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Accident risk assessment in marine transportation via Markov modelling and Markov Chain Monte Carlo simulation

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ABSTRACT

There are many technological and environmental safety factors involved in marine accidents. This paper deals with an analytic approach to accident risk modelling when data for analyzing safety factors is limited or unavailable. The purpose of this paper is to propose a simulated accident model for assessing accident risk in marine transportation. The proposed approach is based on Markov modelling and Markov Chain Monte Carlo (MCMC) simulation and it is illustrated using an example from marine transportation. A three-state continuous time Markov model is used to record and estimate marine occurrence rates and probabilities. The MCMC simulation requires the occurrence data of the Markov model to estimate the accident risk. However, it can be used when only a limited amount of information is available. Compared with other models, the approach in this paper is applicable to any type of marine accident or marine transportation system. A numerical example is also given to illustrate the procedure.

1. Introduction

In the International Maritime Organization (IMO), accident risk in marine transportation is evaluated by the structured Formal Safety Assessment (FSA). Although the FSA is internationally recognized as one of the best methods to describe risk, it is too narrow to show all aspects of risk in the marine transportation domain (Montewka et al., 2014b). Goerlandt and Kujala (2014) also highlighted the lack of reliability and validity of the investigated risk analysis methods through a case study of ship–ship collision risk. From the review of maritime quantitative risk assessment studies, there still exists a gap in their works. In some papers, only one type of marine accident is considered in risk assessment. Therefore, the purpose of this paper is to propose a reliable accident model for assessing any type of accident risk in marine transportation.

Many studies in maritime accident risk modelling are based on summary statistics, such as the expected value of accident frequency over time or some risk control levels (Fabiano et al., 2010). Risk has a probabilistic attribute that is conditioned on the many negative outcomes of the system at different times. Therefore, straightforward statistics, such as a single accident rate value, are not sufficient to explain and predict accident risk over time. To resolve this issue, we apply simulation techniques for updating marine accident/incident data and conditional probabilities to evaluate accident rates and risk.

In general, the uncertainties related to an event or accident can be used to form the concept of risk. However, accident risk is not uniquely defined, formulated and estimated for application to any type of accident and ship. The risks introduced to society from a given activity may be of different types (Vanem, 2012). Commonly, the concept of risk is defined as the likelihood of consequences of undesirable events in different scenarios and marine systems (Vanem et al., 2008). Risk can be defined as a combination of the probability and the degree of possible human injury, damage to property, and damage to the environment. Aven (2010) argued on how to define and describe risk, and also provided some typical definitions. In this paper, we define risk as a measure of the probability of accidents. Similarly, Debnath and Chin (2010) determined collision risk in a port waterway and defined risk as the probability of an unwanted event.

In this paper, we present an accident risk model using a Markov modelling approach and Markov Chain Monte Carlo (MCMC) simulation that can be used for any type of marine accident or transportation system when data about safety factors is not available. The advantage of our model and MCMC simulation is its simplicity and also that there is no need for large-scale data collection. Monte Carlo simulation is a commonly used method in uncertainty modelling because of its flexibility for realistic performance assessments of complex phenomena (Cadini et al., 2013).

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The remainder of this paper is organized as follows. Firstly, the most recent risk assessment models of accidents together with limitations in their results and approaches are reviewed in Section 2. Next, our modelling approach is presented in Section 3. The approach includes Markov modelling for three states of marine systems and MCMC simulation for risk assessment. An application example is shown in Section 4. Sensitivity analyses of the initial transition rates of the model are shown in Section 5. Conclusions are drawn at the end of the paper in Section 6.

2. Literature review

Despite significant efforts to improve safety at sea, many studies have highlighted that there are still an enormous number of accidents in the marine transportation industry (Gaonkar et al., 2011; Wang et al., 2011b, 2011c). Recently, some researchers have proposed different methodologies for quantitative risk assessment of operations in the offshore and marine industries (Akhtar and Utne, 2014; Balmat et al., 2011; Cai et al., 2012a, 2013, 2012b; Montewka et al., 2014a). Also, risk modelling of transportation systems is regarded as one of the most important research topics in transportation (Sun et al., 2012). Therefore, it is of great interest to model accident risk in marine transportation.

The existing literature on risk modelling has mainly focused on probabilistic risk analysis arguments, simulation modelling, and statistical data analysis. Early works concentrated on assessing the risk of individual vessels or marine structures (Merrick and van Dorp, 2006). However in recent years, probabilistic risk assessment models have been introduced for various maritime domains. In Table 1, a summary of recent accident risk assessment models is presented. A brief explanation about the limitations of their results and approaches is given in this table. Mazaheri et al. (2013) reviewed ship grounding models from a risk management perspective. Li et al. (2012) also reviewed the current accident risk models for marine transportation systems. Both studies concluded that there is no single model capable of serving all types of systems, issues, and needs in the marine industry at all times.

In some papers, only one type of marine accident is considered in the risk assessment. For example, Kujala et al. (2009) and Goerlandt et al. (2012) modelled marine risk using ship traffic data and defined risk as collision probability. However, different types of data must be collected. For example, the collision frequency model requires data on visibility while the grounding frequency model requires data on ship drift speed in advance. Moreover, many of these papers were aimed at investigating the associations between marine accident risk and safety factors. For example, Wang et al. (2011a) presented a quantitative accident analysis model to assess the contribution of human and organizational factors in accidents. Yang et al. (2013) investigated human reliability factors in marine safety. Mentes and Helvacioglu (2011) combined the effects of operational failures and human errors in risk analysis by using the fuzzy fault tree method. Yip (2008) used the regression method to show the contribution of safety factors in accident risk modelling. In all of these studies, there were specific factors involved in risk modelling, such as human failure, accident count, vessel count, weather conditions, vessel size, and season.

3. General modelling approach

Probabilistic risk assessment models should be improved dynamically due to the dynamic changes in safety levels of maritime transportation systems. On the other hand, simplicity and flexibility of the models are also important. With these considerations, the general structure of the accident risk model is presented in Fig. 1. The depicted structure consists of three steps, namely Markov modelling, MCMC simulation algorithm, and sensitivity analysis. Following these steps, marine accident risk can be estimated from the mathematical relations between the occurrence rates and occurrence probabilities of the Markov model. MCMC simulation is a Monte Carlo simulation using a Markov chain. In a Markov chain, the probability of obtaining a value for a sample is dependent only on the previous sample. In this way, it can be paired with Bayesian updating to develop a new probability density function for Markov occurrences.

Table 1
Literature review on examples of recent studies: discussing accident risk assessment models with the limitations observed.

Publications	Models/methods	Limitations
Akhtar and Utne (2014)	A risk model of marine accidents which was developed by a Bayesian network	The model cannot be generalized without some constraints and quantified data such as ship types
Chang et al. (2014)	A risk scale by ranking factors using mean value and stochastic dominance methods, and a risk map to identify the levels of risk	The results were applied for decision making in container shipping companies. For other marine contexts, more risk factors should be identified
Montewka et al. (2014a)	A framework for estimation of risk parameters was developed with Bayesian belief network (BBN)	Not all accident scenarios (e.g. fire or grounding) were covered by BBN
Paefgen et al. (2014)	A multivariate regression model of accident relationship with some risk factors	A limited dataset with a case-control study
Bolat and Jin (2013)	A structured analytical approach using RADTRAN code for a case study of Turkish Straits	Few scenarios for accident events; might not have accurate results
David et al. (2013)	A risk assessment model according to BWM convention and IMOG7 guideline requirements	In order to ensure data reliability, some risk factors were eliminated in risk assessment modelling
Heij et al. (2013)	Risk measures were analysed for two vulnerable sea areas which had increasing shipping activities	Risk was mainly evaluated in terms of pollution incident probabilities and other types of risk were ignored
Heij and Knapp (2012)	Risk was modelled in terms of some factors such as age, type, and history of ships	A wide range and rich shipping datasets on accidents and inspections are required for such a model
Hu and Zhang (2012)	A risk model based on a 10-year data collection on the accidents of marine traffic at a coastal water area	The model is focused on a specific case and is more qualitative than quantitative
Balmat et al. (2011)	A fuzzy approach for pollution prevention and risk assessment. Environmental conditions and ship characteristics were considered	Validation of the results was based on experts' comments which might not be consistent in different scenarios
Yang (2011)	A risk assessment model for a maritime supply chain in Taiwan by identifying risk factors, and their severities and frequencies	The definition of risk was mostly associated with financial and operational problems, and is different from marine accident risk
Celik et al. (2010)	A risk-based modelling approach by using fuzzy fault tree analysis	Lack of data for probability values of basic events in fault tree

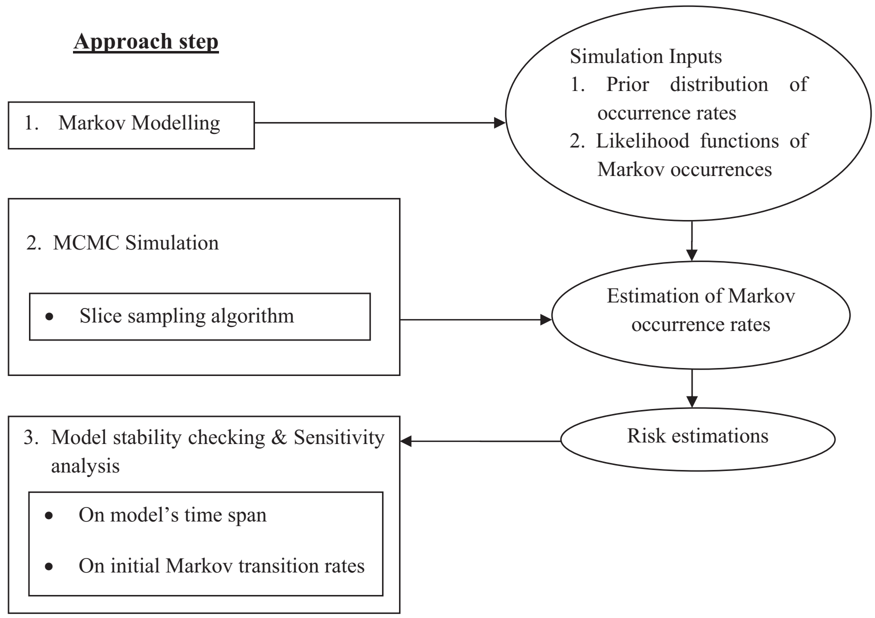

Fig. 1. Structure of the proposed accident risk model.

3.1. Markov model

In the concept of risk, there is a distinction between "accident" and "incident" in terms of the magnitude of consequences (Mullai and Paulsson, 2011). We provide a definition for each of these events after reviewing different marine statistics and annual reports published by various marine organizations (e.g., ATSB[1], TSBC[2], EMSA[3], HELCOM[4], and AIBF[5]). Based on these definitions, a three-state graph is drawn that can show accident occurrences for any type of marine transportation system (Fig. 2).

- Marine accident
  An occurrence involving a vessel where it is destroyed or seriously damaged as a result of an occurrence associated with the operation of the vessel (Transition S1–S3).
- Marine serious incident
  An occurrence involving a vessel where a person dies or suffers serious injury as a result of an occurrence associated with the operation of the vessel (Transition S2–S3).
- Marine incident
  An occurrence, other than an accident, associated with the operation of a vessel that affects or could affect the safety of operations (Transition S1–S2).

We consider the states as follows: S1: Normal, S2: Near Fail, and S3: Fail. Transitions from S1 to S3 and S2 to S3 may have various consequences but both form one unique cluster, i.e., the state of Fail.

In the Markov model, each occurrence between states is characterized by an occurrence rate λ_{kl}. k and l are the indices for the start and end states, respectively (Modarres, 2006). It is assumed that the occurrence probability in state k at time t, $p_k(t)$, is differentiable. Thus, we can write Kolmogorov's forward equations

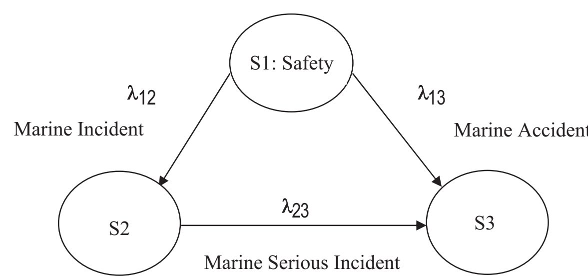

Fig. 2. Markov accident model (λ_{kl}: occurrence rate from state k to state l).

for the Markov model as follows:

$$\frac{dp_k(t)}{dt} = -\left(\sum_l \lambda_{kl}(t)\right) \bullet p_k(t) + \sum_l \left(\lambda_{lk}(t) \bullet p_l(t)\right) \quad (1)$$

For the numerical example in this paper, the above set of differential equations is solved and the time-dependent probabilities of the states are calculated.

In the Markov diagram, it is shown that serious incidents occur after marine incidents. Sometimes the exact time of a serious incident is unknown because the system is not controlled and observed continuously. However, we can distinguish incidents and serious incidents after a period of time. Therefore, we consider a time span that starts from S1 and ends with S3. We count the occurrences in this time span independently from which route is taken from S1 to S3 through the Markov model. We call this partial observation. In this way, partial data can be collected from marine statistical reports.

The first step in the risk and reliability assessment is to know the history of failures and accidents observed for the system of interest. The data collected on the number of failures and accidents of the system is the prior knowledge. From this step, by identifying the most frequent type of accidents, we know the main states of the Markov model. If the frequency of one type of accident is high or considerable, then the related data for that accident should be recorded. Using the collected data, prior distributions for failure and accident rates of the system are

[1] Australian Transportation Safety Board.
[2] Transportation Safety Board of Canada.
[3] European Maritime Safety Agency.
[4] Helsinki Commission.
[5] Accident Investigation Board of Finland.

estimated. These distributions are required to initiate the simulation algorithms.

3.2. MCMC simulation

To begin MCMC simulation, we need to consider two distributions in advance. The first distribution is the prior distribution of unknown occurrence rates. The prior distribution, $\pi_0(\lambda)$, refers to the initial belief of the value of the occurrence rate (λ) to be true. It is typically an estimate of the distribution for the continuous parameter λ. Although the choice of a prior distribution is often subjective, a rational agreement can be achieved by analyzing historical data from the same or similar databases (Thodi et al., 2010). The second distribution that must be considered is the likelihood function of occurrences. The likelihood function, $f(r|\lambda)$, is the prior distribution of observations (r) conditioned by the assumed values for the occurrence rate (λ).

In MCMC simulation, Bayes' theorem states how to update the prior probability distribution of occurrence rates, $\pi_0(\lambda)$, with a likelihood function, $f(r|\lambda)$, to obtain the posterior distribution of occurrence rates. The commonly used formula for Bayesian updating is:

$$\pi(\lambda|r) = \frac{f(r|\lambda) \times \pi_0(\lambda)}{f(r)} \propto f(r|\lambda) \times \pi_0(\lambda) \tag{2}$$

In this formula, the samples for the posterior distribution of occurrence rates, $\pi(\lambda|r)$, will be generated by combining the prior distribution with the observed data. The posterior density, $\pi(\lambda|r)$, summarizes the total information after viewing the initial occurrence data, and it provides a basis for inference regarding the parameter λ (vector of occurrence rates).

There are a number of MCMC simulation methods such as Gibbs sampling, slice sampling, and the Metropolis–Hastings algorithm (Gilks, 2005). Of these methods, the slice sampling algorithm is applied to run the simulation. Slice sampling algorithm is an MCMC simulation method that can generate random numbers from a distribution with an arbitrary form for the density function (Kelly and Smith, 2009). It serves the same purpose as Gibbs sampling and Metropolis–Hastings algorithms. However, in contrast to these two methods, the implementation of the slice sampling algorithm is found to be easier and more efficient (Neal, 2003). The slice sampling procedure can be described as follows:

1. Assume initial values for occurrence rates λ_0 within the domain of posterior distribution $\pi(\lambda|r)$, which is estimated by the multiplication of the likelihood function and prior distribution from Eq. (2). The values can be selected randomly from a uniform distribution that covers all observed transition rates over time.
2. When dealing with uncertainty estimations, the uniform distribution has a usage ease advantage and it is recommended for obtaining a quick solution, while the algorithm should be repeated many times. Therefore, draw a real value for occurrence rates λ^* uniformly between 0 and λ_0 (i.e. $[0, \pi(\lambda_0|r)]$). In this way, the horizontal slice is defined as $S = \left\{\lambda | \lambda^* < \pi(\lambda|r)\right\}$. It should be noted that λ^* is a non-negative normalized number between 0 and 1.
3. Set an interval $I = (L, R)$ around λ_0 that contains all or as much as possible of slice S. Ideally, consider:

   $$L = \inf(S), \text{ and } R = sup(S) \tag{3}$$

4. Draw the new point λ_1 within interval I.
5. Repeat steps 2 through 4 starting with new point λ_1 until the desired number of samples is reached.
6. Find the mean and variance of the occurrence rates for the sample resulting from step 5.

In the Markov model, there are relationships between the probability of occurrences and the occurrence rates (Eq. (1)). In the three-state Markov model, if we assume that the occurrence of states is a homogeneous Poisson process with mean λ_{kl} in matrix G, the state occurrence probabilities can be calculated as the elements of matrix $P(t)$:

$$G = \begin{bmatrix} -(\lambda_{12}+\lambda_{13}) & \lambda_{12} & \lambda_{13} \\ 0 & -\lambda_{23} & \lambda_{23} \\ 0 & 0 & 0 \end{bmatrix} \tag{4}$$

$$P(t) = \begin{bmatrix} \pi_{11}(t) = e^{-(\lambda_{12}+\lambda_{13})t} & \pi_{12}(t) = \frac{\lambda_{12} e^{-\lambda_{23}t}(1-e^{-(\lambda_{12}+\lambda_{13}-\lambda_{23})t})}{(\lambda_{12}+\lambda_{13}-\lambda_{23})} & 1-\pi_{11}(t)-\pi_{12}(t) \\ 0 & e^{-\lambda_{23}t} & 1-e^{-\lambda_{23}t} \\ 0 & 0 & 1 \end{bmatrix} \tag{5}$$

where $\pi_{kl}(t)$ is equal to the occurrence probability from state k to l at time t.

Using the slice sampling algorithm, we can estimate the expected values of the occurrence rates (incident rate, serious incident rate, and accident rate). We can then put the estimated occurrence rates into the Kolmogorov equations and find the probability of occurrences by solving these equations. The solved occurrence probabilities are representative of marine risk.

$$Risk(t) = \pi_{13}(t) + \pi_{23}(t) \tag{6}$$

4. An illustrative example of a marine accident risk modeling

4.1. Data and case description

In this section, we demonstrate the application of the proposed methodology for accident risk modelling in marine transportation. The purpose is to estimate the accident risk of Australian commercial vessels. We referred to marine research and analysis reports by the Australian Transport Safety Bureau (ATSB) in 2011. The reports included the most adaptable and matching data based on the definitions of the Markov states and occurrences given in Section 3.1. In these reports, data is provided for occurrences involving ships with Australian flag operating as trading ships (cargo and/or passenger ships) around the world and trading vessels with foreign flags within Australia's maritime jurisdictions. Although there is little data available, we took advantage of the proposed algorithm which can take a few observations and create a simulated set of data using MCMC simulation.

Table 2 presents the number of occurrences from years 2005 to 2010 related to Australian vessels or vessels within Australian marine jurisdictions. In this table, the observed occurrences from S2 to S3 are given in the category of serious incidents. The variation for incidents and serious incidents is insignificant, but it is significant for accident rates. Uniform distributions are considered for the prior distribution of occurrence rates. For example, $Uniform\,(65,\,98)$ is used for incident rate distribution.

Table 2
Australian commercial shipping occurrences over the 5-year period (2005–2010).

Occurrence type	2005	2006	2007	2008	2009	2010
Accident	8	8	8	3	3	3
Serious incident	4	5	3	3	2	5
Incident	81	98	81	65	94	72

We then started the slice sampling algorithm by considering and normalizing the mean values of uniform distributions as initial transition rates λ_0. The sample data in Bayesian inference is expressed by the likelihood function. Empirically, by assuming identical and independent trials in the experiments, the likelihood distribution of the occurrence rate vector λ, $f(r|\lambda)$, is assumed to be the multinomial distribution. With this assumption, the occurrences for each row k of matrix G are drawn from a multinomial distribution with the following probabilities:

$$(r_{k1}, r_{k2}, \ldots, r_{kl}) \sim \text{Multinomial}\,(\pi_{k1}(t), \pi_{k2}(t), \ldots, \pi_{kl}(t); r)_k \qquad (7)$$

4.2. Some numerical results

The proposed algorithm described in Section 3.2 (slice sampling algorithm) was implemented in MATLAB R2013b software and ran 1000 times. The resulting estimations of occurrence probabilities and rates over a 5-year time span are shown in Fig. 3. From the MCMC simulation results for the mean probabilities of marine occurrences in Australian waters, the determination of marine risk for the next 5 years is possible.

Based on the simulation results, the mean probabilities for incidents, accidents, and serious incidents of vessels in Australian waterways are respectively 0.1004, 0.0059, and 0.0069 over time. It can be seen that the observed accident and serious incident rates change only slightly during the 5-year time span. However, the averages of the estimated accident and serious incident rates in five years are lower than the averages of the observed initial rates. Similarly, when comparing the expected incident rates with the observed initial ones, the decreasing trend is clearly observable. This decrease is consistent with what has been expected to happen in the real world: marine occurrences are decreasing slightly because of IMO standards, industry initiatives, and improving technology.

We can observe the variation in the probability and rate of marine occurrences at different times by using contour plots. For this purpose, the curve-fitting tool in MATLAB R2013b was used with the Bi-harmonic (v4) method under the category of interpolation fit. The contour plots of the simulated occurrence probabilities versus time and rates are shown in Fig. 4a–c.

The results reveal that for more than 90% of the occurrence rates, the estimated occurrence probabilities are located in the same color or contour area over time. Thus, the occurrence probabilities remain stable over time while the occurrence rates vary. For example, the contour plot of serious incidents clearly shows this fact. This means that the risk associated with serious incidents is almost constant over the 6-year period. Intuitively, the contour areas with the highest/lowest occurrence probabilities are distinguished with higher (red)/lower (yellow) level colors.

4.3. Model stability

In this section, we check the stability of the proposed model with an analysis carried out on the time span of the model to see how it may affect the results of running the algorithm. In the numerical example, we considered a 5-year time span for the

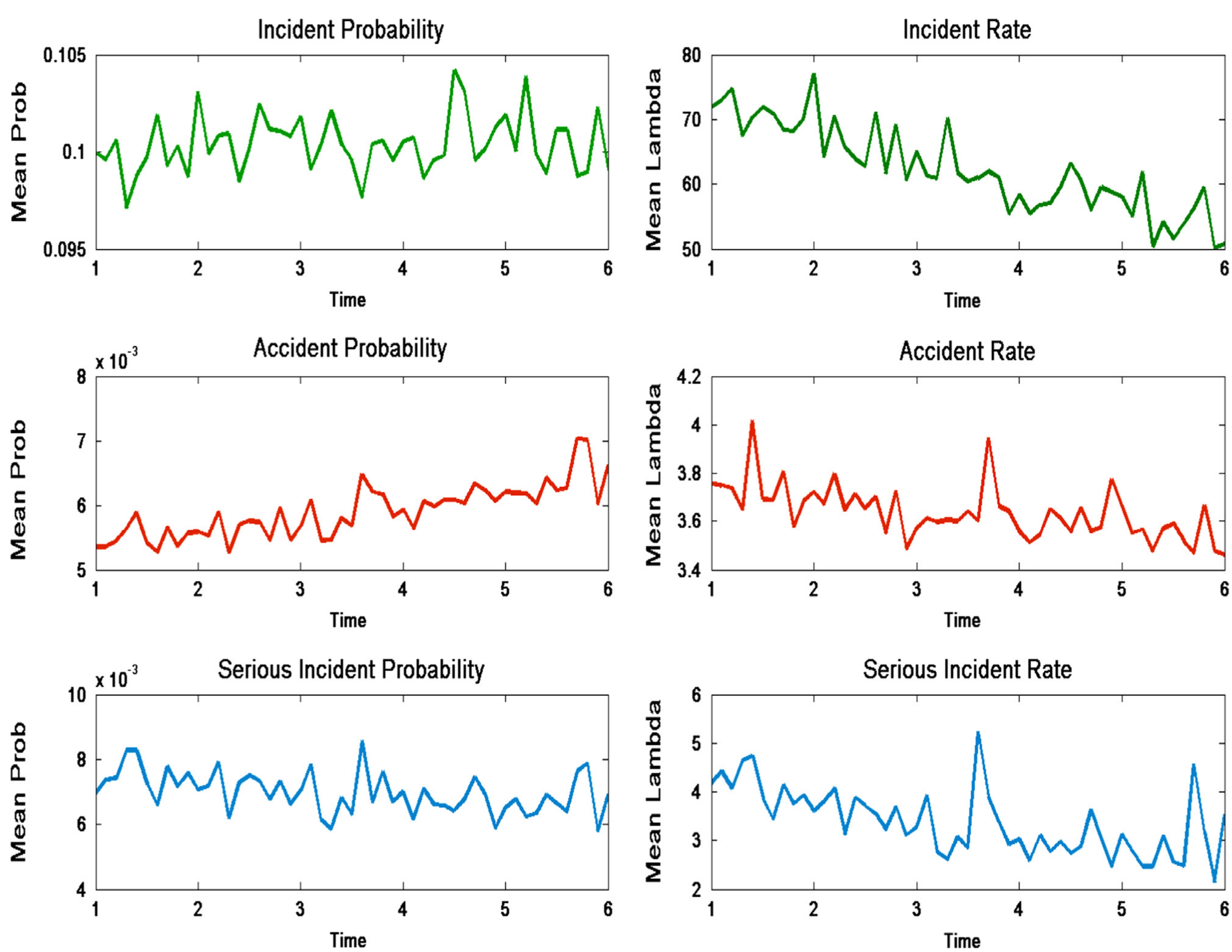

Fig. 3. Marine occurrence probabilities and occurrence rates for Australian commercial vessels in a 5-year time span obtained from 1000 runs of MCMC simulation.

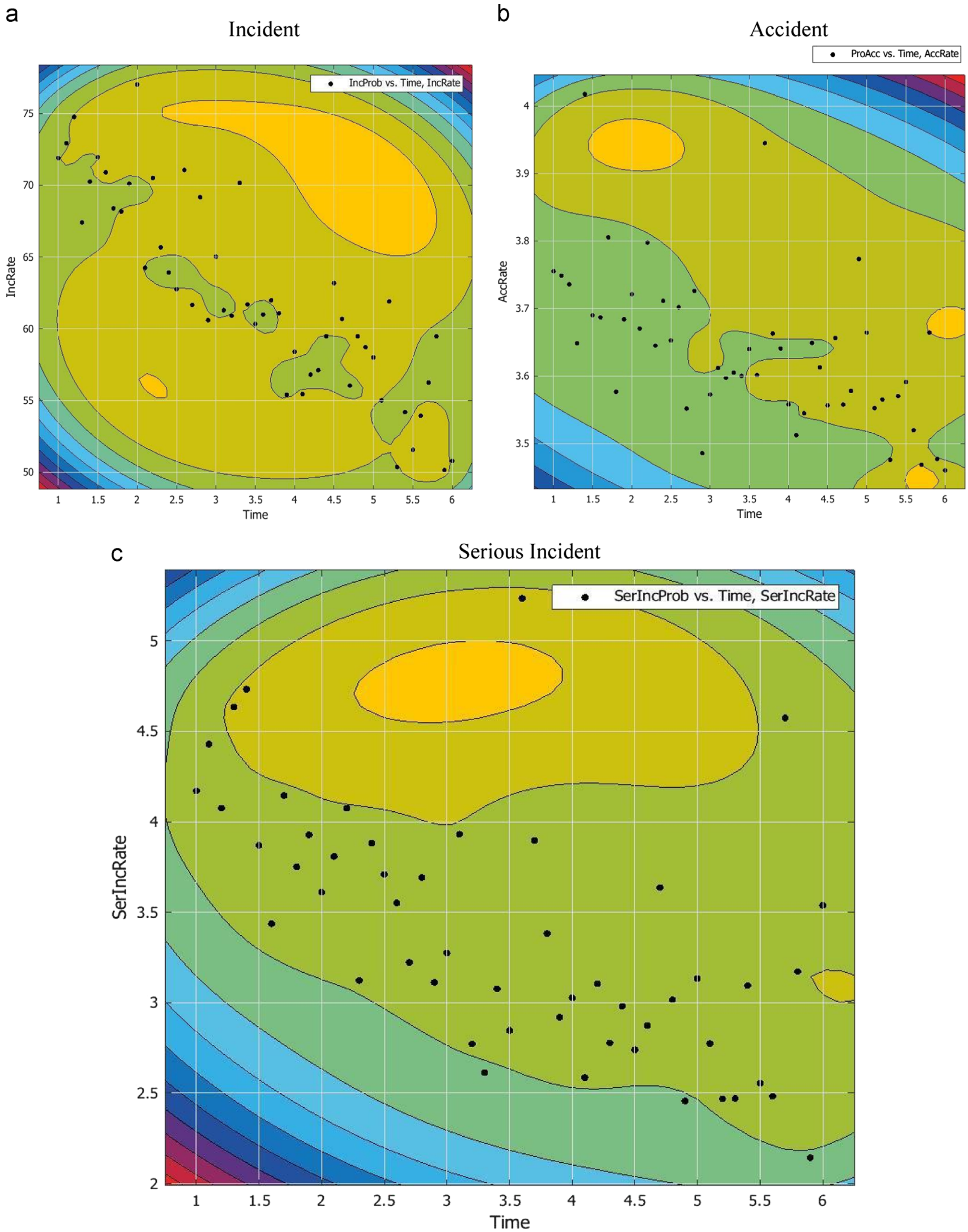

Fig. 4. The contour plot of simulated probability vs. time and rate for: (a) incident, (b) accident, (c) serious incident.

estimation of marine risk by running the slice sampling algorithm 1000 times. Without changing other initial assumptions, we changed the model's time span from 5 years to 20 years with a step length of half a year (i.e., thirty-one estimations for occurrence probabilities). It should be noted that the number of runs was fixed (1000 times) for every variation. For each time span, the model resulted in different estimations for occurrence probabilities. We observed and saved the variations of the occurrence probabilities in response to changes in the simulation time span. Next, the mean and standard deviation of the estimated incident and accident probabilities were calculated (see Table 3). We then set up $\bar{x}$ and (s) control charts for the estimated incident and accident probabilities using the SPSS 20.0.0 software. In total, 31 samples with 31 observations (31 estimations for occurrence probabilities) were considered. The three-sigma control limits for $\bar{x}$ and (s) were calculated and stated in Table 3. In this way, there is 95% confidence that the estimated probabilities and standard deviation values are within the control limits.

The statistical information shows that the risk of incidents and accidents does not dramatically change with different time spans. This can also lead to the interpretation that although marine occurrence rates decrease with time (what was shown in the previous section), the estimated occurrence risk changes slightly over time. This result is significant and can be observed in reality. Despite current safety improvements, the risk of accidents and incidents still exists. We cannot consider that this probability will significantly decrease or become zero over time.

5. Sensitivity analyses

Recent works in the assessment of risk in maritime transportation systems have used simulation-based probabilistic risk assessment techniques (Merrick et al., 2005). In simulation-based models, we combine the characteristics of real marine accidents and make them serve as future events. Therefore, to investigate the applicability of the model and draw conclusions, a sensitivity analysis of the main characteristics and assumptions is important. We should be able to point out which initial assumptions are appropriate candidates for additional data collection to narrow the degree of uncertainty in the results.

In most marine accident reports, the number of accidents is updated regularly over time (e.g., monthly, annually). Therefore, it is necessary to propose a model that is flexible in updating accident rates and probabilities over time.

In this section, we investigate the effect of initial transition rate values on the simulation results and estimations of probabilities. The slice sampling algorithm begins with a set of initial transition rates (λ_{12}, λ_{13}, and λ_{23}). For example, the mean value of the Uniform (a_{12}, b_{12}) distribution was assumed as the initial incident rate, where a_{12} and b_{12} are the minimum and maximum incident rates in Table 2, respectively.

The initial rates were increased by a step length of $(b-a/20)$ for 10 iterations. At each step, the timespan of the model was considered to change from 5 to 10 years. MCMC simulation was run 1000 times at each step. Fig. 5 includes the plots of the mean values of the occurrence rates (λ_{12}, λ_{13}, and λ_{23}) versus time.

The plots show symmetric error bars, which indicate the confidence intervals of the resulting transition rates. It can be seen that the mean values of the occurrence rates have a decreasing trend over the model's timespan. For example, the mean of the accident rate decreases from 3.7 in 5 years to 1.7 in 10 years. On the other hand, for each timespan, the error bars are small and the mean variation is not significant. This means that by fixing the model's timespan, the simulation results do not vary considerably when the initial transition rates are selected at any point of the uniform distribution. However, when different timespans are considered, a reduction in the accident rate is expected and the model follows what is expected to happen over time in the real world.

Table 3
Statistical information of incident and accident probabilities over time.

(1–6) Years statistical information	Incident	Accident
Mean of probabilities ($\bar{x}$)	0.10030	0.00601
Standard deviation (s) of probabilities	2.037E−03	4.573E−04
Upper control limit for $\bar{x}$	0.10646	0.00731
Lower control limit for $\bar{x}$	0.09414	0.00471
Upper control limit for (s)	2.680E−03	4.971E−04
Lower control limit for (s)	1.394E−03	4.175E−04

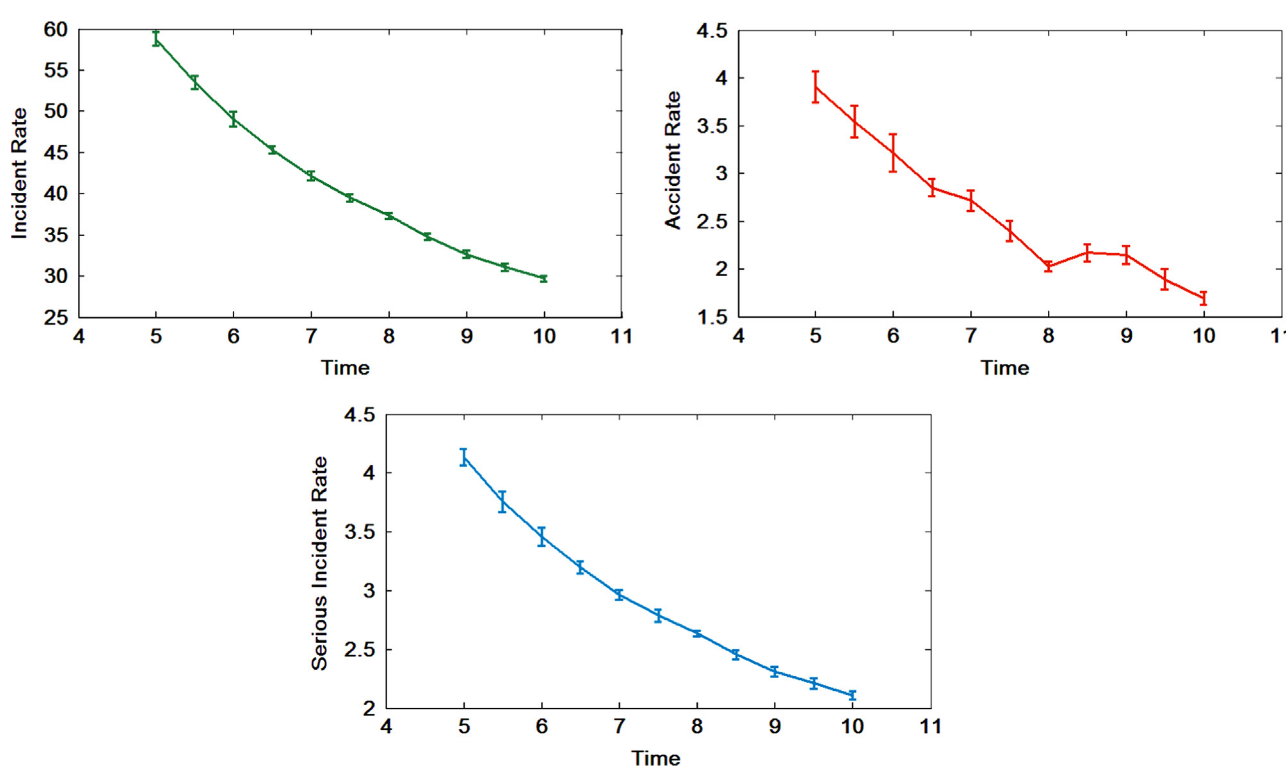

Fig. 5. Error bar plots of marine occurrence rates after running MCMC simulation with different initial rates.

6. Conclusion

In this paper, an approach involving Markov modelling and MCMC simulation was presented to estimate incident and accident risks in marine transportation systems. In the application example, initial data was collected from ATSB annual reports. However, this model is applicable to any database in which marine accidents are recorded regardless of their type and severity. MCMC simulation was applied for estimation of the occurrence rates and probabilities. MCMC simulation also showed that the accident and incident probabilities remain constant for different timespans, thus confirming the stability of the model. Sensitivity analysis of the initial transition rates showed that marine occurrence rates generally decrease with time. However, the simulated occurrence rates at each time were not affected significantly by the initial rates.

There are two main advantages of the approach presented in this paper. First, in contrast to the recent risk models proposed for specific types of accidents or vessels, our model can generally consider any accident or marine system. Second, our model and MCMC simulation is a simple approach and there is no need for large-scale data collection. Usually, risk modelling could have been a complicated process that includes networks with many basic events, large databases, and various factors to estimate probabilities. Overall, this paper intends to fill the gap related to information about safety factors in maritime systems.

Although the application of MCMC simulation for probability estimation is not new, it is novel for this area of estimating marine accident probability and risk. In the current context, there is no similar work that we can compare our results with. Instead, we performed some sensitivity analyses and checked the model's stability. With this in mind, proposing a more efficient method that is comparable with this paper's algorithm and with a larger database would serve as an immediate future work of interest. The research in this study could also have potential applications in other sectors, such as the oil and gas industries, as well as in other systems, such as railways and road transportation systems.

Acknowledgments

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