Proceedings of the 2003 Winter Simulation Conference
S. Chick, P. J. Sánchez, D. Ferrin, and D. J. Morrice, eds.

PROPAGATION OF UNCERTAINTY IN A SIMULATION-BASED MARITIME RISK ASSESSMENT MODEL UTILIZING BAYESIAN SIMULATION TECHNIQUES

Jason R.W. Merrick
Varun Dinesh

Department of Statistical Sciences
& Operations Research
Virginia Commonwealth University
1001 West Main Street
Richmond, VA 23284, U.S.A.

Amita Singh
J. René van Dorp
Thomas A. Mazzuchi

Department of Engineering Management
& Systems Engineering
George Washington University
1776 G Street NW
Washington, D.C. 20052, U.S.A.

ABSTRACT

Recent studies in the assessment of risk in maritime transportation systems have used simulation-based probabilistic techniques. Amongst them are the San Francisco Bay (SFB) Ferry exposure assessment in 2002, the Washington State Ferry (WFS) Risk Assessment in 1998 and the Prince William Sound (PWS) Risk Assessment in 1996. Representing uncertainty in such simulation models is fundamental to quantifying system risk. This paper illustrates the representation of uncertainty in simulation using Bayesian techniques to model input and output uncertainty. These uncertainty representations describe system randomness as well as lack of knowledge about the system. The study of the impact of proposed ferry service expansions in San Francisco Bay is used as a case study to demonstrate the Bayesian simulation technique. Such characterization of uncertainty in simulation-based analysis provides the user with a greater level of information enabling improved decision making.

1 INTRODUCTION

In maritime transportation systems, aleatory uncertainty, i.e. uncertainty ascribed to system randomness, maybe introduced, for example, by constantly shifting traffic patterns caused by weather changes. Epistemic uncertainty, i.e. uncertainty due to lack of knowledge of the system, results from uncertainties in input data to simulation models and truncating estimates made on the results (output) of simulation models. There is extensive literature recognizing the need to incorporate uncertainty analysis in risk assessment, however in practice it often is categorized under simplifying assumptions. Bayesian simulation analysis allows treatment of aleatory and epistemic uncertainties (Apostolakis 1978; Hora 1996; Hofer 1996; Cooke 1991) as contributing elements to risk analysis. In addition, this approach allows the user to make informed decisions based on output uncertainty rather than using point estimates (Glynn 1986; Chen and Schmeiser 1995; Chen 1996; Chick 1997; Chen et al. 1999; Cheng 1999; Chick and Inoue 2001; Chick 2000, 2001).

Over the years, various safety implementation measures have been developed to prevent and mitigate the damage caused by maritime accidents, such as the recent sinking of the *Prestige* off the Spanish Galician coast and the grounding of the *Exxon-Valdez* in the Prince William Sound. Probabilistic Risk Assessment (PRA) is a relatively new method developed to quantify maritime risk and estimate the effect of such safety measures (Hara and Nakamura 1995; Roeleven et al. 1995; Kite-Powell 1996; Slob 1998; Fowler and Sorgard 2000; Trbojevic and Carr 2000; Wang 2000; Guedes Soares and Teixeira 2001). Pate-Cornell (1996) provides a step-wise approach to characterize uncertainty in probabilistic risk analysis. A six step treatment is defined to address aleatory uncertainty as well as epistemic uncertainty:

1. Identification of hazards
2. Worst case analysis
3. Plausible upper bound analysis
4. Best estimates
5. Probability and risk analysis
6. Display of risk uncertainties.

The PWS (Merrick et al. 2000; Merrick et al. 2002) and WSF (van Dorp et al. 2001) risk assessments capture the elements of aleatory uncertainty in a more explicit manner through integrated systems simulation with PRA techniques and expert judgment data. Both these analyses are considered at level 5 of the Pate-Cornell scale. So far and to the best of our knowledge, epistemic uncertainty has not been modeled as a risk element in maritime safety. The uncertainty representation described in this paper advances to level 6 by considering aleatory and epistemic uncertainty distinctly as well as input and output uncertainty, using Bayesian analytical methods in simulation models.

Representation of aleatory and epistemic uncertainty in a risk assessment the PWS and WSF risk assessments comprises of the following 4 steps:

1. Representation of uncertainty in simulation
2. Representation of uncertainty in expert judgment
3. Propagation of uncertainties through the entire model
4. Performing a trial uncertainty analysis

This paper describes the first step, the representation of uncertainty in simulation models by incorporating input and output uncertainty in a Bayesian framework. As proof of concept, we will expand upon the existing San Francisco Bay simulation model to address simulation uncertainty (Merrick, et al. 2003).

2 BAYESIAN SIMULATION OF SAN FRANCISCO BAY VESSEL TRAFFIC

The San Francisco Bay ferries expansion project was undertaken to analyze the impact of increasing ferry operations on San Francisco Bay as a measure to relieve traffic congestion on the freeways. The state of California proposed three expansion scenarios:

1. Enhanced Existing System (least aggressive)
2. Robust Water Transit System (more aggressive)
3. Aggressive Water Transit System (most aggressive)

To assess the proposed expansion impact, a detailed simulation of vessel movements in San Francisco Bay is developed. Figure 1 presents a snapshot of the SFB simulation. Movies of the simulation can be viewed at `SFB Simulation Movies`. The simulation assesses vessel interaction under the three expansion scenarios defined above.

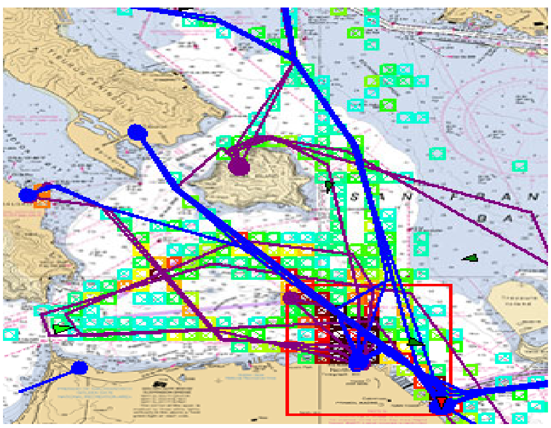

Figure 1: The Simulation of San Francisco Bay

A simulation of the San Francisco Bay maritime transportation system is developed under a Bayesian framework; the model estimates the frequency of possible system states. The arrival of vessels and environmental conditions are inputs to the model, modeled using available data. The input data (vessel arrivals into San Francisco Bay) is limited and reflects input uncertainty (Chick 2001), thereby introducing epistemic uncertainty. The aleatory aspect of input uncertainty is captured by assigning a probability distribution on the arrivals times using the standard renewal process (Law and Kelton, 2001). All non-ferry traffic except scheduled regatta events is modeled. Prior distributions are specified for the input parameters to model epistemic uncertainty and under the Bayesian paradigm, available vessel arrival data is used to update these prior distributions to obtain the posterior distributions.

3 THE INPUT UNCERTAINTY MODEL

The SFB exposure assessment considers 5,277 arrival processes of various types of vessels using different routes (Merrick et al. 2003). Historical inter-arrival times are calculated using Vessel Traffic Service (VTS) data based at Treasure Island. Let $D^k = \{T_1^k, \ldots, T_{m^k}^k\}$ be the m^k independent inter-arrival times for the k-th arrival process (k = 1,….,5277).

In classical simulation modeling, the distribution of inter-arrival times is selected by first determining best estimates of parameters for families of distributions, e.g. exponential, Weibull, gamma, log-normal, based on the data. Let $F_1^k(t \mid \Theta_1^k)$, ….. , $F_p^k(t \mid \Theta_p^k)$ be p families of probability distributions, where k denotes the 5,277 arrival processes each assigned a different probability distribution and therefore a distinct parameter value Θ_j^k. Estimation procedures such as maximum likelihood or method of moments are used to select the best estimates of the parameters Θ_j^k from the data D^k. The best fit distribution is selected by comparing the fit of each distribution to the data using fit statistics such as Anderesen-Darling, Chi-Square and Kolmogorov-Smirnov (Law and Kelton, 2001). The best fit distribution is selected by taking either the fitted distribution with the lowest appropriate fit statistic or at least a fitted distribution that is not rejected by the corresponding hypothesis test and that has desirable properties, such as simple manipulation of the mean or variance. Using this renewal process to model inter-arrival probability distributions also allows modeling of aleatory uncertainty.

Under the Bayesian framework, $\Pi_1^k(\Theta_1^k)$,…. ,$\Pi_p^k(\Theta_p^k)$ denotes the prior distributions defined for the parameters of the probability models selected for the inter-arrival times. The data D^k is used to update these prior distributions to obtain the posterior distributions $\Pi_1^k(\Theta_1^k \mid D^k)$,….,$\Pi_p^k(\Theta_p^k \mid D^k)$. To demonstrate Bayesian updating procedures consider container ships arriving from an offshore anchor point passing under the Golden Gate Bridge and berthing in the Oakland Outer Harbor. Overall 176 such transits occurred between 7/31/1998 and 12/31/2001, with an average of 4.44 days between transits. We consider the exponential distribution with parameter λ and the gamma distribution is a natural conjugate prior for λ. Thus if we assume a priori that λ is drawn from a gamma distribution with shape parameter a and scale parameter b, then after updating with the inter-arrival time data, λ will follow a gamma distribution with shape parameter $a + \sum_{1}^{m^k} t_i^k$ and scale parameter $b + m^k$. For the container vessel route, we assume a vague prior by setting $a = 0.001$ and $b = 0.001$, which corresponds to a prior mean of 1 and a prior variance of 1000. For this route, $\sum_{1}^{m^k} t_i^k = 781.44$ and $m^k = 176$. and we get a posterior of $a = 781.441$ and $b = 176.001$.

To select the best fit probability distribution, approaches have been described such as the Bayes factors (Kass and Raftery 1995), posterior predictive densities (Gelfand 1996) and the most recent yet, the Decision Information Criterion (Spiegelhalter et al. 2002). In this modeling exercise, we chose to use the Decision Information Criterion (DIC) method. The Bayesian Deviance is defined as

$$D(\Theta_j^k) = -2\ln p(D^k \mid \Theta_j^k) + 2\ln f(D^k) \tag{1}$$

where $f(D^k)$ is a fully specified standardizing term that is a function of the data alone and does not affect the model comparison. The model fit is then represented by

$$\bar{D} = E[D(\Theta_j^k) \mid D^k] \tag{2}$$

which denotes the expected deviance after updating with the available data. An estimate of the effective number of parameters p_D is calculated as the difference between the expected Bayesian deviance after updating with the available data and the Bayesian deviance calculated at the expected value of the parameters after updating with the available data i.e.

$$p_D = E[D(\Theta_j^k) \mid D^k] - D(E[\Theta_j^k]). \tag{3}$$

The DIC is set equal to $\bar{D} - p_D$, which is the model penalized by the number of parameters of the model. We compare the exponential, Weibull, gamma and log-normal distributions for selection of the best fit probability distributions to the arrival process discussed above, with appropriate vague priors chosen for the parameters of each distribution. Table 1 shows the DIC results. The calculations in Table 1 were performed in WinBugs version 1.4 (Spiegelhalter et al. 1996). The effective number of parameters is very close to the true number of parameters in the model. Overall, the gamma distribution has the best ranking, although the difference in the Weibull distribution is negligible and can be attributed to sampling error.

Table 1: DIC Values for the Selected Arrival Process

	D	**p_D**	**DIC**
Exponential	877.778	1.010	878.787
Weibull	838.202	1.750	839.952
Gamma	837.349	2.025	839.374
Log-normal	847.737	1.999	849.736

In the simulation, inter-arrival times for the exponential-gamma process are sampled by first sampling from a gamma distribution with shape 781.441 and scale 176.001 to obtain a sample for λ and then sampling from an exponential distribution with the parameter set to the sampled value of λ (Chick 2000). Equivalently, inter-arrival times could be sampled from a Pareto distribution with shape 781.441 and scale 176.001 (Bedford and Cooke 2001, chapter 4). Thus the simulation models aleatory uncertainty represented by the exponential probability model and the epistemic uncertainty represented by the gamma posterior distribution on the parameter of the exponential.

Overall, we have 5,277 arrival processes and the inter-arrival times follow an exponential distribution with parameters a and b. To update these arrival times to $a + \sum_{1}^{m^k} t_i^k$ and $b + m^k$, a database query is performed using VTS's transit log. The posterior distribution of the arrival rates is obtained using this data. The sum of the inter-arrival times is the same as the time between the first and last arrival in the database. The query returned the first arrival, the last arrival and the total number of log entries for each combination of vessel type, origin and destination.

The ferry transits for the existing schedule as well as the proposed alternatives are based on a pre-defined schedule. Environmental factors such as visibility and wind conditions were obtained from National Oceanographic and Atmospheric Administration (NOAA) observation stations' databases in the study area. The vessel interaction counting methodology is also programmed in to the simulation. Further details of the simulation model are discussed in Merrick et al. (2003).

4 THE OUTPUT UNCERTAINTY MODEL

The output of the simulation model is the (yearly and daily) number of vessel interactions, N_r which denotes the number of vessel interactions in the r-th replication of the simulation. To model output uncertainty under the Bayesian simulation framework, a probability distribution is assigned a priori to the simulation model output and updated with observed data from the true output values. Such treatment of output data is characterized as meta-modeling (Chick 2000; Law and Kelton 2001).

The model output of vessel interaction frequency is assigned a Poisson distribution with rate μ using a conjugate gamma prior on μ with shape and scale parameters α and β respectively. Let

$$L(\mu \mid N_1 = n_1, \ldots, N_r = n_r) = \prod_{i=1}^{r} \frac{\mu^{n_i}}{n_i!} e^{-\mu} \qquad (4)$$

denote the likelihood function for the r replications. This likelihood function is used to update the prior to derive the posterior distribution of the vessel interaction. The posterior distribution is a gamma with updated shape and scale parameters $\alpha + \sum_{i=1}^{r} n_i$ and $\beta + r$, respectively. This modeling approach of output uncertainty described by the posterior gamma distribution includes epistemic uncertainty about the expected number of interactions and the Poisson distribution assigned to the data models aleatory uncertainty of the actual number of interactions.

5 UNCERTAINTY RESULTS OF THE EXISTING FERRY SYSTEM

The results of the simulation of the vessel movements in the San Francisco Bay provide us with a count of the interactions of these vessels in different geographic areas of the Bay under the three proposed ferry expansion scenarios. The interaction count is provided on a daily as well as yearly basis. Daily counts will result in larger uncertainty bands than yearly counts. Hence for the purpose of this paper, we will focus on the daily counts.

To compare interaction frequency between geographic areas and under the proposed expansion alternatives, we compare the distribution of the expected number of interactions in a given period across these cases. Quantile maps of the expected rate of interactions in a grid of cells across the San Francisco Bay are created. Let $\mu^a[x,y]$ denote the expected number of interactions in the grid cell indexed by x and y for alternative a. Maps of the 5th, 50th and 95th percentiles of the posterior distribution of the $\mu^a[x,y]$'s for each alternative are created.

The simulation was run for 1 replication of 1 day of the current ferry system (Base Case). We assume a vague prior for the expected number of interactions in each grid cell, $\mu^a[x,y]$, by setting each $\alpha = 0.001$ and $\beta = 0.001$. This corresponds to a prior mean of 1 and a prior variance of 1000. In total there were 9,430 interactions in the simulated day. The posterior distribution of each $\mu[x,y]$ was calculated and summed over all x and y to find the posterior distribution of the total expected number of interactions. This distribution has a median of 9,430 interactions, a 5th percentile of 6802 interactions and a 95th percentile of 12,711 interactions.

To reflect the results across the grid of cells, 5th, 50th and 95th percentile maps were created as shown in Figure 2. The red box at the center of the map surrounds the ferry building in San Francisco. The accompanying count shows the percentage of the interactions that occur in this vicinity. We observe that with only 1 replication of a day, there is considerable variability about this quantity. However, examining the color of the cells, with darker cells having more interactions, the colors do not change much from the 5th to the 95th percentile especially in the central bay area.

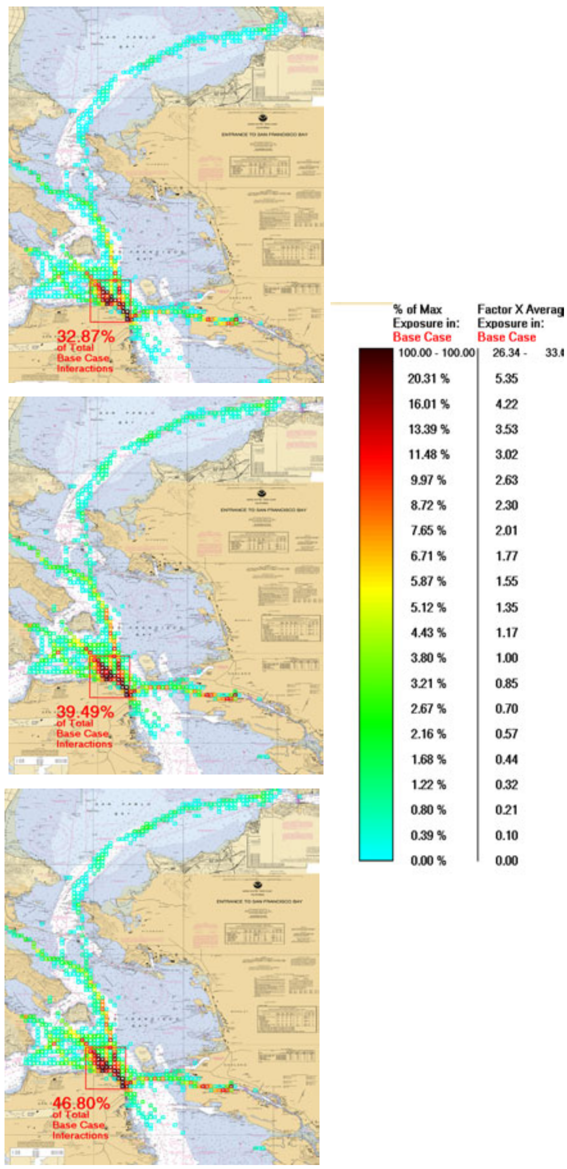

Figure 2: 5th, 50th and 95th Percentiles of the Daily Expected Number of Interactions in the Base Case

Thus any conclusions drawn from these maps are robust to the uncertainties in the simulation, even with only a single replication of a day.

In risk assessment, replications of much higher order need to be performed. Furthermore risk can change throughout the year due to environmental or traffic pattern changes. Therefore, we consider a full year of simulation as one replication and the quantity of interest is the expected yearly number of interactions. We performed 50 replications of a year finding an average of 8,348,381 interactions per year. The posterior distribution of the total yearly expected number of interactions has a median of 8,348,381 interactions, a 5th percentile of 8,333,496 interactions and a 95th percentile of 8,363,357 interactions, indicating a small range of uncertainty.

6 UNCERTAINTY RESULTS FOR THE AGGREGATE ALTERNATIVES COMPARISON

Comparing the existing ferry system (Base Case) to the three proposed expansion scenarios, we make this comparison in aggregate using the posterior distribution of the expected number of interactions in the whole system for each alternative.

One replication of one day was simulated for each of the three alternatives to obtain the posterior distribution of the daily expected number of interactions. Figure 3 shows the comparison, plotting the median of this distribution against the total number of ferry transits in each simulation. Error bars are also added to indicate the range from the 5th to the 95th percentiles of the posterior distribution for each alternative.

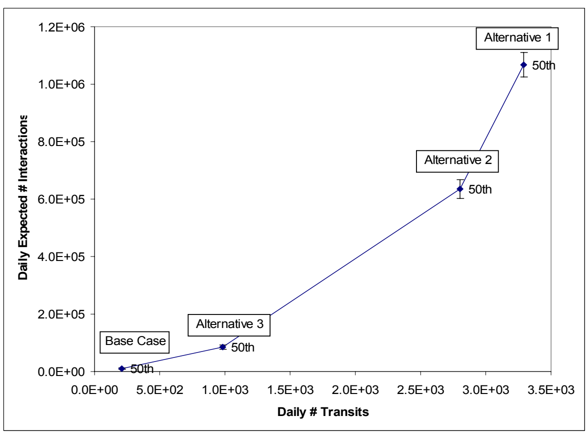

Figure 3: Daily Expected Number of Interactions for the Four Scenarios

A major conclusion drawn from the original study in San Francisco Bay was that the number of ferry to vessels interactions grows exponentially with the number of ferry transits. Thus the safety levels currently enjoyed by the San Francisco Bay ferry service cannot be maintained under the planned expansion scenarios without equally aggressive investment in risk intervention (Merrick et al. 2003). Figure 3 shows that this conclusion is not affected by the epistemic uncertainties in the results. Despite the single replication of a day for each alternative, the level of uncertainty in these posterior distributions is small relative to the large differences between the alternatives.

7 UNCERTAINTY RESULTS FOR THE GEOGRAGAPHIC ALTERNATIVES COMPARISON

Further detail can be obtained by comparing the number of expected interactions in each grid cell across the San Francisco Bay. This is done by calculating the probability that the rate in a given grid cell in one alternative is greater than or equal to that for the same cell in another alternative. We denote the probability of this ratio as $P(\mu^a[x,y] > \mu^b[x,y])$ for all x and y and all combinations of a and b and the maps generated using these calculations are termed probability dominance maps. Since $P(\mu^a[x,y] > \mu^b[x,y])$ cannot be calculated in closed form for the gamma distribution, sampling approximations are made from $\mu^a[x,y]$ and $\mu^b[x,y]$ and the proportion $\mu^a[x,y] > \mu^b[x,y]$ is calculated.

The aggregate analysis shows conclusive differences between the current ferry system and the three alternatives. Each addition of ferry transits results in additional interactions, with the growth being exponential. However examination of the probability dominance maps give a more detailed picture of the differences between the alternatives. Certain areas are observed to be 'hot spots' for ferry interactions while some areas in the Bay see fewer interactions.

Figure 4 shows the probability dominance map for the Base Case compared to Alternative 3. As indicated in the legend, black cells indicate almost certainty that Alterna-

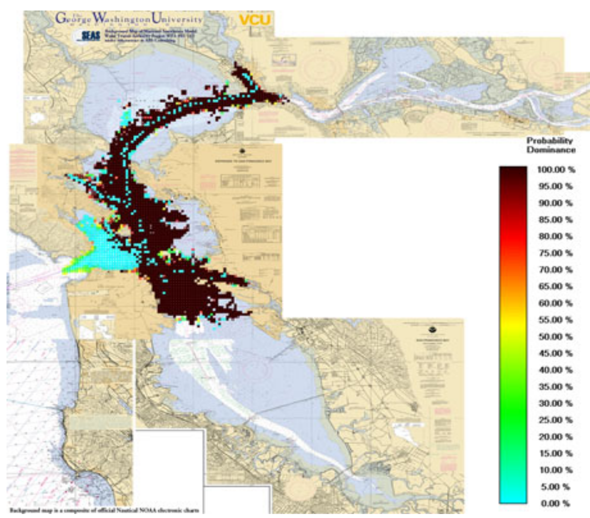

Figure 4: Base Case Compared to Alternative 3

tive 3 will see more interactions in that location than the Base Case, with less certainty shown in red. Blue cells show the reverse with almost certainty, while green indicates less certainty. The numbers of interactions in yellow cells are not different between these two scenarios. That is, the posterior distributions of the expected number of interactions in a yellow cell are almost identical between the two alternatives mapped. Thus, the probability that one is higher than the other is 0.5 (50%) and corresponds to yellow on the color scale.

As observed in Figure 4, the majority of the grid cells are black. This reinforces our conclusions from the aggregate results that Alternative 3 has significantly more interactions overall than the Base Case. We also observe that that there are some blue cells primarily around the Golden Gate Bridge and Richardson Bay. The ferries in this area run from San Francisco to Sausalito and Tiburon or are tours around the Bay visiting the Golden Gate Bridge. The tours were unchanged from the Base Case to the alternatives. The schedules supplied for the alternatives consist of a start time, end time and time between ferries. The Sausalito and Tiburon ferries start at 7 am and run every 30 minutes until 10 pm during the week. On the weekend they run every 60 minutes. This is significantly more than in the Base Case, but this means that there are definite patterns to the transits that are not reflective of a more mature schedule. These ferries do not interact as much because of the timing of the transits. The number of interactions in this area is very low as compared to other areas of the Bay. This is also shown on the northerly routes to Larkspur and Vallejo. The blue in the middle of the black area is actually on the ferry routes. There are only certain places where ferries going in different directions meet due to the schedule (the black cells along the route). In other parts of the route fewer interactions occur (blue cells).

8 CONCLUSIONS

In this paper, we have described an approach to model output uncertainty in simulation models under a Bayesian framework. This methodology also allows treatment of epistemic and aleatory uncertainty introduced through input data and the process of simulation.

The San Francisco Bay ferry expansion simulation was used as proof of concept to provide an uncertainty bandwidth on the simulation output of the expansion alternatives. Quantile maps of the expected rate of ferry interactions were used to conclude that geographic areas in the Bay with an expected high level of vessel interaction show consistency to the interaction (un)certainty. Probability dominance maps were generated to compare interactions between expansion alternatives over different geographic areas in San Francisco Bay.

The methodology presented in this paper discusses a detailed approach to uncertainty representation in simulation. Research for aggregating expert judgment and representing uncertainty therein is ongoing. A forthcoming paper will present a Bayesian model integrating uncertainty representation in expert judgment data to accident probability models.

ACKNOWLEDGMENTS

The research herein was supported by NSF grants SES 0213627 and SES 0213700.

REFERENCES

Apostolakis, G. 1978. Probability and risk assessment: the subjectivist viewpoint and some suggestions. *Nuclear Safety* 19: 305-315.

Bedford, T. M., R. M. Cooke. 2001. *Probabilistic Risk Analysis: Foundations and Method*. Cambridge, UK: Cambridge University Press.

Chen, H. 1996. A lower bound for the correct subset selection probability and its application in discrete event simulations. *IEEE Transactions on Automatic Control* 41(8): 1227-1231.

Chen, H., B. Schmeiser. 1995. Monte Carlo estimation for guaranteed coverage non-normal tolerance intervals. *Journal of Statistical Computation and Simulation* 51(2-4): 223-238.

Chen, H., C. Chen, J. Lin and E. Yucesan. 1999. An asymptotic allocation for simultaneous simulation experiments. *Proceedings of the Winter Simulation Conference*, ed. P. Farrington, H. Nembhard, D. Sturrock and G. Evans, 359-366.

Cheng, R. 1999. Regression metamodeling in simulation using Bayesian methods. *Proceedings of the Winter Simulation Conference*, ed. P. Farrington, H. Nembhard, D. Sturrock and G. Evans, 330-335.

Chick, S. 1997. Bayesian analysis for simulation input and output. *Proceedings of the Winter Simulation Conference,* ed. S. Adradottir, K. Healy, D. Withers and B. Nelson, 253-260.

Chick, S. 2000. Bayesian methods for simulation. *Proceedings of the Winter Simulation Conference,* ed. J. Joines, R. Barton, K. Kang and P. Fishwick, 109-118.

Chick, S. 2001. Input Distribution Selection for Simulation Experiments: Accounting for Input Uncertainty. *Operations Research* 49(5): 744-758.

Chick, S., K. Inoue. 2001. New two-stage and sequential procedures for selecting the best simulated system. *Operations Research* 49(5): 732-743.

Cooke, R. M. 1991. *Experts in Uncertainty: Expert Opinion and Subjective Probability in Science.* Oxford, UK: Oxford University Press.

Fowler, T. G., E. Sorgard. 2000. Modeling ship transportation risk. *Risk Analysis* 20(2): 225-244.

Gelfand, A. 1996. Model determination using sampling-based methods. *Markov Chain Monte Carlo in Practice,* ed. W. Gilks, S. Richardson and D. J. Spiegelhalter, 145-161. London: Chapman and Hall.

Glynn, P. 1986. Problems in Bayesian analysis of stochastic simulation. *Proceedings of the Winter Simulation Conference*, ed. J. Wilson, J. Henrikson and S. Roberts, 376-383.

Guedes Soares, C., A. P. Teixeira. 2001. Risk assessment in maritime transportation. *Reliability Engineering and System Safety* 74(3): 299-309.

Hara, K., S. Nakamura. 1995. A comprehensive assessment system for the maritime traffic environment. *Safety Science* 19(2-3): 203-215.

Hofer, E. 1996. When to separate uncertainties and when not to separate. *Reliability Engineering and System Safety* 54: 113-118.

Hora, S. 1996. Aleatory and epistemic uncertainty in probability elicitation with an example from hazardous waste management. *Reliability Engineering and System Safety* 54: 217-223.

Kass, R., A. Raftery. 1995. Bayes Factors. *Journal of the American Statistical Association* 90(430): 773-795.

Kite-Powell, H. L., D. Jin, N. M. Patrikalis, J. Jebsen, V. Papakonstantinou. 1996. Formulation of a Model for Ship Transit Risk. *MIT Sea Grant Technical Report*, 96-19. Cambridge, MA.

Law, A., W. Kelton 2001. *Simulation Modeling and Analysis*, 3rd Ed. New York: McGraw Hill.

Merrick, J. R. W., J. R. van Dorp, J. Harrald, T. Mazzuchi, J. Spahn, M. Grabowski. 2000. A systems approach to managing oil transportation risk in Prince William Sound. *Systems Engineering* **3**(3): 128-142.

Merrick, J., J. R. van Dorp, T. Mazzuchi, J. Harrald, J. Spahn, M. Grabowski. 2002. The Prince William Sound Risk Assessment*.* *Interfaces* 32(6): 25-40.

Merrick, J., J. R. van Dorp, J. P. Blackford, G. L. Shaw, J. Harrald, T. Mazzuchi. 2003. A traffic density analysis of proposed ferry service expansion in San Francisco Bay using a maritime simulation model. To appear in *Reliability Engineering and System Safety*.

Paté-Cornell, M. E. 1996. Uncertainties in risk analysis: six levels of treatment. *Reliability Engineering and System Safety* 54(2-3): 95-111.

Roeleven, D., M. Kok, H. L. Stipdonk, W. A. de Vries.1995. Inland waterway transport: Modeling the probabilities of accidents. *Safety Science* 19(2-3): 191-202.

Slob, W. 1998. Determination of risks on inland waterways. *Journal of Hazardous Materials* 61(1-3): 363-370.

Spiegelhalter, D., A. Thomas, N. Best, W. Gilks. 1996. BUGS: Bayesian inference Using Gibbs Sampling, Version 0.5. *MRC Biostatistics Unit*: Cambridge, UK.

Spiegelhalter, D. J., N. G. Best, B. P. Carlin, A.van der Linde. 2002. Bayesian measures of model complexity and fit. *Journal of the Royal Statistical Society: Series B* 64(4): 583-639.

Trbojevic, V. M., B. J. Carr. 2000. Risk based methodology for safety improvements in ports. *Journal of Hazardous Materials* 71(1-3): 467-480.

van Dorp, J. R., J. R. W. Merrick, J. Harrald, T. Mazzuchi, M. Grabowski. 2001. A Risk Management Procedure for the Washington State Ferries. *Risk Analysis* **21**(1): 127-142.

Wang, J. 2000. A subjective modeling tool applied to formal ship safety assessment. *Ocean Engineering* 27(10): 1019-1035.

AUTHOR BIOGRAPHIES

JASON R.W. MERRICK is an Associate Professor in the Department of Statistical Sciences and Operations Research at Virginia Commonwealth University. His research interests include Bayesian modeling and it's applications to dynamic simulation models. His e-mail address is <jrmerric@vcu.edu>.

VARUN DINESH will begin studying for his doctorate in Statistics at Virgina Tech in Fall 2003. He received his master's degree from the Department of Statistical Sciences and Operations Research at Virginia Commonwealth University and his bachelor's degree from Lucknow University.

AMITA SINGH is presently pursuing a doctoral degree in the Engineering Management and Systems Engineering department at George Washington University (GWU). She has a master's degree from the Department of Operations Research, GWU and a bachelor's degree in Mathematics from University of Delhi.

J. RENÉ VAN DORP is an Assistant professor in the Engineering Management and Systems Engineering department at George Washington University. His research areas of interest include probabilistic risk analysis and reliability analysis. He can be contacted by e-mail at <dorpjr@gwu.edu>.

THOMAS A. MAZZUCHI is a professor and Chair of the Engineering Management and Systems Engineering department at George Washington University. His research interests include reliability and risk analysis, Bayesian inference and quality control. He can be contacted by e-mail at <mazzuchi@seas.gwu.edu>.