Probabilistic risk assessment of coastal infrastructure systems under climate change

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ABSTRACT: The vulnerability of coastal infrastructure systems can be affected by various climate-related hazards, such as tropical cyclones. Over the long term, the impact of hazards on systems may be magnified due to exposure to more frequent and more intense storm events in a changing climate. Therefore, it is necessary to evaluate the potential change in risk of infrastructure systems during the life cycle under climate change. In previous studies, stationary stochastic models (e.g., homogeneous Poisson process) have been widely employed to model hazard occurrence and magnitude in a stationary environment. However, in a changing climate, uncertainties associated with time-varying and nonstationarity characteristics cannot be ignored. It has been widely indicated that non-stationary stochastic processes (e.g., non-homogeneous Poisson process) should be employed. This study aims to develop a probabilistic framework to assess the risk of systems under tropical cyclones hazards in a changing climate. Nonstationary stochastic models are employed for risk assessment to quantify uncertainties in hazard frequency and intensity. Particularly, the impact of these uncertainties on the probabilistic distribution of total risk and the tail risk will be explored. It is identified that the previous studies purely based on the expected risk neglect potential extreme losses significantly. The proposed approach is applied to a highway bridge for illustration. The proposed probabilistic framework can be further applied to risk assessment of infrastructure networks and other hazard scenarios under changing conditions.

1. INTRODUCTION

Coastal civil infrastructure systems are subjected to various climate-related hazards such as tropical cyclones during their lifetime. Over the long-term, the impact of hazards on systems may be magnified due to exposure to more frequent and more intense climate-related events in a changing climate. For instance, more and more researchers indicated that the frequency and intensity of tropical cyclones can be affected by the changing climate (Raymond et al. 2020; Fischer et al. 2021; Zscheischler et al. 2018). Such a changing trend may increase the system vulnerability and decrease the system resilience under hazards. Under the circumstance, mitigating the risk and enhancing the system resilience can be paramount.

To achieve a climate-resilient system or network, it is essential to evaluate the risk in detail under the changing climate. However, most previous studies have investigated the risk under a stationary environment and neglected the uncertainties resulting from climate change. Additionally, a large number of studies have investigated the mean value of the risk but ignored the uncertainties associated with the probabilistic distribution. Though the expectation has been utilized as a standard decision making criterion, the mean value omits the full information of the probabilistic distribution of the risk. The tail risk associated with the low probability but high consequence losses can be significantly underestimated. Especially, risk averse decision makers pay special attention to mitigate extreme losses. To address these issues, this study proposes a probabilistic risk assessment approach to evaluate the probabilistic distribution of the hazard induced total risk and to quantify the tail risk of the hazard risk under climate change.

Before the risk assessment, uncertainties in hazard frequency and intensity should be carefully evaluated under climate change. Thus, in this study, a nonstationary stochastic process is utilized for the hazard model. Different from previous studies based on the homogeneous Poisson process (HPP) considering a stationary condition, this study utilized a nonhomogeneous Poisson process (NHPP) for the risk assessment (Lin and Shullman 2017). Given the stochastic process, the risk over the system lifetime can be quantified.

The probabilistic risk assessment analysis is based on the first four statistical indicators and the maximum entropy method to compute the probability distribution of the hazard-induced risks. The proposed method is an analytical approach and can be far more efficient than the Monte Carlo simulation. Once the full distribution is obtained, a risk measure referring to the quantile of the risk is proposed to quantify the worst case scenario of the potential tail risk. It is shown that the quantile can capture the low probability high consequence extreme losses compared with the mean value. The proposed approach is demonstrated with an illustrative example of a highway bridge. The approach can be extended for the risk assessment under the infrastructural network.

2. STOCHASTIC HAZARD MODEL

Risk assessment is conditioned on the detailed modeling of uncertainty associated with the frequency and magnitude of hazards. In this section, the stochastic modeling of hazards is presented.

In previous studies, stochastic processes are commonly used to model the arriving process of hazards considering potential uncertainties. Different from the commonly used HPP process, more and more researchers indicated that a NHPP should be utilized to indicate the changes in frequency as well as intensity under climate change (Emanuel 2017; Gori et al. 2022). In this study, a NHPP is introduced for the risk assessment. The NHPP is an arriving process and the total number of tropical cyclones can be denoted as $\{N(t_{\text{int}}), t \geq 0\}$ during the investigated period $(0, t_{\text{int}}]$. Herein, t_{int} is considered as the system lifetime. The arriving times of these hazard events can be represented as a set of random variables, such as $0 < T_1 < T_2 < \ldots T_k$ and T_k refers to the time of the k_{th} arrival of the hazard events. The periods between arrivals are also a set of random variables, and they can be denoted as inter-arrival times X_1, X_2, … X_k. Based on the definition. The NHPP gives $X_k = T_k - T_{k\text{-}1}$, therefore, $T_k = X_1 + X_2 + \ldots + X_k$. An illustrative diagram of a NHPP is shown in Figure 1.

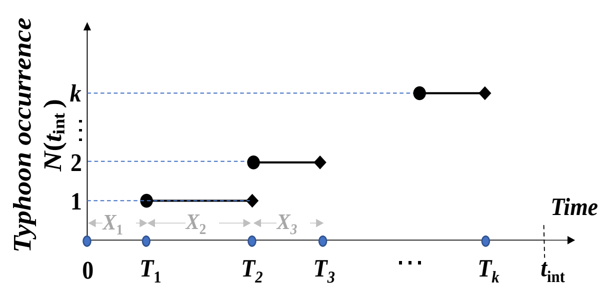

Figure 1: The stochastic nonhomogeneous Poisson process to model hazard events under climate change.

For the NHPP, the occurrence rate of the hazard can be noted as $\lambda(t)$. Then, the expected number of occurrences can be described using this rate, such that

$$E[N(t_{\text{int}})] = \int_0^{t_{\text{int}}} \lambda(t)dt \tag{1}$$

Subsequently, the likelihood of having k number of tropical cyclones can be written as

$$P[N(t_{\text{int}}) = k] = \frac{\left(\int_0^{t_{\text{int}}} \lambda(t)dt\right)^k \exp\left(-\int_0^{t_{\text{int}}} \lambda(t)dt\right)}{k!}, k = 1,2,\cdots \tag{2}$$

As shown in Eq. (2), the likelihood of having k number of events is also dependent on this occurrence rate. Typically, the rate $\lambda(t)$ can be quantified as the annual rate by quantifying the total number of events over the period. Due to the changing climate, the occurrence rate is time-varying. A NHPP will become a HPP when the occurrence rate λ is constant, e.g., under a stationary environment. In the HPP, the inter-arrival time X follows an exponential distribution. Due to its simplicity, HPP has commonly been utilized in previous statistical modeling. However, this distribution does not hold for NHPP. For each storm event, the intensity is also a random variable and is related to the arrival time. However, the probabilistic distribution of intensity is directly linked to the risk, i.e., losses. Therefore, the characteristics of intensities are not discussed herein.

3. PROBABILISTIC RISK ASSESSMENT

The assessment of the total risk consists of two parts. The first step is to compute the probabilistic distribution of the total risk based on the NHPP. Subsequently, the tail risk can be measured based on the distribution by quantifying the quantile of the risk.

3.1. Probabilistic distribution of the total risk

According to the established stochastic NHPP, the probabilistic risk over the system lifetime $(0, t_{\text{int}}]$. Then, the total risk R_{LT} of the system under hazards within the investigated period can be written as

$$R_{LT}(t_{\text{int}}) = \sum_{k=1}^{N(t_{\text{int}})} L_k e^{-rT_k} \tag{3}$$

in which r is the discount rate to discount to the present net value and L is the damage loss associated with the system given the damage. The damage loss can be computed as the product of the repair cost of the system and the system vulnerability under hazards. In Eq. (3), the total risk R_{LT} is a random variable. In previous studies, only the expectation of the total risk is of interest. However, as R_{LT} is a random variable, the expectation may fail to capture the full information associated with the potential losses. Therefore, the probabilistic distribution of the total risk as well as other three statistical indicators such as variance, skewness, and kurtosis should also be investigated. These statistical indicators can either be evaluated based on Monte Carlo simulation or the analytical formation based on the moment generating function (MGF).

If the MGF is defined as M, then, the MGF of the total risk can be given as (Li et al., 2020)

$$M_{R_{LT}(t_{\text{int}})}(\xi) = \exp\left[\int_0^{t_{\text{int}}} \lambda(s)[M_L(\xi e^{-rs}) - 1]ds\right] \tag{4}$$

Once the MGF is assessed, the statistical indicators can be calculated by taking different orders of derivatives of the MGF at zero. For instance, the mean of the total risk can be given by taking the first derivative of the MGF

$$E[R_{LT}(t_{\text{int}})] = M'_{R_{LT}(t_{\text{int}})}(0) \tag{5}$$

Similarly, the qth order moments of the total risk can be calculated by using the concept described in Eq. (5)

$$E[R_{LT}{}^q(t_{\text{int}})] = \frac{dM_{R_{LT}(t_{\text{int}})}{}^q(\xi=0)}{d\xi^q} \tag{6}$$

Given the first four orders of moments, the PDF and CDF of the total risk can be calculated by using the maximum entropy method Zhang (et al. 2022). Compared with the conventional Monte Carlo simulations, this method can be more efficient and saves lots of computational costs.

3.2. Measure of "worst case"

This study proposes the concept of "quantile" to measure the uncertain "worst case" of the total risk. Such a worst case is associated with the tail risk, indicating particularly the low probability but high losses of the total risk (Tyrrell Rockafellar and Royset 2015). However, it should be noted that such a risk measure may only be meaningful when decision makers are risk averse, as risk neutral decision makers may only care about the expected total risk. The quantile is defined as

$$[R_{WC}(t_{\text{int}})] = Quantile_{\alpha}(R_{LT}(t_{\text{int}})) \quad (7)$$

where a indicates the accepted level of the worst case and refers to the a-quantile of the random variable R_{LT}. Figure 2 gives an illustrative sketch of the quantile of the total risk. Usually, the worst case scenario can be much greater than the mean value of the total risk.

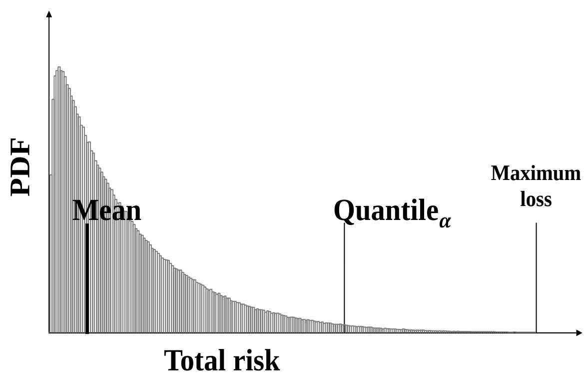

Figure 2: Illustrative diagram to show the quantification of the quantile of the total risk.

4. ILLUSTRATIVE EXAMPLE

An illustrative example based on a highway bridge is provided to demonstrate the inputs for the probabilistic risk assessment. The investigated highway bridge is vulnerable to deck unseating failure in tropical cyclone events due to storm-induced surges and waves. There are several inputs for the probabilistic risk assessment. For the NHPP, the inputs for the annual occurrence rate for the tropical cyclone events and the investigated period are needed. Given the NHPP, the probabilistic distribution of loss, the financial discount rate should be provided to quantify the total risk. Subsequently, the first four statistical moments, i.e., statistical indicators, can be calculated. Ultimately, the probabilistic distribution of the total risk can be computed and the worst case scenario can be measured. Herein, the initial inputs are directly utilized based on Li (2020).

Given these inputs, the four statistical indicators of the total risk can be calculated as mean 12.9048×10^6 USD, standard deviation 4.4686×10^6 USD, skewness 0.59, and kurtosis 3.51. Consequently, the probabilistic risk assessment can be computed as shown in Figure 3. Then, the 5% worst case can be calculated as 45.0988×10^6 USD. It indicates that there is a 5% likelihood that the risk will be greater than the value of 45.0988×10^6 USD. Compared with the mean value of 12.9048×10^6 USD, it can be identified that this worst case scenario can result in a tremendous loss.

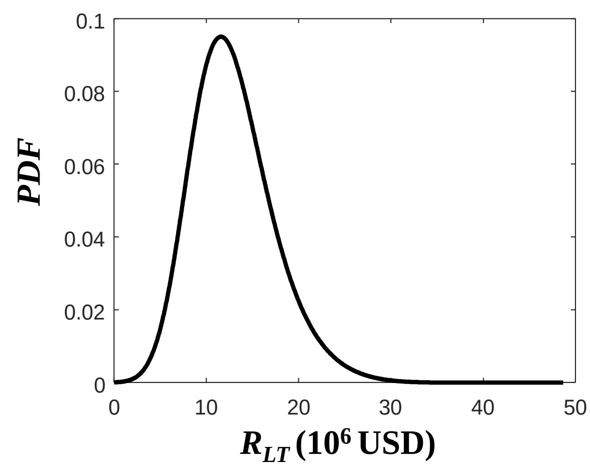

Figure 3: The PDF of the total risk by using the proposed probabilistic risk assessment method.

If the acceptance level of the quantile changes to 1%, then there is a 1% likelihood that the total risk will be larger than 47.9605×10^6 USD. However, if the acceptance level a changes to 10%, the associated extreme risk can be smaller and changes to 41.5217×10^6 USD. Based on different levels of acceptance risk levels, decision makers can provide different responses for the potential risk. Generally, the tail risk will be significantly higher than the mean. Therefore, decision makers should pay special attention to such tail risks associated with the hazard.

5. CONCLUSIONS

This study proposes a probabilistic risk assessment approach to evaluate the probabilistic distribution of the hazard induced risk under climate change and measures the tail risk by using quantile. A NHPP is employed to model the uncertainties associated with frequency and intensity of tropical cyclones under climate change. The proposed approach is applied to a highway bridge for illustration. Results show that the risk assessment purely based on the mean may neglect potential extreme losses significantly. The proposed probabilistic framework can be further utilized to assess the risk of infrastructure networks and other hazard scenarios under changing conditions.

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