Propagation of Uncertainty in a Simulation-Based Maritime Risk Assessment Model Utilizing Bayesian Simulation Techniques

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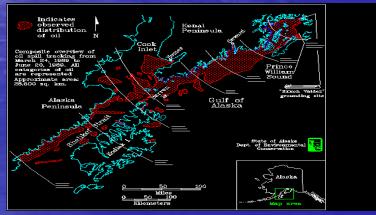
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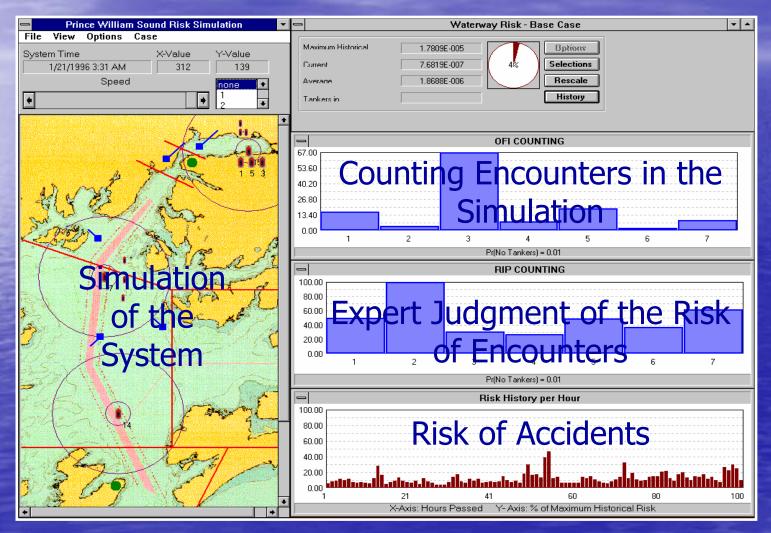
Prince William Sound Risk Assessment



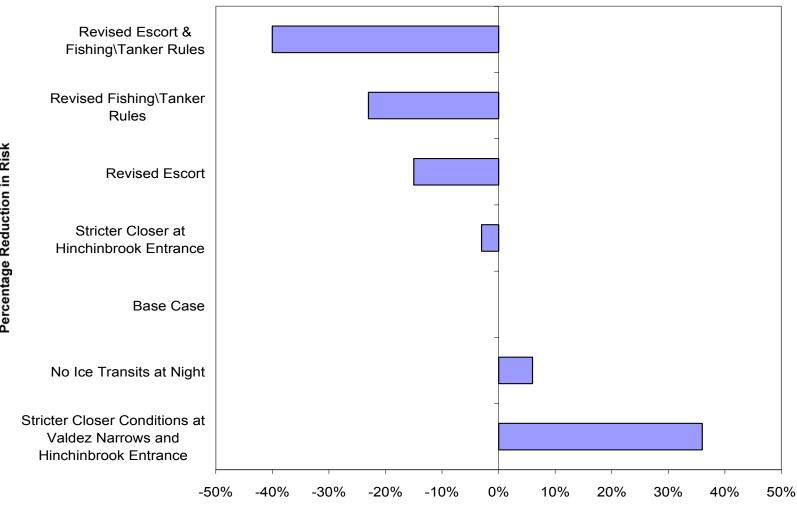




Assessing Maritime Risk



Evaluating Risk Reduction



Percentage Reduction in Risk

National Research Council Review

• "The truth is that we are uncertain. The language of uncertainty is probability Therefore, speaking the truth means to develop analyses results in terms of probability curves rather than in terms of point estimates."

 Kaplan S. "The Words of Risk Analysis", Risk Analysis, 1997; 17(4) 407-417.

Modeling the Uncertainty

Uncertainty in the System Simulation

 Bayesian Simulation Model

 Uncertainty in the Expert Judgments

 Bayesian pair-wise comparison model

 Propagate the Uncertainty throughout the Model

 Monte Carlo methods

– Grid Computing implementation

Classical Simulation Input Modeling

🖆 pearson6: Data Table 🛛 🗱 pearson6: Goodness of Fit			Input Density					
Inte	rvals	: 1 Poi	goodness of fit	0.16	- .			
		0.499793	data points					
		0.624182	estimates	0.08				
		0.748334	accuracy of fit					
		1.15452	level of significance					
		0.651068						
		0.984828				_		
		0.96521	summary	0.00 L 0.0	0 1. 2.	3.	4. 5.	
		0.406324	<u> </u>					1
		0.762326			Kolmogorov	Anderson		
)		0.942273	distribution		Smirnov	Darling		
1		0.713083						
2		1.28106	Beta(7.02e-002, 4.08, 2.24, 10.7)		5.3e-002	46.9		
3		0.345255	Chi Squared(7.02e-002, 1.37)		0.273	1.17e+003		
4		0.767546	Erlang(6.77e-002, 3., 0.229)		3.14e-002	11.9		
5		0.21011	Exponential(7.02e-002, 0.684)		0.209	658		
5		0.253966	Gamma(6.77e-002, 2.85, 0.241)		2.9e-002	10.8		
7		0.332802	Lognormal(-3.71e-002, -0.365, 0.511)		7.34e-003	0.632		
3		1.51206	Pearson 5(-0.24, 7., 5.98)		7.49e-003	0.617 3.37	빈	
9	_	0.75204	Pearson 6(7.02e-002, 1.96, 3.7, 11.6)	1)	1.03e-002 0.353	3.37 1.7e+003		
			Power Function(7.02e-002, 4.08, 0.51 Rayleigh(5.e-002, 0.585)	9	9.24e-002	121		
			Triangular(6.83e-002, 4.08, 0.255)		0.413	2.73e+003		
			Uniform(7.02e-002, 4.08)		0.592	5.81e+003		
			Weibull(7.e-002, 1.7, 0.771)		5.22e-002	53.8		

Bayesian Simulation Input Modeling

 Computations are simple with conjugate prior distributions

Probability Model	Conjugate Prior-Posterior
Exponential	Gamma
Log Normal	Normal-Gamma
Gamma	???
Weibull	???

To sample inter-arrival times in the simulation

- Sample from the posterior distribution of the parameters
- Sample from the probability model given the sample parameters

Bayesian Inference

- Conjugate prior distributions are not always available
 - No close form solution
 - Multiple model parameters => multivariate posterior
- Answer Gibbs Sampling
 - Sample from posterior, full-conditional distributions of each parameter repeatedly
 - This Markov Chain has the multivariate posterior distribution as its limiting, stationary distribution
 - Start at arbitrary values and iterate until warmed up

How do you choose the best probability model?

- Traditionally Bayes factors and posterior predictive densities
 - Deviance Information Criteria is a newer development

Bayesian Deviance	$D(\Theta_j^k) = -2\ln p(D^k \mid \Theta_j^k) + 2\ln f(D^k)$
Expected Deviance	$\overline{D} = E[D(\Theta_j^k) D^k]$
Exp. Nos. Parameters	$p_D = E[D(\Theta_j^k) D^k] - D(E[\Theta_j^k])$
DIC	$DIC = \overline{D} + p_D$

 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.

Deviance Information Criterion

	Expected Deviance	Nos. Parameters	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

Bayesian Output Model

 Our output is a count of the number of encounters per year

- Poisson distribution is a natural probability model
- Gamma distribution is the conjugate prior distribution for the expected number of encounters per year
- Prior shape \rightarrow Prior Shape + Total Encounters
- Prior scale \rightarrow Prior Scale + Nos. Simulated Years
- We can run 50 years of simulation and collect the total number of simulated encounters!

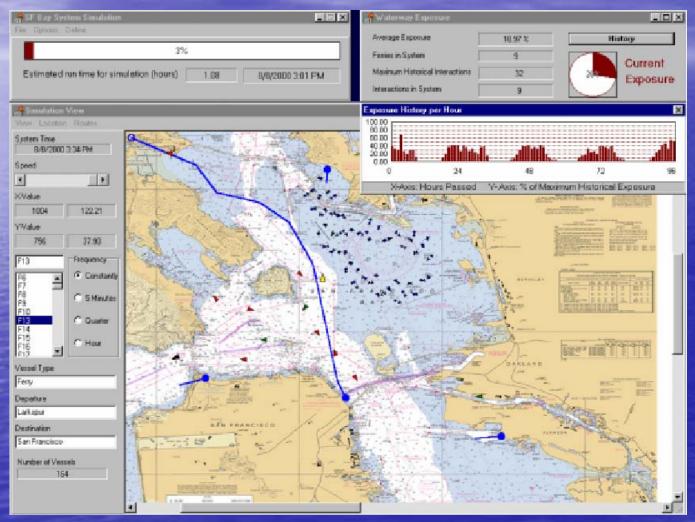
Example – Ferries in SF Bay

Three proposed expansion alternatives

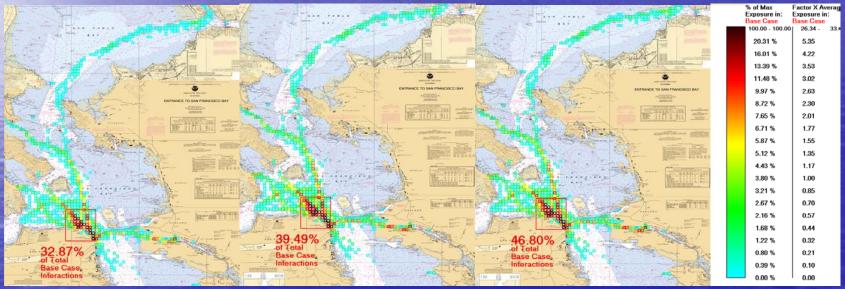
 Alternative 3: Enhance Existing System
 Alternative 2: Robust Water Transit System
 Alternative 1: Aggressive Expansion

 These are to be compared to the existing ferry system operating in SF Bay

SF Bay Simulation



After just one day of simulation

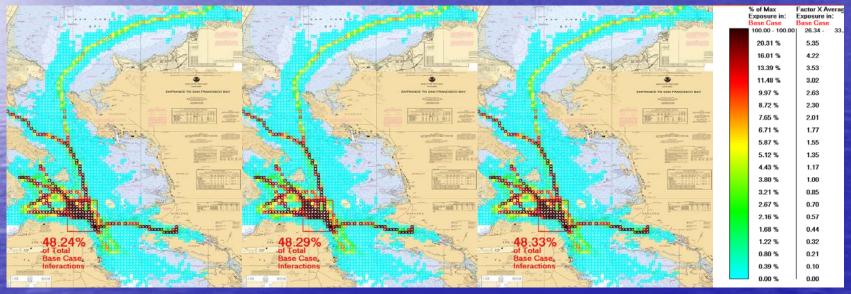


Posterior 5-th percentile

Posterior 50-th percentile

Posterior 95-th percentile

After 50 years of simulation

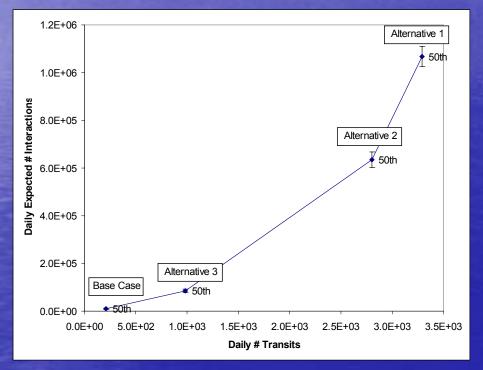


Posterior 5-th percentile

Posterior 50-th percentile

Posterior 95-th percentile

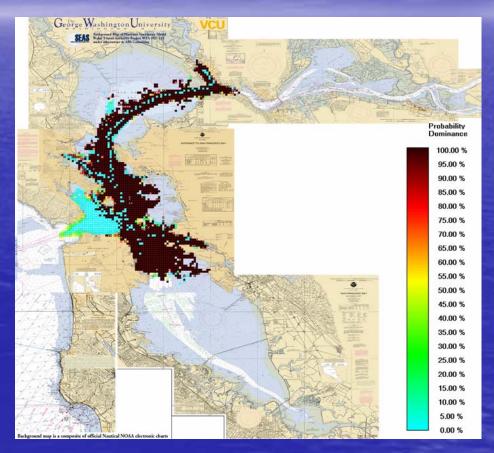
After 1 day of simulation



After 50 years of simulation the credibility interval bars are not visible
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 What is the probability that there will be more interactions in Alternative A than in Alternative B across the study area?

A = Alternative 3B = Current Ferry System



- What is the probability that there will be more interactions in Alternative A than in Alternative B across the study area?
 - A = Alternative 1B = Alternative 2

