How can a risk-based approach be effectively used in design and operation of large marine transportation systems under uncertainties?

Prof. Jin Wang
Director of Liverpool Logistics, Offshore and Marine (LOOM) Research Institute
Associate Dean (Research), Faculty of Engineering and Technology
Liverpool John Moores University, UK

j.wang@ljmu.ac.uk / +44 231 2445/ Byrom Street, Liverpool, L3 3AF, UK
Liverpool

- North-west England
- Central UK location
- 45 minutes from Manchester airport
- International flights to/from Manchester
- Flights to many European cities from Liverpool John Lennon Airport
- 2hrs 10 mins from London by train
Liverpool
Liverpool
LJMU

- 1825: Liverpool Mechanics’ School of Arts
- 1892: Liverpool Nautical College
- Many other colleges, eventually leading to:
  - 1970: Liverpool Polytechnic
- 1992: LJMU
Maritime Industry

- The UK’s maritime industry directly contributes up to £13.8 billion to the UK economy.
- The sector indirectly contributes a further £17.9 billion.
- The sector accounts for over 2% of the entire economy, supports one in every 50 jobs and creates nearly £8.5 billion in revenue for the UK Exchequer each year.
Maritime Safety

- The maritime industry continued to improve its safety record in 2014 with 75 total losses reported worldwide; the lowest in 10 years.
- Losses declined by 32% compared with 2013 (110).
- The 2014 accident year also represents a significant improvement on the 10-year loss average (127).
- Shipping losses have declined by 50% since 2005.
More than a third of 2014’s total losses were in two maritime regions. As in 2013, South China, Indo China, Indonesia & Philippines had the most losses (17), followed by Japan, Korea and North China (12).

Losses in both regions declined year-on-year. Total losses in the British Isles and surrounding waters (6) doubled.
Causes of Total Losses 2005-2014

- Founder (sunk or submerged) is the main cause of loss accounting for almost half (47%) of all losses over the past decade.
- Wrecked/stranded (aground) is the second major cause of total losses (20%). However, such incidents have declined year-on-year since 2011.

Source: Lloyd's List Intelligence Casualty Statistics
Basis for maritime transport safety and security assessment:

1. FSA in maritime risk assessment.
3. Proactive “goal setting” regime in offshore industry.
Formal safety assessment (FSA)
  – Hazard identification.
  – Risk estimation.
  – Risk reduction measures.
  – Cost benefit assessment.
  – Decision making.
Potential incentives offered by FSA

• Provide improved performance of the current fleet and then be able to measure the performance change.

• Ensure that experience from the operational field is used in the current fleet, and that any lessons learnt are incorporated into new ships.

• Provide a mechanism for predicting and controlling the most likely scenarios that could result in incidents.
Benefits of adopting FSA as a tool

1. A consistent regulatory regime which addresses all aspects of safety in an integrated way.

2. Cost effectiveness, whereby safety investment is targeted where it will achieve the greatest benefit.

3. A pro-active approach, enabling hazards that have not yet given rise to accidents to be properly considered.

4. Confidence that regulatory requirements are in proportion to the severity of the risks.

5. Rational basis for addressing new risks posed by ever changing marine technology.
UK’S Maritime Security Strategy

1. Understand.
2. Influence.
3. Prevent.
4. Protect.
5. Respond.
1. **Understand** the maritime domain – gathering intelligence, sharing information, building partnerships, analysing data and identifying concerns.

2. **Influence** to help achieve the objectives.

3. **Prevent** maritime security concerns from arising or escalating.

4. **Protect** the country’s interests by taking action to reduce the vulnerability of the shipping and maritime infrastructure as well as efforts to increase the resilience in the event of an attack.

5. **Respond** whenever appropriate or necessary.
A fault tree for an attack in container chains

- Cut sets.
- Basic events and their occurrence probabilities.
- Critical basic events and cut sets.
- In combination with other methods such as simulation.
A bow-tie diagram

Identify Threats

T1 T2 T3 T4
B1.1 B1.2 B1.3 B1.4
EF1.1.1 EF1.1.2
EFC1.1.1.1 EFC1.1.1.2

Identify Consequences

C1 C2 C3 C4
RPM1.1 RPM1.2 RPM1.3 RPM1.4
EF1.1.1 EF1.1.2
EFC1.1.1.1 EFC1.1.1.2

For each threat/ consequence, identify appropriate barriers/ recovery preparedness measures be put in place.

For each barrier/ recovery preparedness measure, identify appropriate Escalation Factors and associated Controls.

Adopt a numbering system which clearly demonstrates link between Threats, Barriers, Escalation Factors & Escalation Factor Controls.
Question: What are possible challenges in marine risk and security assessment?

Answer: Uncertainties in data due to randomness, fuzziness, incompleteness, unpredictability, etc.
Three techniques highlighted

1. Fuzzy set modelling.
2. Bayesian networks.
3. Evidential reasoning.
1. Fuzzy set modelling (possibilistic modelling)

P(success) + P(failure) may not be equal to 1.

- Expert knowledge elicitation.
- Fuzzy set modelling.
- Interval-based risk assessment.
- Use of linguistics and subjective modelling.
- Possibility theories.
- ....
Fuzzy modelling

- **Mutually Exclusive.**
  (not possible to have membership of more than one set)

- **Not accurate.**
Fuzzy set representation

Membership Function

- **Overlapping** (Smooth transition between states)
- Describes the phenomenon more accurately
Likelihood of occurrence = \[ (0, \text{Very High}), (0.62, \text{High}), (1, \text{Moderate}), (0.46, \text{Low}) \]


Fuzzy rule base

IF probability is high AND consequence severity is high, THEN risk is high.

IF probability is high AND consequence severity is high, THEN risk is medium with a belief degree of 0.2, high with a belief degree of 0.5 and very high with a belief degree of 0.3.

Rules can be developed by expert judgements or data records.

Rules can also be trained.

Rules can be fired to produce estimates of the criteria for decision making.

With fuzzy set modelling with other techniques

IF very low (L1) and negligible (C1) and reasonably unlikely (E3), THEN {(0.88, good (S1)), (0.12, average (S2)), (0, fair (S3)), (0, poor (S4))}

$P(S_{safety}|L1, C1, E3) = (0.88, 0.12, 0, 0)$

where “|” symbolises conditional probability.

Seafarer’s reliability model

Pros and cons of fuzzy set modelling

Pros

• Its ability to represent ignorance or lack of information.
• Allows expert elicitation and enables qualitative and imprecise reasoning.
• Can better depict situational reality.

Cons

• Model validation.
• Interpretation of the obtained results.
Bayes’ rule/theorem states that:
“The probability distribution of a model parameter, \( \theta \), after observing data, \( x \), is proportional to the likelihood of the data, \( x \), assuming that \( \theta \) is true, times the prior probability distribution of \( \theta \).”

Symbolically, this is written as:

\[
p(\theta|x) = \frac{p(x|\theta) p(\theta)}{p(x)}
\]

Conventionally, this is read as:

\[
\text{posterior} = \frac{\text{likelihood} \times \text{prior}}{\text{evidence}}
\]

Inverse of the “Evidence” term is a normalizing constant, \( \propto \). The “Likelihood” term expresses a measure of confidence degree and can be written as \( l(\theta|x) \).

Thus, in Likelihood Principle:

\[
\text{posterior} = \propto \text{likelihood} (l(\theta|x)) \times \text{prior}
\]
Bayesian networks

Formulation of BNs

- Data-driven BNs.
- Investigation of relationships between influencing nodes (parents/children).
- Probability theory.

Characteristics of BNs

- Capable of combining diverse data, expert judgement and empirical data.
- Easy updating of prediction and inference.
- Computational complexity/difficulty (e.g. NP-hard).
Simple examples of BN

\[ P(\text{free-fall lifeboat launch}) = P(\text{free-fall lifeboat launch} \mid \text{no-evacuation}) \times P(\text{no-evacuation}) + P(\text{free-fall lifeboat launch} \mid \text{evacuation}) \times P(\text{evacuation}) \]

\[ P(\text{Evacuation}) = \sum_{i=1}^{2} \sum_{j=1}^{2} \sum_{k=1}^{2} P(\text{Evacuation} \mid \text{Fire}_i, \text{Collision}_j, \text{Flooding}_k) \times P(\text{Evacuation} \mid \text{Fire}_i, \text{Collision}_j, \text{Flooding}_k) \]
Generic Model for Evaluating a Container Security Score (CSS)

Container Security Score: 72.85%
Reliable; 27.15% Unreliable.

An accident Data-based Approach for Congestion Risk Assessment

Navigational Risk Estimation of the Yangtze River

3. Evidential reasoning (ER) algorithm

- If more pieces of evidence support a hypothesis, then it is more likely that the hypothesis is true.
- Used in synthesis of evidence without data losses.
- Based on Dempster-Shafer rules.

\[
\tilde{m}_D^{I(k+1)} = K_{I(k+1)} \left[ \tilde{m}_D^{I(k)} \tilde{m}_D^{k+1} + \tilde{m}_D^{I(k)} \overline{m}_D^{k+1} + \overline{m}_D^{I(k)} \tilde{m}_D^{k+1} \right] \\
\overline{m}_D^{I(k+1)} = K_{I(k+1)} \left[ \overline{m}_D^{I(k)} \overline{m}_D^{k+1} \right]
\]

\[
K_{I(k+1)} = \left[ 1 - \sum_{j=1}^{N} \sum_{t=1}^{N} m_i^{I(k)} m_t^{k+1} \right]^{-1} \\
k = (1,2,\ldots,L-1) \quad \beta_j = \frac{m_j^{I(L)}}{1-\overline{m}_D^{I(L)}} \quad j = (1,2,3,4) \quad \beta_D = \frac{\tilde{m}_D^{I(L)}}{1-\overline{m}_D^{I(L)}}
\]


Choose the best vessel in a dynamic environment by a charterer.

Evidential reasoning: If more pieces of evidence support a hypothesis, then it is more likely that the hypothesis is true.

Collision Assessment for Coastal Radar Surveillance

Human error probability quantification (CREAM)

- Evaluation of common performance conditions (CPCs)
- Human Error Probability (HEP) quantification.
- Different weights of CPCs can be taken into account.

Model validation

• Comparison of the obtained results with benchmarks.
• Tests in real applications.

There is a dilemma. If there are existing benchmarks, then why is the new model developed? If there are no existing benchmarks, then how can the model be fully validated?

Partial validation

• Sensitivity study.
• Partial validation with axioms (e.g. if a component’s safety is improved then the system safety should be improved).
• Further tests.
Other methods for dealing with uncertainties in data

• Artificial neural networks.
• Dempster-Shafer theory.
• Entropy theory.
• Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)
• Analytical Hierarchy Processing.
• .......
Conclusion

• Uncertainties in data are large challenges in maritime risk and security assessment.
• Different modelling approaches can be used for treatment of uncertainties in data.
• Modelling approaches can be used in a complementary manner.
• There are needs for further investigation (e.g. model validation).
Use of Functional non-infrared spectroscopy to help improve training and reduce human error

- Measuring the performance in simulator based training.
- Reduce human error in challenging circumstance in ship operations.
- Decision-making model incorporating the parameters from fNIRS.
Thank you for your attention.

Any questions?

(contact: j.wang@ljmu.ac.uk)