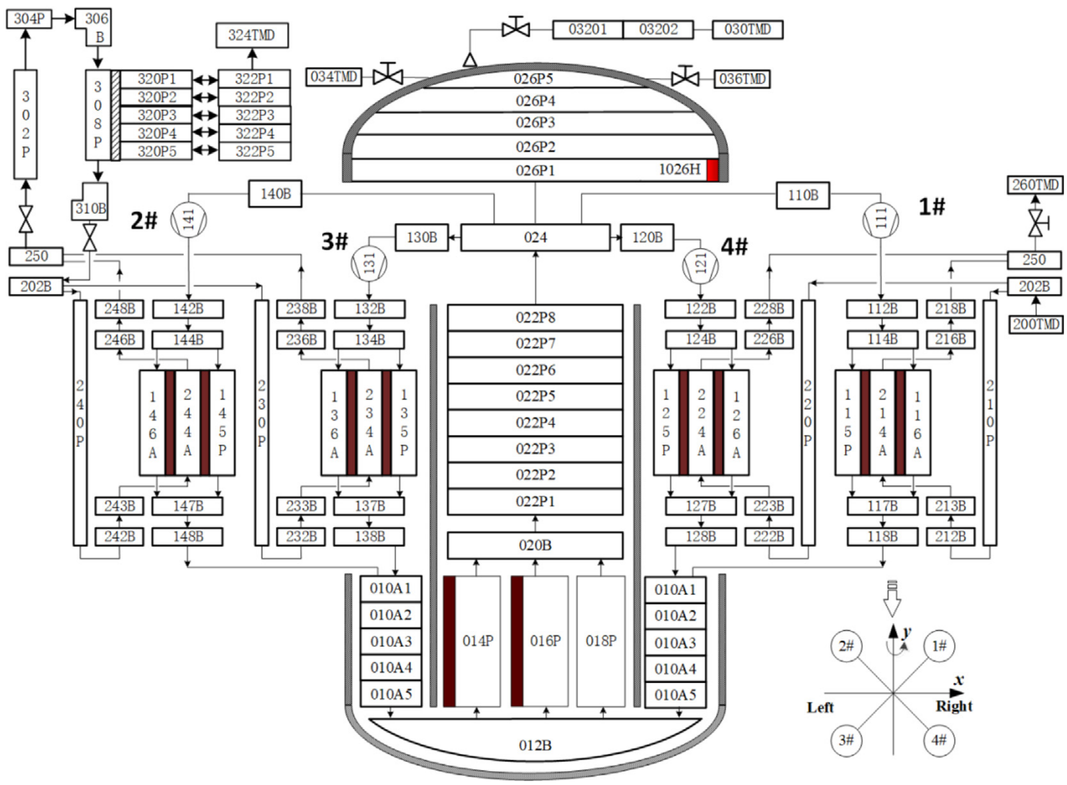


Fig. 4. The RELAP5 model nodalization.

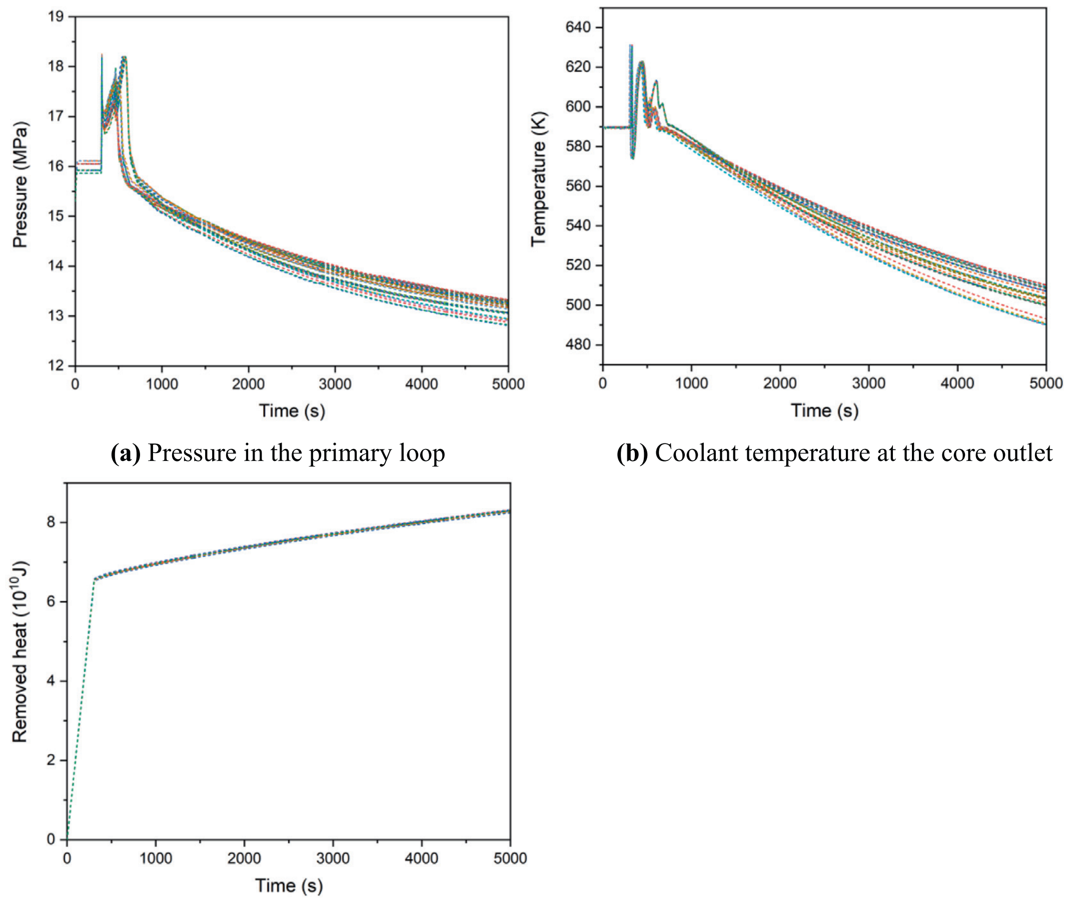
Table 1
Input parameters uncertainties with their probability distribution.

Parameters	Distribution	Lower value	Upper value
X_1, Reactor power (MW)	N(220, 3.34)	215.1	225.5
X_2, Pressure in the primary coolant system (MPa)	N(15.5, 0.48)	14.8	16.3
X_3, Initial steam pressure (MPa)	N(3.0, 0.122)	2.8	3.2
X_4, PRHR heat transfer area (m^2)	N(21.2, 2.58)	17.0	25.4
X_5, PRHR-HX tube thickness (mm)	U	1.0	2.0
X_6, Flow area of upcomer section (m^2)	N(0.0113, 0.003)	0.00723	0.0163
X_7, Flow area of down comer section (m^2)	N(0.0113, 0.003)	0.00723	0.0163
X_8, Water tank temperature (K)	N(293.0, 33.3)	280.0	348.0
X_9, Tank water level (m)	U	3.6	4.5
X_{10}, Flow area of heat transfer tubes (mm)	N(0.678, 0.08)	0.543	0.814
X_{11}, Forward/reverse energy loss coefficient of PRHRinlet valve	U	0.0	10.0
X_{12}, Forward/reverse energy loss coefficient of PRHR outlet valve	U	0.0	10.0
X_{13}, Wall roughness of heat transfer tubes (mm)	U	1.0	5.0
X_{14}, Opening delay of PRHR valve (s)	U	0.0	300.0
X_{15}, Change rate of PRHR valve (s^{-1})	U	0.01	0.1
X_{16}, Rolling period (s)	N(15.0, 9.1)	0.0	30.0
X_{17}, Rolling amplitude (°)	N(12. 5, 7.59)	0.0	25.0
X_{18}, Heaving period (s)	N(15.0, 9.1)	0.0	30.0
X_{19}, Heaving amplitude (m/s^2)	N(1.5, 0.91)	0.0	3.0
X_{20}, Inclining angle (°)	N(0.0, 18.2)	−30.0	30.0
X_{21}, Wall friction coefficient factor	N(1.0, 0.06)	0.9	1.1
X_{22}, Heat transfer coefficient factor in single-phase flow	N(1.0, 0.09)	0.85	1.15
X_{23}, Heat transfer coefficient factor in condensation	N(1.0, 0.121)	0.8	1.2
X_{24}, Heat transfer coefficient factor in boiling	N(1.0, 0.121)	0.8	1.2

is, the range and distribution types are subsequently identified. On this basis, the trajectory matrix which is used as the input samples for thermal–hydraulic codes is generated according to Morris sampling strategy.

(2) Thermal-hydraulic simulation: an ocean-based thermal–hydraulic has been developed for simulating the system behavior under ocean conditions. All the samples generated in the previous step are given to the modified RELAP5 code as input. After these simulation runs, simulation outputs are gathered for sensitivity analysis.

(3) Post-processing: the sensitivity indices are calculated based on the results of thermal–hydraulic simulations. The importance of each input parameter is obtained, which helps identify the key parameters.



(a) Pressure in the primary loop

(b) Coolant temperature at the core outlet

(c) Total heat amount removed by the system

Fig. 5. Transient calculation results of the passive system under SBO accident.

3.2. Thermal-hydraulic model

Firstly, a brief description of the Integral-type Pressurized Water Reactor (IPWR200) is provided. IPWR200 small modular reactor designed for ship propulsion with 220 MW thermal output. Plate-type fuel assemblies were used to achieve a compact core arrangement. Additionally, twelve once-through steam generators (OTSGs) are divided into four groups and the outlet of OTSGs is connected to the main steam line. Each group is equipped with one main coolant pump, which is connected to the inlet of the OTSGs primary side. The schematic diagram of IPWR200 is shown in Fig. 3.

An ocean-based thermal–hydraulic code was developed based on the RELAP5, which can simulate transient behaviors under ocean conditions. Relative to the ground (inertial system), coordinate system fixed to the ships belongs to the non-inertial system. An additional force term should be introduced into the momentum equation and we take the liquid phase equation as an example:

$$\alpha\rho A\frac{\partial v}{\partial t}+\frac{1}{2}\alpha\rho A\frac{\partial v^2}{\partial x}=-\alpha A\frac{\partial P}{\partial x}+\alpha\rho(B_X+f_a)A+S \tag{8}$$

where f_a is the additional acceleration acting on the fluid and it can be expressed as follow:

$$f_a=f_t+f_c+f_u=[\vec{\omega}\times\left(\vec{\omega}\times\vec{r}\right)+\vec{\beta}\times\vec{r}+2\vec{\omega}\times\vec{u}] \tag{9}$$

where $\vec{\omega}$ is the angular velocity, $\vec{\beta}$ is the angular acceleration; $\vec{u}$ is the fluid particle velocity relative to the moving coordinate. $f_t=\vec{\beta}\times\vec{r}$ is the tangential acceleration; $f_c=\vec{\omega}\times\left(\vec{\omega}\times\vec{r}\right)$ is centripetal acceleration and $f_u=2\vec{\omega}\times\vec{u}$ is Coriolis acceleration. B_x is the modification of the gravity term in the momentum equation. The heaving motions can change the gravity acceleration directly, acceleration in flow direction can be defined as follow:

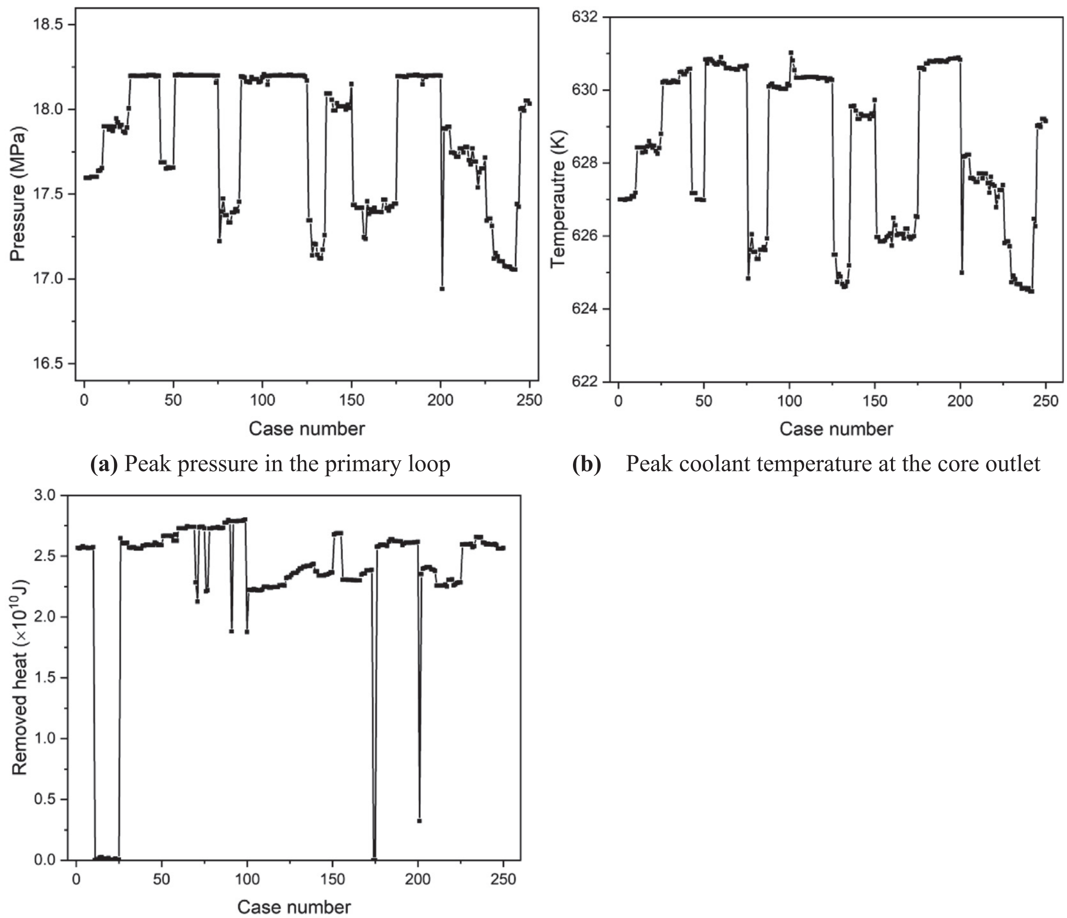
$$B_x=\left[1+Asin\left(\frac{2\pi t}{T_h}\right)\right] \tag{10}$$

where A is the heaving acceleration amplitude, g is the gravity acceleration and T_h is the heaving period. Other details about model development and validation can be seen in our previous work (Wang et al., 2019; Xia et al., 2018).

The modified RELAP5 was applied to establish the thermal–hydraulic model of IPWR200. Fig. 4 shows the nodalization of the RELAP5 model. Under the accidents such as station blackout (SBO), the protection system scrams the reactor and trips the turbine by closing the main steam isolation valves (MSIV) and the main feedwater isolation valve (MFIV). Subsequently, the isolation valve of PRHRS opened automatically. The decay heat from reactor core can be continuously removed via natural circulation to the ultimate heat sink water tank.

3.3. Identification of uncertain parameters

Passive safety systems, which rely on the natural circulation to perform system function, are much more sensitive to the variation of the input parameter. The operation of passive systems usually involves more uncertainties due to the relatively small natural driving force. Especially in marine nuclear power plants, the



(a) Peak pressure in the primary loop

(b) Peak coolant temperature at the core outlet

(c) The heat removed by the system

Fig. 6. System responses of different cases.

complex and changeable ocean conditions will introduce more uncertain factors that may affect natural circulation ability. On the other hand, the effective gravity head between the cold and heat sources will be directly changed due to the ocean motions. Furthermore, the ocean motions such as rolling motions will introduce additional force on the fluid, thereby affecting the natural circulation flow. Unfortunately, the flow and heat transfer mechanism under ocean conditions is more complicated. The related empirical correlations are not mature enough, because they are not supported by extensive experiments or operational data. Therefore, the flow and heat transfer characteristics under ocean conditions suffer from larger uncertainty.

As listed in the Table 1, twenty-four uncertain parameters are studied in this work. These uncertainties mainly stem from (1) aleatory uncertainty due to the randomness of those physical and geometric parameters in the operation, and (2) epistemic uncertainty due to the limited knowledge and data about the properties and conditions of related phenomena. The probability distribution functions and range of the parameters are determined by the expert judgments, engineering experience, and previous research. 'N' denotes the normal distribution and 'U' means the uniform distribution. As far as normal distribution is concerned, the former value in parentheses represents the mean value, followed by the standard deviation. The joint probability distribution of wave parameters was studied in our previous work based on the function proposed by Longuet-Higgins (1975). The distribution of ocean motions in Table. 1 was supported by the results of that research. X_{21} to X_{24} are factors introduced to consider the model uncertainty. It's a multiplier used in the calculation of the model coefficients, which can be expressed as follow:

$$f = f_0 \times \varepsilon \tag{11}$$

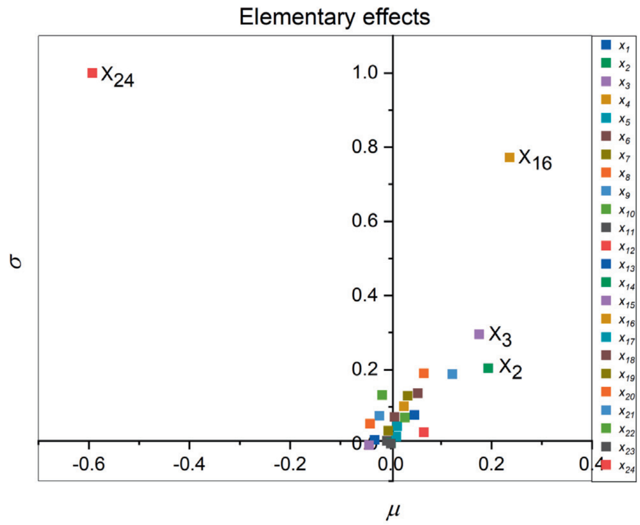
where f_0 is the empirical correlation coefficients calculated from the original model, ε is the factors introduced and f is the empirical correlation coefficients after considering the uncertainty.

The mean value μ is determined according to the thermal-hydraulics simulations or design value. The standard deviation can be calculated by $\sigma=|X_R-\mu|/Z_{0.95}$, where $Z_{0.95}$ is a distance of left-side confidence level of 95%. It's worth noting that the choices of these distribution characteristics may change as more experimental data are obtained and more knowledge is accumulated in the future. Therefore, the list of input uncertainties and their distributions may need to be updated in case new knowledge is acquired (Marquès et al., 2005).

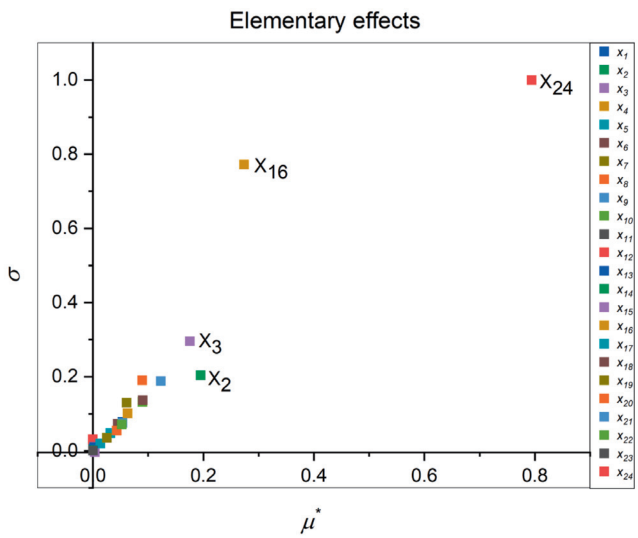
4. Results and discussions

4.1. Thermal-hydraulics calculation results

In the present work, the station blackout (SBO) accident is selected as the initial event because of its challenging nature as well as the widespread concern after the Fukushima accident. The samples generated by the trajectory-based sampling strategy

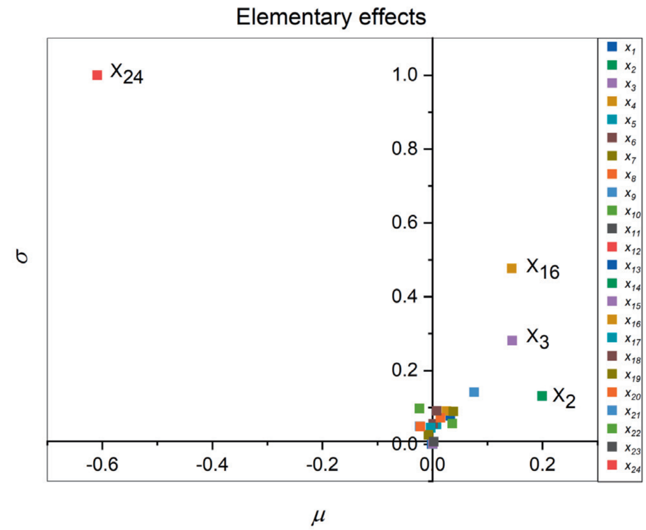


(a) σ versus μ

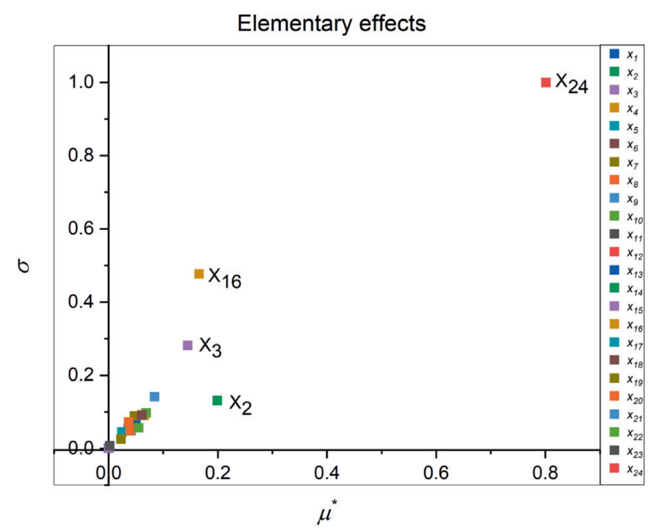


(b) σ versus μ*

Fig. 7. Normalized sensitivity indices for P_{peak}.



(a) σ versus μ



(b) σ versus μ*

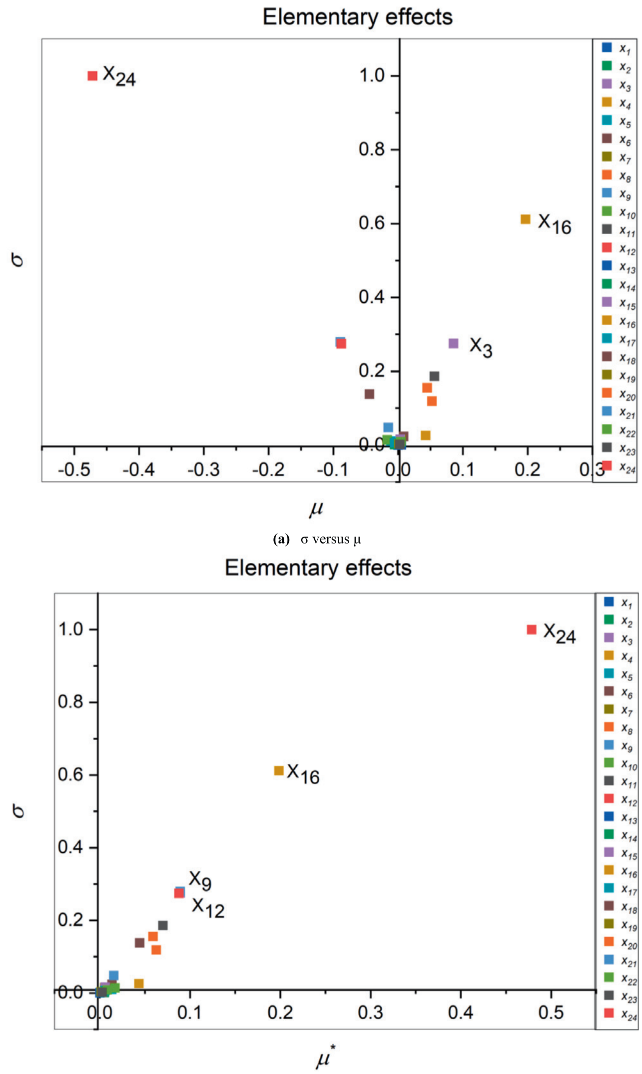
Fig. 8. Normalized sensitivity indices for T_{peak}.

are given as input to the thermal-hydraulics code RELAP5. Each simulation is performed to obtain the corresponding response. The number of trajectories in this work is chosen as 10. Part of the transient calculation results can be seen in Fig. 5 and each line represents the result of one simulation of RELAP5. The expected function of the passive residual heat removal system is to ensure the sufficient decay heat removed and to ensure the pressure and temperature within the acceptable limits. Practical experience suggests that a single criterion is not adequate to measure the real importance of observed input parameters. Multiple outputs should be considered to measure the overall sensitivity on the passive safety system performance (Liu and Sun, 2010). Three system responses, coolant peak temperature at the reactor core outlet (T), peak pressure in the primary loop (P), and decay heat removed (Q) are considered for sensitivity analysis. Fig. 6 shows the system response values of different cases. As we can note, the system responses are significantly affected due to the input uncertainties

4.2. Sensitivity analysis results

For each system response, the σ is plotted versus μ and μ^* as shown in Figs. 7–9. The results in these figures are shown with the standard Morris format: the x-axis represents the mean value of the elementary effects related to each variable, while the y-axis represents the corresponding standard deviation. The points that are close to the origin point mean unimportant parameters, which can be neglected during the construction of the response surface. In contrast, those far from the origin point are important. The farther away from the origin point in the y-axis, the stronger degree of nonlinearity or/and interaction the parameters have.

As we can see, X_{24} the heat transfer coefficient in boiling has a significant impact in passive system performance. Regardless of any output, it has the highest value of σ, μ and μ^*. It is undoubtedly an important input parameter. It mainly stems from the importance of boiling phenomenon on the decay heat removal process. The OTSGs are applied in the IPWR200, therefore, the boiling heat transfer coefficient will directly impact the heat removal from the core. In a further step, the peak coolant temperature and peak pressure in the primary loop will be influenced. X_{16} rolling period has a high value of σ and relatively small μ and μ^*. The rolling period is a parameter that reflects the intensity of ocean motions. The rolling condition is a continuous transient process that causes a periodic oscillation of the natural circulation flow. At the same time, the rolling motions will cause the uniform coolant temperature



(a) σ versus μ

(b) σ versus μ*

Fig. 9. Normalized sensitivity indices for Q.

distribution, which will influence the natural circulation flow rate and further influence the passive system performance. The natural circulation ability relies on the driving force generated by the height difference between the heat source and sink. Sustained flow oscillations will damage the operation of passive systems. The heaving motions can cause the periodic change of the gravity acceleration, which will result in the oscillations of the natural circulation flow. Compared with the rolling motions, however, the impact on the average flow rate is very limited. Additionally, X_3 and X_2 have a similar influence on each output. The pressure value affects the saturation temperature, which in turn affects the heat transfer.

The normalized sensitivity indices for different output are summarized in the Table 2. The ranking of parameters varies from one output to another, so the average μ^* is calculated in order to rank the parameters.

Summarizing the results above, 4 of the 24 parameters have a more significant impact on the passive system performance. Other parameters that are near the origin point can be seen as negligible parameters.

These parameters can be filtered out to reduce the difficulty of constructing the response surface. The boiling heat transfer coefficient and the ocean motions, especially the rolling period also have great contributions to the passive residual heat removal system ability. Efforts should be devoted to studying the influence of these physical process and carrying out more theoretical research. Moreover, these important parameters should be considered fully to ensure enough safety margins during design optimization.

5. Conclusions

To improve the efficiency of the reliability assessment of passive systems, the dimension of input parameters should be reasonably limited. Morris method, a fast-screening technique, is applied to identify the important parameters for a marine passive residual heat removal system. The passive system performance under ocean conditions is obtained with the ocean-based T-H code. The results of the sensitivity analysis demonstrated that four parameters are important during the SBO accident. Among these four parameters, the boiling heat transfer coefficient and rolling period shows dominant impact on the system performance. The assess-

Table 2
Normalized sensitivity indices for uncertain input of IPWR200.

	P_{peak}			T_{peak}		Q				*Average* μ^*	*Rank*
	μ	σ	μ^*	μ	σ	μ^*	μ	σ	μ^*		
X_1	0.047	0.078	0.054	0.032	0.077	0.050	0.005	9.2×10^{-4}	0.005	0.036	14
X_2	0.193	0.204	0.195	0.199	0.131	0.199	0.001	0.002	0.002	0.132	4
X_3	0.175	0.295	0.176	0.145	0.281	0.145	0.086	0.275	0.090	0.137	3
X_4	0.026	0.101	0.063	0.026	0.090	0.066	0.043	0.026	0.044	0.057	10
X_5	0.013	0.047	0.032	0.007	0.055	0.036	−0.01	0.010	0.013	0.027	17
X_6	0.008	0.073	0.045	0.002	0.056	0.040	0.009	0.023	0.014	0.033	15
X_7	0.033	0.130	0.061	0.038	0.089	0.0473	0.005	0.015	0.006	0.038	13
X_8	0.068	0.190	0.089	0.015	0.072	0.037	0.045	0.155	0.059	0.062	7
X_9	−0.022	0.076	0.054	−0.023	0.049	0.041	−0.089	0.280	0.089	0.062	8
X_{101}	−0.017	0.132	0.090	−0.023	0.097	0.069	−0.017	0.014	0.017	0.059	9
X_{11}	−0.007	0.008	3.4×10^{-4}	4.5×10^{-4}	0.001	1.2×10^{-4}	0.056	0.186	0.070	0.023	18
X_{12}	0.066	0.031	1.6×10^{-4}	5.1×10^{-4}	6.3×10^{-4}	2.0×10^{-4}	−0.088	0.27	0.088	0.029	16
X_{13}	−0.032	0.011	0.002	−0.001	5.2×10^{-4}	1.1×10^{-4}	-5×10^{-6}	3.2×10^{-4}	1.7×10^{-4}	$5. \times 10^{-5}$	24
X_{14}	6.1×10^{-4}	0.002	6.1×10^{-4}	1.5×10^{-4}	3.8×10^{-4}	6.8×10^{-4}	−0.005	0.001	0.005	0.002	22
X_{15}	−0.043	−0.003	0.004	4.4×10^{-4}	0.001	4.2×10^{-4}	0.004	0.016	0.006	0.002	21
X_{16}	0.236	0.772	0.274	0.14433	0.477	0.166	0.197	0.611	0.199	0.213	2
X_{17}	0.011	0.020	0.014	−0.003	0.045	0.025	−0.005	0.006	0.006	0.015	20
X_{18}	0.054	0.136	0.090	0.008	0.091	0.061	−0.044	0.138	0.044	0.065	6
X_{19}	−0.005	0.035	0.025	−0.007	0.026	0.023	0.001	0.003	0.002	0.017	19
X_{20}	−0.040	0.054	0.043	−0.022	0.048	0.040	0.052	0.119	0.063	0.049	11

Table 2 (*continued*)

	P_{peak}			T_{peak}		Q				*Average* μ^*	*Rank*
	μ	σ	μ^*	μ	σ	μ^*	μ	σ	μ^*		
X_{21}	0.122	0.188	0.123	0.076	0.141	0.084	−0.015	0.048	0.016	0.074	5
X_{22}	0.028	0.071	0.052	0.036	0.056	0.055	0.004	0.009	0.008	0.038	12
X_{23}	2.8×10^{-4}	9×10^{-4}	2.9×10^{-4}	0.002	0.007	0.002	0.003	0.002	0.003	0.002	23
X_{24}	−0.593	1	0.794	0.610	1	0.801	−0.47	1	0.479	0.691	1

ment of the reliability of passive systems is a crucial issue to be tackled for their extensive use in future nuclear power plants. The results of sensitivity analysis provide a systematical guide to select the parameters during the construction of the response surface. Besides, the presented work can help designers identify the key parameters, which could be further researched for the enhancement of system reliability and design optimization.

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Appendix A. Supplementary data

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