Risk Factor Analysis, Continuous Monitoring and Root Cause Analysis for Teekay Shipping

by

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Abstract

This thesis is based on an industry project with Teekay Shipping Co., which is an international transportation service provider for oil companies, refiners and traders. Teekay is interested in knowing which factors contribute most to its operating incidents and accidents. Based on available data, namely vessel name, team, type, hull, and age, as well as incident and accident records, we quantified in this thesis the effects of these factors on the incident and accident frequency. The thesis presented the technical details of the Poisson regression analysis, which we used for quantifying the risk factors.

Teekay is also interested in having a consistent method to present Teekay's overall risk picture, and to indicate best investment areas for its risk reducing purpose. Teekay has already implemented an Online Root Cause Analyses (ORCA) system, which collects the direct cause and root cause soon after an incident happens. We reviewed the ORCA system and made suggestions about certain parts of the system which were subsequently revised. Furthermore, we designed a bubble chart tool to present the overall risk faced by Teekay. The bubble chart tool has the capacity to indicate best investment areas clearly, and it is consistent over time, thereby enabling Teekay to evaluate easily the risk mitigation effect of its earlier investment in risk management.

Finally, we designed a continuous monitoring tool, which allows Teekay managers to interactively explore the relationships among near misses, incidents and accidents, and to compare event frequencies of various vessel groups, such as vessel team, age, type and hull structure. The powerful continuous monitoring tool provides Teekay managers a full-range view of the risks the company faces. The design and the sample usage of this continuous monitoring tool are discussed in this thesis.

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1. Introduction

Risk management is extremely important for an oil tanker company because of three major reasons. First of all, the pressure from government agencies and legal requirements put high demand on safety in this industry. Though the regulations vary from country to country, all of them are quite rigid. For example, if an oil spill accident happened along the US and Canada coast, the transportation company involved may permanently lose the right to run business in that area.

Secondly, the financial loss incurred in a tanker accident is generally massive and can easily lead the involved company to bankruptcy. Accidents like collisions, foundering, flooding and explosions frequently end up with total loss of the vessel and even the crew. The tremendous cleaning cost due to oil spills is another huge part of the financial loss. Furthermore, the potential loss due to worsening business reputation after a major accident is too titanic to be weighted.

Finally, the environmental pollution due to an oil spill may be catastrophic. There have been various notorious oil spill accidents. For example, the accident of oil tanker Exxon Valdez in 1989 in the Gulf in Alaska spilled 11 million gallons, which cost Exxon $2.1 billion on cleanup effort. The carcasses of more than 35,000 birds and 1,000 sea otters were found after the spill. Since most carcasses sank, this was considered to be a small fraction of the actual death toll. The best estimates of the loss of wildlife are: 250,000 seabirds, 2,800 sea otters, 300 harbor seals, 250 bald eagles, up to 22 killer whales, and billions of salmon and herring eggs. Today Exxon Valdez Spill has dropped out of the top 50 spills.

Teekay's "Safety First" operational principle and outstanding records have won Teekay lasting reputation in the industry. As an effort to continuously improve the safety and environmental protection, Teekay launched the Online Root Cause Analysis (OCRA hereafter) system, which is part of its successful Marine Operations Management System (MOMS hereafter). The ORCA helps masters and chief mates conduct the root cause

analysis online and systematically. The industrial project that this thesis is based on mainly targeted at enhancing risk analysis and investment decision-making by analyzing data from ORCA.

The industrial project was initiated just before the company-wide implementation of the ORCA system. It was concerned mainly with two problems: 1) once the ORCA collects enough data, what kind of analysis can we do to enhance risk analysis? 2) how to make investment decision so as to improve the company's safety performance? During the process, we analyzed historical incident and accident data and quantified the risk factors, provided suggestions for further improving the ORCA system, and developed online monitoring tool to further enhance the risk management. In particular, we designed a bubble chart tool for analyzing the ORCA data and for helping make investment decision.

In this thesis, we first provide background information about Teekay and the oil shipping business. Secondly, in section 3, we review the relevant literature and methodologies on three concepts: quantifying risk factors, root cause analysis, and continuous monitoring. Then we analyze the risk factors in detail in section 4, where we introduced the data, developed the ordinary regression model and the Poisson regression model, and gave the main findings of both models. Following that, in section 5 we present the continuous monitoring tool on its design and uses. Finally, in section 6, we describe the bubble chart tool we developed for analyzing the ORCA data, and enhancing the risk analysis and investment decision making.

2. Background

2.1 Oil Tanker Industry and Teekay Shipping

Global oil demand has gone up steadily due to strong economic growth, a dramatic shift in the population to urban centers, and the rapid increasing demand for transportation. And despite the prospects for the increasing non-OPEC supply of oil, the greatest potential to supply the bulk of the projected increase remains in the five OPEC countries

in the Middle East (i.e., Saudi Arabia, Iran, Iraq, Kuwait, and the United Arab Emirates), and in Venezuela, though the referendum in Venezuela reduced its production recently. Hence the oil transportation retains similar route network, but has the prospect of increasing capacity. The oil tanker demand is accordingly increased. The new industry rule "heavy oil on double hulls only" further accelerates the development of new double hull oil tankers.

Teekay Shipping Corporation is a leading provider of international crude oil and petroleum product transportation services, with the world's largest fleet of medium sized oil tankers. The company's fleet has a total cargo capacity of approximately 10.4 million tonnes. Teekay's Aframax tankers represent approximately 13% of the total tonnage of the world Aframax and oil/bulk/ore carriers (OBO) fleet, and its shuttle tankers represent approximately 26% of the total tonnage of the world shuttle tanker fleet. As of March 1, 2003, the company's fleet consisted of 101 vessels: 67 Aframax oil tankers, including five vessels time-chartered-in, two Aframax-size OBO trading exclusively as crude oil carriers, two Aframax tankers converted to floating storage and off-take vessels (FSO) and seven new vessels; 18 shuttle tankers, including two new vessels, one vessel converted to an FSO and three vessels owned by joint ventures; eight OBOs that are operated through an OBO pool managed by the company; two smaller oil tankers; one very large crude carrier; two Suezmax tankers, including one vessel owned by a joint venture, and three Suezmax-size new vessels.

Teekay competes with other large operators of Aframax tonnage. Among them are General Maritime Corporation (approximately 28 Aframax vessels), American Eagle Tankers Ltd. (approximately 25 Aframax vessels), Tanker Pacific Management (Singapore) Pte. Ltd. (approximately 13 Aframax vessels), and Overseas Shipholding Group (approximately 12 Aframax vessels).

Headquartered in Nassau, Bahamas, with offices in ten other countries, Teekay employs 300 onshore and more than 2,700 seagoing staff around the world. The Company's modern fleet and "safety first" operational principle has earned a reputation for safety and excellence in providing transportation services to major oil companies, major oil traders

and government agencies worldwide. Teekay's common stock is listed on the New York Stock Exchange where it trades under the symbol "TK".

2.2 Tankers

An oil tanker or tanker is a specialized vessel designed for carrying crude oil and petroleum products. Its design permits quick loading and discharging, and hence ensures the fast turn-rounds essential to good utilization. Crude oil is transported from oilfields to refineries, and petroleum products are shipped from refineries to distribution centers and bunkering ports. So there is a worldwide network of tanker routes. By far the largest proportion of tankers are owned and operated by oil companies and employed on regular routes. Most independently owned tankers are on long-term charter to the oil companies too.

There are several ways to categorize a tanker. Most used categories are the size, the commodities that oil tankers carry, the hull types, the special functions, the manufactures, and the classification societies. Tanker size is divided into following categories: Panamax, with a capacity of 80,000 dead-weight tons (dwt); Aframax (100,000 dwt); Suezmax (150,000 dwt); and VLCC (280,000 dwt). The vast majority of Teekay vessels are Aframax tankers.

Tankers are also categorized by the commodities they carry. In this dimension, tankers are divided into: OBO (Oil, Bulk, and Ore), O/O (Oil and Ore), LNG/LPG (Liquefied Gas Carrier), Products (Petroleum Products from refiners), and Chemical (Chemical products from refiners). Tankers have following hull types: SH (Single Hull), DS (Double Side), DB (Double Bottom), DSIDB (Double Side and Double Bottom), and DH (Double Hull).

Some tankers are used for special purposes and this leads to another categorization: FSO, FPSO, STBL and SS. An FSO stands for Floating Storage Offloading, which is in fact a kind of terminal. An FSO is used to take crude oil directly from a well and store the oil.

A "takeoff" vessel will moor in tandem to FSO to take the stored oil away. An FSO can cast of its permanent mooring and proceed to safety in case of severe storms. FPSO stands for Floating Production, Storage and Offloading. It is usually larger than FSO since it has processing plant inside its hull. STBL stands for Ship-To-Be-Lightered. Some large tankers (usually VLCC or ULCC) cannot berth in a port due to the depth limit, berth area limit or narrow entrance. Hence its oil has to be transferred to a smaller tanker outside of the port. Lightering is such a process that involves ship-to-ship transfer of oil cargo. SS stands for Service Ship. It is the smaller tanker used in the lightering process.

Finally, tankers are categorized according to the manufacture of its main engine. The main engines of most Teekay tankers are produced by following manufactures: Hyundai, Mitsui, Samsung, and Sulzer.

2.3 The Classification Societies

Classification societies are established in principal maritime countries. A society assures the quality of vessels in its class. It establishes its own standards, surveys vessel during construction, ensures that vessels maintain the standard, reaffirms vessels' standards from time to time and after casualty, and maintains records of vessels. Teekay tankers are registered in various classification societies including DNV, LRS, NKK, ABS, BV, and GL. For example, DNV stands for DET NORSKE VERITAS, which is one of the world's largest ship classification societies. DNV is authorized to act on behalf of more than 100 national maritime authorities. The head office of DNV is in Oslo, Norway.

2.4 Manning

18-25 people operate each Teekay tanker. Key senior officers are the master, chief engineer, chief mate (officer), and first assistant engineer. The master's responsibility is to ensure that the vessel is maintained in a safe and efficient condition, and to ensure that crew is appropriately supervised.

The chief engineer must ensure the maintenance of all mechanical, electrical and control equipment onboard the vessel; administer, supervise, and control the operation of the planned maintenance system onboard the vessel; conduct class item inspections; and ensure that a high standard of cleanliness and appearance is maintained for the engine room spaces, emergency generator and AC rooms, and steering gear room.

The chief officer should report all defects in deck and cargo equipment to the chief engineer or first engineer; maintain fire fighting, life saving, and pollution prevention equipment; ensure the greasing and general lubrication of deck machinery, pump room machinery and associated equipment; ensure that a high standard of cleanliness and appearance is maintained for the deck area including forecastle, pump room and hydraulic room, accommodation externals and hull above water; discuss and coordinate with the chief engineer, or first engineer, the maintenance of deck machinery, hull and equipment; and ensure that appropriate entries are made in the planned maintenance system.

The first engineer should report the condition of the engine room and all attached areas to the chief engineer; supervise and control maintenance as required by the chief engineer; ensure that a high standard of cleanliness and appearance is maintained for the engine room, steering flat with its attached machinery areas and associated equipment, and accommodation internals that contain machinery; discuss and coordinate efforts with the chief officer when the maintenance involves deck machinery, hull and equipment; ensure that appropriate entries are made in the planned maintenance system.

2.5 Team

Each Teekay tanker belongs to a certain team. Each team has a fleet general manager, three voyage managers, a certain number of vessel managers, a purchasing manager and other staff. A ship team's responsibilities include vessel support, adherence to company standards and policies, technical management, cost control and budget management, voyage management, manning, customer responsiveness and performance monitoring.

Our analysis suggests that teams behave quite differently with respect to risk management practice.

2.6 Event

Event or adverse event is further grouped into three categories: near miss, an adverse event without any loss; incident, an adverse event with limited loss; and accident, an adverse event with a immense loss.

Accidents recorded in Lloyds Maritime Information Service (LMIS) typically had minimum financial loss of $200,000. It is noted that the actual cost of an accident is hard to compute, especially for personal loss and pollution. Hence incident and accident delimit serves only as a guideline. And in Teekay's dataset, near miss sometimes incur financial loss, which is a more or less subjective 'penalty' rather than real cost. For this project, we set $5,000 as near miss and incident delimit, and $100,000 as incident and accident delimit.

3. Literature Review and Methodologies

Many statistical models and qualitative methods are used in evaluating long-term risk factors. For the low probability and high consequence accident, however, the main statistical approach is Poisson regression analysis. McCullagh and Nelder (1983) proposed the generalized linear model (GLM), which covers Poisson regression model, and is widely adopted in statistical software including SAS and NCSS. In particularly, the book considered a very similar Poisson regression model, where the number of wave damage incident to cargo ships is the response variable, and the ship type, year of construction and the service period are three explanatory factors.

The two monographs by Cameron et al (1983) and Santner et al (1989) extensively explored the theory and uses of Poisson regression and related models. Poisson regression models are widely used in recent years in medicine, patent data, and natural

disaster etc. Siddiqui et al. (1999) presented research work on the analysis of adolescents' current level of smoking under the influence of peer students, where the influence from peer student is modeled as Poisson process. Wang et al (1998) studied the use of mixed Poisson regression method in patent data. Hedeker et al (1996) developed the freeware MIXREG for mixed effect Poisson regression analyses. We shall use Poisson regression to analyze the effects of the risk factors on incident and accident rates.

Methods to analyze the direct cause and root cause of an incident are different from industry to industry. Risk management systems have been developed for the chemical process, airline, rail, nuclear, and medical disciplines. A compilation of papers with a cross-industry perspective is provided in Van Der Schaaf (1991). Phiminster et al (2004) provided a comprehensive survey of near miss management in chemical industry, which also summarized the general approach used in the risk management in the process industry.

As summarized by Phimister et al (2004) paper, a proper risk management system requires: identification of an incident; disclosure; distribution of the incident information; direct and root cause analysis; solution determination; dissemination of the follow-up action to a wider audience to increase awareness; and resolution. And most studies on root cause analysis focus on the organizational effort to find out the real cause of an incident, such as U.S. Department of Energy (1992). Aside from inquiry, discussion and field investigation, various methods have been developed and widely used to guide the analysis process. The widely-used methods include: event and causal factor diagrams, event tree analysis, fault tree analysis, failure mode and effect analysis, the 'Why Test', Eckes (2000), Factorial and Taguchi methods, Peace (1992) and Eckes (2000).

As for the Teekay case, we have a slightly different focus than the problems studied in the above literature. Teekay has already developed the ORCA system to identify both the direct cause and root cause for each incident and accident. What we do is to take the data from ORCA, produce a higher-level summary of all incidents and accidents, and specify the investment areas to reduce the incident and accident rate. The step "solution

determination" mentioned above by Phimister et al. (2004) is designed for finding remedy solution case-by-case, whilst we are interested in setting up long term risk reducing strategies based on aggregate level risk information. We didn't find any software or literature that explicitly deals with such a problem. Hence we need to develop our own method to analyze direct causes and root causes at an aggregate level and to indicate investment area for risk reducing purpose. Our method presented in the section 6 tries to present the overall risk picture efficiently, to explore the correlations among the direct and root causes, to indicate the possible investment areas, and to evaluate the risk mitigation effect of investments.

Continuous monitoring tools are widely used in industries where the ongoing performance monitoring and improvement analysis are required. Such continuous monitoring system collects key performance indicators, automatically analyzes system performance and generates reports from high-level summaries to specific event alarms. Typical examples are the "*XCEED UAA*" for monitoring Honeywell Xceed air compresses system, and "S.M.A.R.T.", developed by Seagate Technology, Inc., for monitoring hard drive performance and protectively saving data before disk failure. Another major application of continuous monitoring is for financial operational risk control, where large number of transactions call for an automatic and online mechanism to filter out the highly risky events from normal operations. Though the continuous monitoring systems are different from case to case depending on the process under consideration, they share the same basic elements: collect key performance indicators, online analysis according to the preset risk tolerance and regulatory requirement, generate reports, and alarm.

For Teekay, we realized that the requirement is different from the cases mentioned above. Teekay vessels have fewer than five incidents and accidents per year on average. This feature distinguishes it from other applications where online analysis is necessary. On the other hand, continuous monitoring functionality at Teekay demands high ability of risk pattern recognition. Patterns correctly suggesting potential disasters are invaluable for Teekay. We have therefore developed the continuous monitoring tool to assist Teekay

managers to interactively explore the patterns among the near miss, incident and accident, and also among the various vessel groups, such as age groups, teams, hull structures and so on. These will be discussed in more details in the following sections.

4. Risk Factor Analysis

4.1 Data Compilation and Structure

We used the following data provided by Teekay: each vessel's name, year built, team, type, hull, and each vessel's near miss, incident and accident records for 2000, 2001, 2002 and the first four months of 2003. For confidentiality reasons, this thesis will replace real vessel names and team names by symbols, not display the incident and accident numbers and costs, and skip details about Teekay's unique Online Root Cause Analysis (ORCA) system. Information accessible from public channels, such as the Teekay website and company profiles from New York Stock Exchange, is used however. The methodologies applied and their findings are presented in this thesis, and we believe that some results are general and helpful for the industry.

We have spent great efforts to clean, verify and categorize the dataset. We observed that different ways of categorizing data led to different results, and in some cases they even led to confounding variables. Hence we preprocessed the dataset very carefully to address issues on: 1) different reporting periods; 2) vessel age grouping; 3) near miss data; 4) hull structure grouping; 5) vessel type grouping; 6) confounding variables. The following paragraphs present our approaches on these six issues one by one.

First of all, reporting periods are different from vessel to vessel. Some vessels were sold during the period in study and some started reporting later than others. Instead of finding the common period, which will reduce the number of data points, we counted the exposure period vessel by vessel, and took the exposure period into account in all our analyses. This approach won't be acceptable if the data has seasonality pattern. However the incident patterns don't appear to be seasonal. It is understandable since Teekay vessels are in fact operated in different time zones and hemispheres, and are exposed to

different seasons at any time point. One way to cope with this is to use a subset of vessels that are operated in the same region. But due to the mobility of oil tankers, this approach is easy to say but hard to do. We would like to do this research in the near future when the temperature and the region data is available. Another reason we did this way is that vessel ages are captured in another factor. Since we captured age factor in the age group variable, we are not going to worry that the period of year 1993 and 1994 is different from the period of year 2000 and 2001. After carefully considering the above two issues, we believe that it is reasonable to use exposure period to capture the factor of different reporting periods.

Secondly, vessel age is different from the vessel age at incident. For example, suppose a vessel built in 1995 had 5, 8 and 6 incidents in year 2000, 2001 and 2002 respectively. We would have to expand it into three data points in order to correctly capture the age at incident. Thus these three data points are exactly the same as regard of team, vessel type and hull type, except for the age at incident. This approach spread out the data along the age dimension and consequently produced data that was too sparse for analysis. Another approach is to use the vessel age at 2001, which is sort of the midpoint of the period 2000, 2001, 2002 and the first 4 months of 2003. However we cannot justify this approach. On the other hand, we suspect that such a nominal age variable won't make sense since people in the field knows that a vessel performance won't decrease gradually year after year though very old vessels did have worse records. Teekay is actually only interested in knowing the difference among age groups regarding the incident rate. Thus we grouped vessels into age groups 0~6, 7~19, and above 20. This grouping best reflects Teekay fleet composition as shown in Figure 1. Both Teekay and we believe that such a grouping is practical and meaningful.

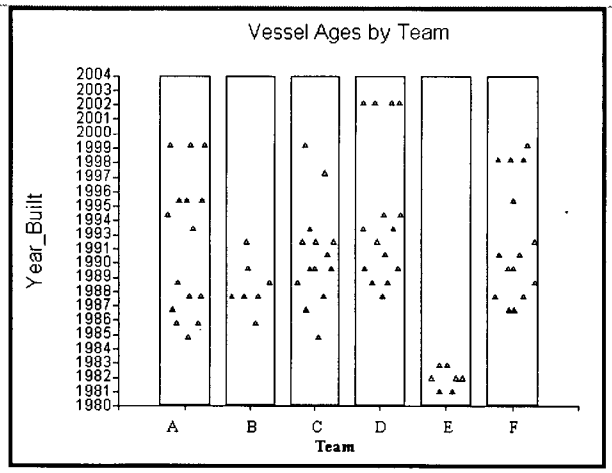

Figure 1: Vessel ages in different teams

Thirdly, we didn't use the near miss data. It is widely observed that for each severe accident with enormous financial loss, a large number of incidents result in limited impact, and even more near misses result in no loss. This observation is well presented in the figure of *Safety Pyramid* in Bird (1996). Thus near miss data is usually invaluable in predicting severe accident rate. Unfortunately, the near miss data from Teekay is not consistent from team to team due to the different team cultures and different reporting policies. Near miss reporting is voluntary at Teekay at the time of this research. For example, some teams are oversensitive compared with some other teams that seldom report any events except for accidents. Teekay is working on setting company-wide near miss reporting policy though. As shown in the figure below the near miss number is not a good indicator for the incident or accident number. We therefore didn't use near miss data in our analysis.

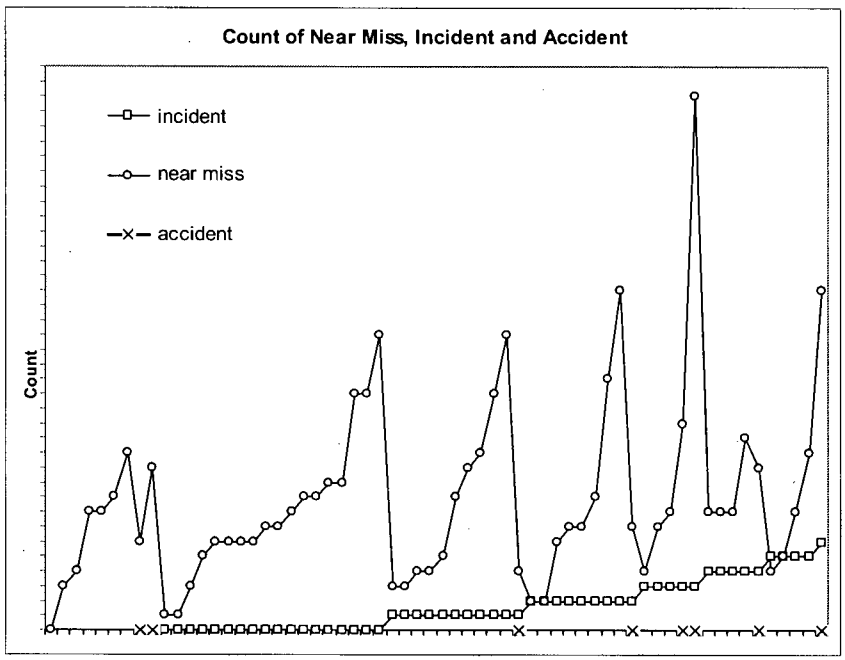

Figure 2: Relationship between near miss, incident and accident

Vessels are sorted from left to right by number of incident. For confidentiality, the vessel names beneath the tick mark on x-axis, and the counts of events aside the tick mark on the y-axis were removed.

Fourthly, we grouped hull structure into three groups. Single hulls are old design for oil tankers; double side (DS), double bottom (DB), double side and double bottom (DSIDB) are interim designs; double hull (DH) is the modern design and is mandatory structure for heavy oil tanker. We observed that the hull structure is in fact partially associated with age. But they are not completely confounded, since new SH vessels still appear in recent years, and there are a few pilot DH vessels in the early years. DS, DB, DSIDB and DH vessels are Segregated Ballast Tankers (SBT) by their design. Single hull structure doesn't have such a feature in nature, though it can also protectively load ballast in one or more specific tanks in practice. In the Teekay fleet under study, there are only 1 DB and 2 DSIDB vessels, 16 DS vessels, 19 SH vessels and 26 DH vessels. We grouped DB, DSIDB and DS together as "IntH" (interim hull structure). Thus there are three hull structure groups: SH (19), IntH (19) and DH (26).

Fifthly, as regard to vessel type, categorizations of all kinds (see section 2.2) are used together in practice. In our analysis we follow the convention: Aframax, OBO, Products and VLCC. In such a way of categorizing the type of vessels, "Aframax" actually degenerates to the meaning of "common vessel", which performs the majority businesses at Teekay, transporting oil from port to port; "OBO" refers to the vessels that switch cargoes among oil, bulk grain and ore; "Products" refers to vessel that transport petroleum products but not crude oil; and "VLCC" is the extra large vessel. The last three groups have their own unique features, which make them distinct from each other, and from the common vessel Aframax. People in the field use such categorization because it captures the difference among vessels well. For example, the vessel of type "OBO" needs more operations in port so as to prepare its tanks for different cargoes, and it follows different loading and discharging procedures for different cargoes. Thus it is meaningful to treat "OBO" differently from the type "Aframax", though most "OBO" vessels are Aframax from size point of view. Group "Aframax", "OBO", "Product" and "VLCC" have 59, 2, 2, and 1 vessel respectively.

Table 1: Confounding of team and age group variables

Team	*0~6*	*7~19*	*Above 20*
A	3	12	
B		6	
C	2	12	
D	4	11	
E			7
F	3	11	

Finally, we discuss the issue of confounding variables. Confounding leads to difficulties in analyzing data because there is no way to distinguish their effects. For example, as shown in the Figure 1, all vessels in age group "above 20" are in team "E", and team E doesn't have vessels in other age group. Thus team "E" is confounded with the age group "above 20", since there is no way to determine, in case of very bad safety performance of team "E", whether it is because that the very old vessels caused more incidents, or because that team "E" was not good at risk management. Table 1 shows that the entry "7"

at the intersection "above 20" and "E" is unique both vertically and horizontally, and hence there are no comparisons on both directions. Consequently we treated team "E" separately, and the age group number decreases to 2, namely "0~6" and "7~19".

We carefully checked all possible confounding variables to make sure that there is no confounding categories such as team "E" and age group "above 20". For the four factors, namely the vessel type, team, age group, and hull structure, we checked C_4^2=6 two-dimension tables in **Table 2**. These tables also provide a clear view of the fleet composition.

Table 2: Teekay fleet composition

Team and Hull

Team	*DH*	*IntH*	*SH*
A	8	5	2
B	2	2	2
C	4	5	5
D	7	4	4
F	5	3	6

Team and Vessel Type

Team	*Aframax*	*OBO*	*Products*	*VLCC*
A	15			
B	4		2	
C	13			1
D	13	2		
F	14			

Age Group and Hull

Age	*DH*	*IntH*	*SH*
0~6	12		
7~19	14	19	19

Age Group and Vessel Type

Age	*Aframax*	*OBO*	*Products*	*VLCC*
0~6	12			
7~19	47	2	2	1

Vessel Type and Hull

Type	*DH*	*IntH*	*SH*
Aframax	25	16	18
OBO		2	
Products	1	1	
VLCC			1

Team and Age Group

Team	*0~6*	*7~19*
A	3	12
B		6
C	2	12
D	4	11
F	3	11

From the table *Team and Hull*, we can see that hull types are evenly distributed in the different teams. From the table *Type and Hull*, we see that the majority of vessels, the Aframax vessels, have almost equal number of three hull types, and none of OBO, Products and VLCC confound with any hull type. From the table *Age Group and Hull*, we see that vessels in age group 7~19 have equal number of different hull types, and all new vessels (0~6) are of DH structure. 0~6 age group is not confounded with DH since there are other DH vessels. From the table *Team and Vessel Type*, we see that Aframax is evenly distributed among teams, and the other vessel types are not confounded with any team. From the table *Age Group and Vessel Type*, we saw the similar pattern as in table *Age Group and Hull*. From the table *Team and Age Group,* we know that these two factors are not confounded.

4.2 Ordinary Regression with Variance Stabilizing Transformation

We first conducted multiple linear regression analysis to comprehensively quantify the four risk factors. However, for data with equal mean and variance (see the test part of the Poisson regression model), the variance increases with mean, which violates the assumption of constant variance of the multiple linear regression models. Thus we applied a standard square root transformation of the response variable to stabilize the variance.

The variables are as defined in the Table 5 except that the response variable is the square root of incident rate, COUNT divided by EXPOSURE. The model has R-squared 0.37 and p-value 0.003, which shows that the model is significant (please see **Table 3**). The p-values for age group, hull, team and type are 0.96, 0.04, 0.005, and 0.65 respectively, which shows that team and hull are two significant risk factors, while age group and vessel types are not.

The estimates of main effects from the model are also summarized in **Table 4**. The results agree with that of the Poisson regression model, and will be discussed after Poisson regression model.

Table 3: Variance analysis of the ordinary least squares model

Term	*DF*	*R2*	*F-Ratio*	*P-value*
model	10	0.3704	3.118	0.0034
age group	1	0	0.002	0.965
Hull	2	0.0755	3.177	0.0498
Team	4	0.1974	4.155	0.0053
Type	3	0.0192	0.539	0.6576
error	53	0.6296		
total(adjusted)	63	1		

Table 4: Estimates of the main effects in the ordinary square model

Parameter		*Estimate*	*Standard Error*	*P-value*
Intercept		1.47	0.54	0.01
age group	0~6	0.01	0.20	0.97
	7~19	0.00		
Hull	DH	-0.29	0.19	0.14
	IntH	0.18	0.18	0.32
	SH	0.00		
Team	A	0.35	0.19	0.08
	B	1.17	0.29	0.00
	C	0.30	0.20	0.13
	D	0.33	0.20	0.10
	F	0.00		
vessel type	Aframax	0.56	0.53	0.30
	OBO	0.35	0.68	0.61
	Products	0.38	0.71	0.60
	VLCC	0.00		

4.3 Poisson Regression Model

We used Poisson regression model to quantify the factor effects of age group, team, vessel type, and hull structure on the incident and accident rate. The variables are defined in Table 5.

Table 5: Variable definitions for Poisson regression model

Variables	*Definitions*
COUNTS	Number of the incidents and accidents
EXPOSURE	The period of operation
AGE	Dummy variable for age group "0~6"and "7~19"
HULL	Dummy variable for hull group "SH", "IntH" and "DH"
TYPE	Dummy variable for vessel type "Aframax", "OBO", "Products" and "VLCC"
TEAM	Dummy variable for team "A", "B", "C", "D", "F"

The Poisson MLE model specifies that COUNTS, $\boldsymbol{y}$, given all variables AGE, EXPOSURE, HULL, TYPE and TEAM, vector $\boldsymbol{x}$, is Poisson distributed with density

$$f(y_i \mid x_i, t_i) = \frac{e^{-u_i t_i}(u_i t_i)^{y_i}}{y_i!} \tag{1}$$

i is the index of vessel and t_i is the period of operation of vessel i. And the expected mean number of incidents and accidents is:

$$E(y_i \mid x_i, t_i) = u_i t_i = e^{x_i' \beta} t_i \tag{2}$$

Hence

$$\begin{aligned} &\log(E(y_i \mid x_i, t_i)) \\ &\quad = \log(e^{x_i' \beta} t_i) \\ &\quad = \log(t_i) + x_i' \beta \\ &\quad = \log(t_i) + \beta_1 + \beta_2 x_{age} + \beta_3 x_{hull} + \beta_4 x_{type} + \beta_5 x_{team} \end{aligned} \tag{3}$$

From (2) we know that

$$\log(E(y_i \mid x_i, t_i)) = \log(u_i t_i) = \log(u_i) + \log(t_i) \tag{4}$$

From (3) and (4) we get

$$u_i = e^{\beta_1+\beta_2 x_{age}+\beta_3 x_{hull}+\beta_4 x_{type}+\beta_5 x_{team}} \tag{5}$$

The term $\log(t_i)$ in (3) is sometimes called an *offset*, and equation (5) is also called the *exponential mean function.* The model specified by (1) and (2) is formally called a Poisson regression with exponential mean function, or sometimes called log-linear model in statistical literature since the logarithm of the conditional mean is linear in the parameters as shown in (3). We will refer it as the Poisson regression model thereafter for simplicity.

Given the independent observations of incident and accident counts of vessels y_i, and the variables x_i and t_i, we want to maximize the log-likelihood with regard to β. Given the assumption that the observations are independent, the overall likelihood is

$$\begin{aligned} Likelihood &= \prod_i f(y_i \mid x_i, t_i) \\ &= \prod_i \frac{e^{-u_i t_i}(u_i t_i)^{y_i}}{y_i!} \end{aligned} \tag{6}$$

Hence the log-likelihood function is

$$\begin{aligned} \log(Likelihood) &= \log(\prod_i f(y_i \mid x_i, t_i)) \\ &= \sum_i \log(\frac{e^{-u_i t_i}(u_i t_i)^{y_i}}{y_i!}) \\ &= \sum_i [-u_i t_i + y_i \log(u_i t_i) - \log(y_i!)] \\ &= \sum_i [-e^{x_i'\beta} t_i + y_i x_i'\beta + y_i \log(t_i) - \log(y_i!)] \end{aligned} \tag{7}$$

The Poisson MLE $\hat{\beta}$ is the solution to the first-order condition of (7). Once we take the first order derivative of (7) with regard to β. The last two terms vanish and we get

$$\sum_i (y_i - e^{x_i'\beta} t_i) x_i' = 0 \tag{8}$$

The standard method for computing $\hat{\beta}$ is the Newton-Raphson iterative method. We used both NCSS 2000 and SAS 8.0 to run the regression analysis, and the results are the same.

4.4 Poisson Regression Model Evaluation and Findings

The model fitted data well judged by the output of goodness of fit criteria from SAS 8.0 in the **Table 6**. Further we observed that team (p-value 0.0008), hull (p-value 0.0127) were significant, while age group (p-value 0.8284) and vessel type (p-value 0.5955) were not. This agrees with the OLS analysis with variance stabilizing transformation.

Table 6: Goodness of fit of Poisson regression model

Criterion	*DF*	*Value*	*Value/DF*
Deviance	53	51.87	0.98
Pearson Chi-Square	53	51.57	0.97

Table 7: Chi-Square test of Poisson regression model

Source	*DF*	*Chi-Square*	*P-value*
age group	1	0.05	0.83
team	4	19.02	0.00
type	3	1.89	0.60
hull	2	8.74	0.01

The Deviance and Pearson Chi-Square have approximately Chi-square distribution with the number of degrees of freedom in the DF column in the **Table 6**. Deviance and Chi-square divided by the degrees of freedom are used to detect overdispersion or underdispersion. Poisson regression model requires that the mean should be equal to the variance. If the variance is greater than the mean, it is called overdispersion; otherwise, it is underdispersion. For Poisson distribution the mean and the variance are equal, which implies that the deviance and the Pearson statistic divided by the degrees of freedom should be approximately one. Any value greater that 1 indicates overdispersion; otherwise it is underdispersion. Evidence of underdispersion or overdispersion indicates inadequate fit of the Poisson model. In case of overdispersion, a negative binomial model or Poisson mixture model is normally used, which does not restrict equality between mean and variance. In our case, the ratios are 0.9787 and 0.9729, and we conclude that

the fit of Poisson model is adequate. The Pearson residual plot and Deviance residual plot is shown in the chart below, which suggests that the variance is constant.

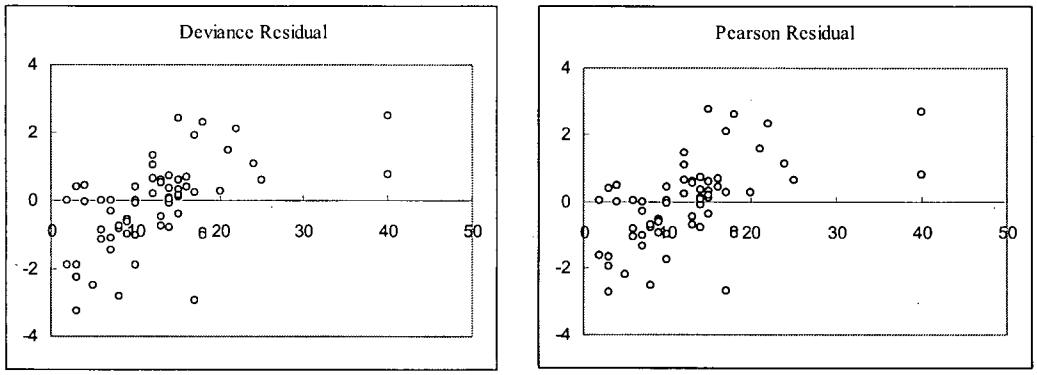

Figure 3: Residual plot of Poisson regression model

The coefficient estimates, and the p-values in the Chi-Square test are summarized in the table below.

Table 8: Estimates of the main effects in the Poisson regression model

Parameter		*Estimate*	*P-value*
intercept		0.87	0.14
age group	0~6	0.04	0.83
	7~19	0.00	
team	A	0.32	0.06
	B	0.92	<0.0001
	C	0.28	0.12
	D	0.27	0.14
	F	0.00	
type	Aframax	0.60	0.30
	OBO	0.41	0.55
	Products	0.47	0.47
	VLCC	0.00	
hull	DH	-0.30	0.07
	IntH	0.15	0.27
	SH	0.00	

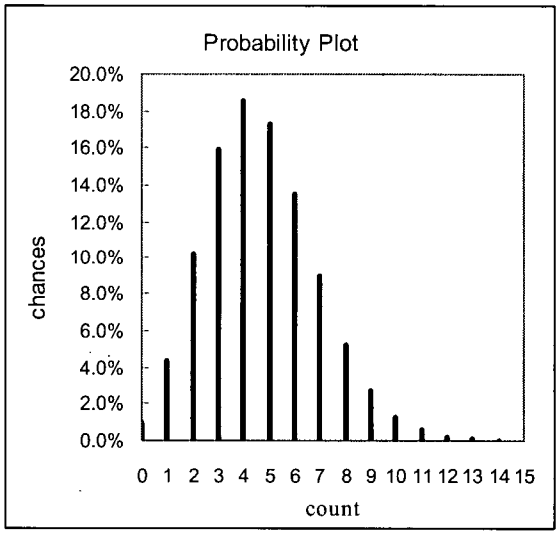

Figure 4: Probability plot of number of incidents and accidents
For a "DH", "Aframax" vessel in team "A" and in age group "0~6", the chances for possible count of incidents and accidents are shown in the chart.

To calculate a vessel's expected annual mean number of incidents and accidents, what we need to do is to fit the estimate into the equation (5). For example, for a "VLCC" and "SH" vessel in age group "7~19"and team "F", its expected annual mean number of incidents and accidents $u = e^{x_i \beta} = 2.38$. Similarly, a "DH" and "Aframax" vessel in team "A" and in age group "0~6" would have expected annual incident and accident rate of 4.67.

One benefit that Poisson regression model has over the OLS model is that we can not only calculate the expected incident and accident rate, but also the probability for each possible count of incident and accident. What we need to do is to fit the estimates and variable values into equation (1), where t_i equals to 1 since we are interested in annual rate. For example, the a "DH", "Aframax" vessel in team "A" and in age group "0~6", its chance to have 4 incidents and accidents within one year is

$P(y=4 \mid \text{DH,Aframax,A,0~6,1}) = \frac{e^{4.67}(4.67)^4}{4!} = 18.6\%$, where 4.67 is the annual mean calculated in the last paragraph. Similarly we can compute chances for other possible outcomes and make a plot as in Figure 4.

Another advantage of the Poisson regression model is that the response variable is the incident rate rather than the square root of rate, hence the result has more direct interpretation. Note that all variables in the model are dummy variables. Interpreting dummy variable coefficients is different from those of continuous variables. For example, let dummy variable ***d*** takes only value 0 and 1, and suppose $E(y \mid d, x) = e^{\beta_1 d + x'\beta_2}$. Then

$$\frac{E(y \mid d=1, x)}{E(y \mid d=0, x)} = \frac{e^{\beta_1 + x'\beta_2}}{e^{x'\beta_2}} = e^{\beta_1}$$

So the conditional mean is e^{β_1} times larger if the dummy variable is unity rather than zero.

Following this procedure and Table 8, we obtain the following important findings:

i. Vessels in age group "0~6" on average have 4% more incidents and accidents than vessels in age group "7~19" do. This finding challenges the concept that vessel safety performance will decrease gradually as the vessel age increases. On the contrary, the "7~19" age group has slightly better safety performance.

ii. Vessels of double hull type have 29% fewer incidents and accidents than single hull vessels. Vessels of interim hull (DS, DB, and DSIDB) have 17% more incidents and accidents than single hull vessels do. This finding further confirmed the new policy "heavy oil only on double hull" since double hull vessels have significantly better safety performance than all others. However, the finding also raises a decision problem: in the process of phasing-in double hull vessels, should we first replace those interim hull vessels or the single hull vessels? As for Teekay case, the 19 interim hull vessels and 19 single hull vessels are both in the age group 7~19, if only considering the safety performance as studied in this dataset, we would like to first replace the interim hull vessels with double hull vessels.

iii. Compared with vessels in team "F", vessels in team "A", "B", "C" and "D" have 32%, 92%, 28%, and 27% more incidents and accidents respectively.

iv. Compared with vessels of type VLCC, vessels of type Aframax, OBO and Products have 60%, 41%, 47% more incidents and accidents respectively.

The above findings are consistent in both the ordinary regression model and the Poisson regression mode, and both models are tested to be adequate. The interpretation of estimates from Poisson regression model is more intuitive and yields more useful results, and hence we elaborate on the main findings according to the Poisson regression model as shown above.

4.5 Future Work

We would like to further explore the seasonality of the incidents and accidents. The detailed data about which vessel was in which region was not ready at the time of the project. We need this information to infer which season a vessel is experiencing at the time of an incident or accident. Teekay vessels are in fact operated in different time zones and hemispheres, and are exposed to different seasons at any time point. We intend to get the temperature, wave height, and current speed data and use these data in a seasonality study.

Besides the environmental data mentioned above, we are working on getting the trading pattern data. It is believed that more operations, such as loading, unloading and lightering mean more risks. An oil tanker at sea faces less risk than the oil tanker in port conducting the operations mentioned above. And it is known that voyages are quite different in terms of number of ports visited, number of loading and unloading operations, and the length and speed of a voyage. The information will be helpful in explaining the extra variance of incident and accident rates.

Certain cargoes are more dangerous than others. For example, cargo containing H_2S is toxic. Some cargoes need higher pressure to be pumped into tank. Some cargoes need

heating during the voyage while others don't. The cargo information should also explain certain amount of the variance of incident and accident rates. We are working on incorporate these information into our model.

Manning data should also contribute to the model since different crewmembers have different sea experience, education, nationalities and cultures. One might assume those experienced seafarers are safer than those novice ones, and data can be used to test this.

5. A Continuous Monitoring Tool

The continuous monitoring tool was a side product of preparing data for Poisson regression analyses, where a simple chart to show the process for each vessel is needed. Later on both Teekay and us thought that such a chart is not only useful for showing the Poisson processes, but also has the potential to visualize of the whole dataset. Thus we further developed the chart with much extra functionality, which enables Teekay managers to visually explore its risk database from all perspectives they are interested in.

We used EXCEL chart functionality to make full-range views of all historical data, and we designed easy-to-use user interface in VBA. Teekay managers can specify any view through the user interface and get the dynamic chart instantly. Such a view could be event (near miss, incident and accident) histories of all vessels or a subset of vessels; or it could be comparisons among groups chosen by the user, such as team or age group; or it could be comparisons among near misses, incidents and accidents. All views mentioned above could spread over any period chosen by the user, and of any subset of all Teekay vessels. And for each view, the involved vessels could be sorted according to their number of event, total cost, average cost, year built and so on. The possible number of views is colossal. It is intended that the user would gain insight of the dataset, or verify his or her concept from experience through all these perspectives provided by these extremely flexible views. To use this continuous monitoring tool, a user will first specify his or her interested parameters via the continuous monitoring tool interface as shown in Figure 5.

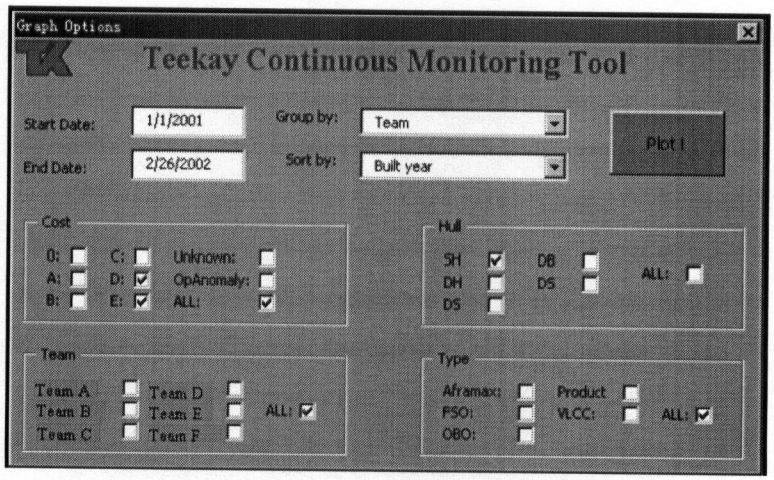

Figure 5: User interface of continuous monitoring chart

After the user finished specifying the parameters, he or she should push “plot” button and the tool will generate the correspondent view immediately.

The x-axis of the continuous monitoring chart is the time scale specified by the user input of "start date" and "end date" as shown in Figure 5. The y-axis is the vessels name, which could be grouped by various categories specified by user in "Group by" drop list. Grouping categories include "team", "hull", "type", "class", "shipyard", and "no grouping". Within each group the relative position of vessels is determined by the sorting criteria specified in "sort by" in Figure 5. Sorting methods include vessels' "year built", "number of incidents", "average cost" and "total cost". These sorting statistics is shown on the right hand side of the second y-axis. User may choose different subset of vessels under study by choosing the "hull", "team" and "type". User can also determine which kind of events shown in the chart by choosing "cost", where "0~E" is cost categories, "OpAnomaly" is "operational anomaly", "unknown" stands for all events not fallen in any of above categories. For each vessel, its events were plotted on a horizontal line representing the period specified by the user, with different shapes of dot representing different cost categories of the events.

The vessels in the example Figure 6 used artificial data for confidentiality reason. It is easy to see from the chart that those vessels are from five teams, “A”~”E”, sorted by

"total incident number", in the period from Jan 1st, 2001 to Feb 26th, 2002. The user can easily to make comparison whether there is difference among the five teams in this period. The user can also group vessels according to their "hull", and make comparison about whether different hull types lead to different incident and accident rates. Similarly a user may group these vessels by "age group", "type", "class" or "shipyard" and perform any other comparisons of interest. Further by plotting only one event type once a time and compare the different outputs, a user may expect to see the patterns among these events. The possible uses of this tool are tremendous and experienced managers should be able to find valuable results via its help.

The continuous monitoring tool doesn't share the concerns with the risk factor analyses model, where confounding variables should be avoided. The continuous model takes basically anything in Teekay's risk database and displays them graphically. The continuous monitoring tool automatically incorporates the most updated information as long as the user puts the information into the EXCEL sheet. Thus it achieves the quasi-continuous monitoring functionality. To make it a real online monitoring tool, we need to link it with the ORCA system which is introduced later. This is an area for future work.

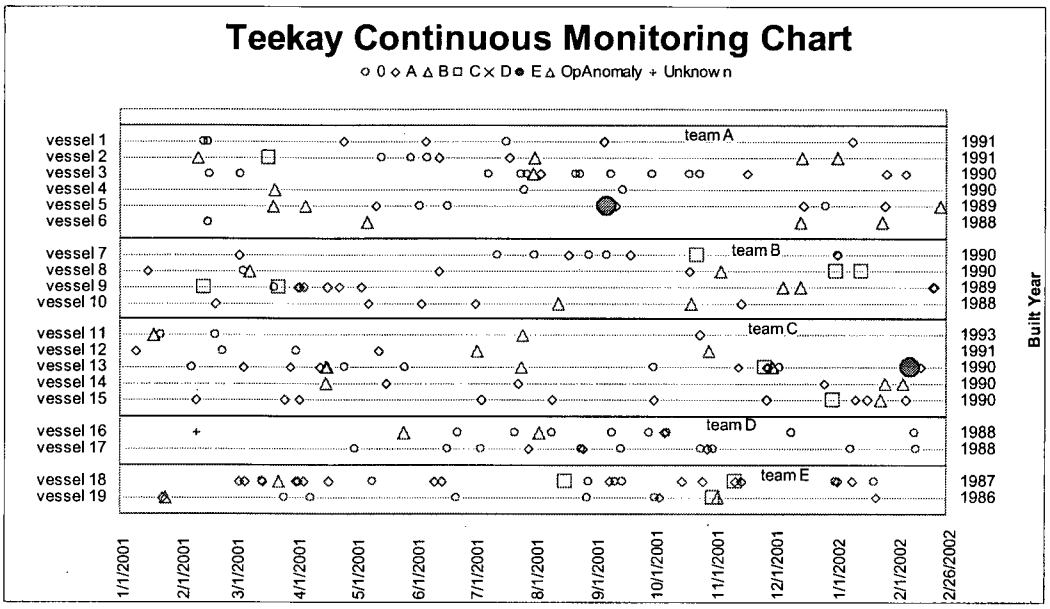

Figure 6: An example of continuous monitoring chart (artificial data)

6. Root Cause Analysis

6.1 Online Root Cause Analyses System

The data used in the study is from Teekay's ORCA system. ORCA actually performs what other commercial root cause analysis software does: help the user to detect the real cause of an event. It leads a user through a hierarchical reasoning structure and reach conclusion of the root cause of an event. The hierarchical reasoning structure is defined by Teekay experts and managers based on their knowledge and years' experience.

There are four levels in the ORCA hierarchical structure, and user make exactly one choice among various available options, and on the fourth level the user reach conclusion of the root cause of an event under research.

On the first level of ORCA, a user can choose between two options: operational incident or personnel incident. The later is defined as incidents involving only personnel loss. All other incidents fall into the first category.

Then depending on the user's choice on the first level, ORCA presents the user with relevant choices on the second level.

For all these incident types presented in second level, there are certain direct causes applicable. Teekay has compiled direct causes for each category of operational and personnel incidents. All together, there are 32 direct causes. The relationship between incident type and applicable direct causes are defined in an incident matrix not shown for confidentiality.

Teekay has defined 8 root causes, which indicate the possible managerial challenges Teekay is facing. Any direct cause can be due to any root cause.

6.1.1 Relationship among ORCA levels

ORCA level one is a broad categorization of an incident from its consequence point of view. At level one, an incident is of type "personnel incident" if that is the only loss incurred; all other incidents fall into the category of "operational incident". There should be of no ambiguity at level one. As we take a closer look at level two, one should be aware that at the first glance multiple choices are applicable for an incident or accident. However, we should always choose the one which is at the source. For example, both "Loss of Stability" and "Falls from Same Level" are direct causes in the second level. If an accident started as "Loss of Stability", which means a tanker loses its stability, and consequently led to something like "Fall from Same Level", we would categorize the incident as "Loss of Stability". Similarly, an incident "Collision" might cause "Fire/Explosion/High Pressure", but we will categorize is as the former.

At level three and level four, we will also assign only one direct cause and one root cause to an incident. This sounds a little bit arbitrary at the first place, since experience tells that some incidents happen because of various reasons. For example, an incident of "Man Overboard" may be due to both "Adverse Weather or Sea Conditions" and "Failure to wear PPE" (Personal protective equipment), since neither one cause alone would not have made such an incident. One might suggest letting user choose multiple direct causes and root causes according to his analyses. However, weight information about which direct cause is more critical must accompany the multiple choices; otherwise such an approach leads to difficulties in analysis. While associating multiple direct causes and root causes with an incident, the relationship between an incident *i* and its causes is shown as in Figure 7 and Figure 8.

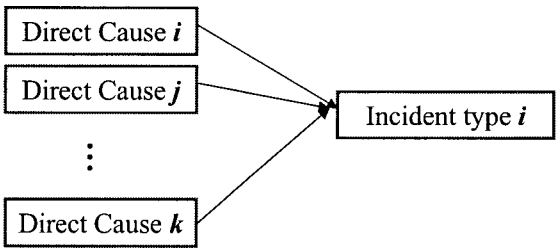

Figure 7: Un-weighted relationship between direct causes and incident

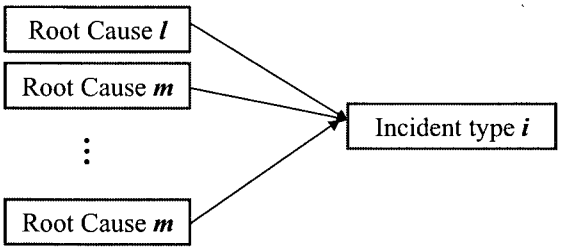

Figure 8: Un-weighted relationship between root causes and incident

However latter on we wanted to know which direct cause or root cause is more critical for Teekay. An appropriate approach is to compare the sum of the incident cost due to each direct cause or root cause. Since an incident is associated with multiple direct causes and root causes, we have to distribute the incident cost into those chosen direct causes and root causes. We have to know the weight of each cause so as to reasonably distribute the cost. However, this weight information is missing in the ORCA system. For example, an incident cost $30,000, and its root causes were "Inadequate Leadership" and "Inadequate Maintenance". At the time of inputting this record, the master might believe that 90% of the incident is due to "Inadequate Leadership" and 10% due to "Inadequate Maintenance". In this case, a proper distribution of the incident cost should be $27,000 for "Inadequate Leadership" and $3,000 for "Inadequate Maintenance". However, this weighting information is not captured by ORCA. Later on the cost has to be distributed as $15,000 for "Inadequate Leadership" and $15,000 for cause "Inadequate Maintenance". The aggregation of such inaccuracy could lead to distorted result. A hypothetical example is that a certain direct cause is associated with every incident though its weight is always tiny, later on we have to distribute half of the cost to it (in case of two direct causes) and the result is that this minor but not critical direct cause is associated with most incident cost.

Now consider another flaw of multiple choices. Suppose an incident is recorded in the ORCA system as shown in the figure below.

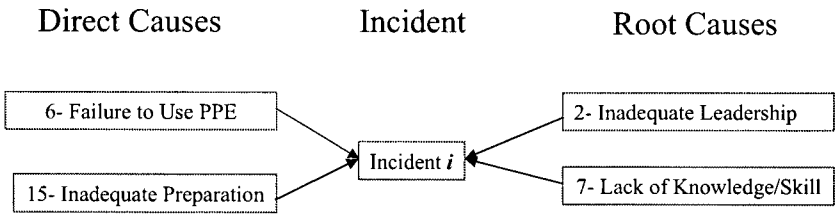

Figure 9: An example of incident record in ORCA system

For management purposes, it will be interesting to know which root cause is the most significant for each direct cause, or the other direction. For the example shown above, it is not possible to determine why the crew member in incident didn't use PPE (Personal Protective Equipment). As a result, if many incidents of direct cause "Failure to Use PPE" happens and the Teekay managers want to improve it, there is no indication whether Teekay should tackle "Inadequate Leadership" or "Lack of Knowledge/Skill". Two of the possible combinations are shown below.

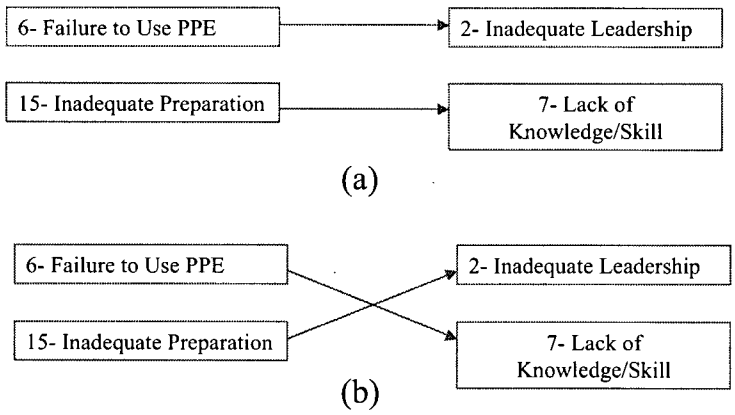

Figure 10: Ambiguous interpretations of ORCA record

A solution might be to let Master or other crewmember to choose explicitly which chosen root cause lead to the chosen direct cause. Thus the direct cause and root cause are always paired.

However to weight each direct cause, and to pair the direct cause and root cause increases the cost of data collection, since the crew members have to spend more time on weighting each direct cause, and the onshore managers need to spend more effort to verify the result. Teekay managers finally made up a decision to only allow single choice at each level of ORCA. This approach eliminates both ambiguities. And this approach is reasonable for Teekay case since almost every Teekay incident had by nature one explicit direct cause and one root cause.

6.2 Bubble Chart Analysis

ORCA outputs the root cause for each incident or accident at a very high level such as "Inadequate Leadership" or "Inadequately Maintenance". It is useful for the organization to understand what the real cause for an incident or accident is. However, to make long-term investment strategy, it is not sufficient to analyze the incident or accident case by case, Teekay needs another tool to analyze at the aggregate level what's the main or most critical cause for most incidents and accidents, and which cause has incurred most risk cost.

For example, one incident due to "Inadequate Leadership" doesn't necessarily mean that Teekay's managers are in general short of leadership. What if this is just a unique case? One needs to analyze at aggregate level to draw sensible conclusion on which root cause is the most general problem and try to improve it.

On the contrary, one might only pay attention to the severest accident, analyze its root cause, and make long-term strategy accordingly. This approach is widely used in practice. Most often, the board only hears the report of the severest accidents and makes decisions accordingly. But this approach sometimes leads to unsatisfactory results, since the current most severe accident might not represent Teekay's actual managerial challenges. As shown in the Figure 11, 99% percentage of incidents incurred 63% percent of financial lost; while only a few, roughly 8 incurred 37% financial loss. It is reasonable to believe that the root cause analysis of 99% of incidents should be able to reveal the real

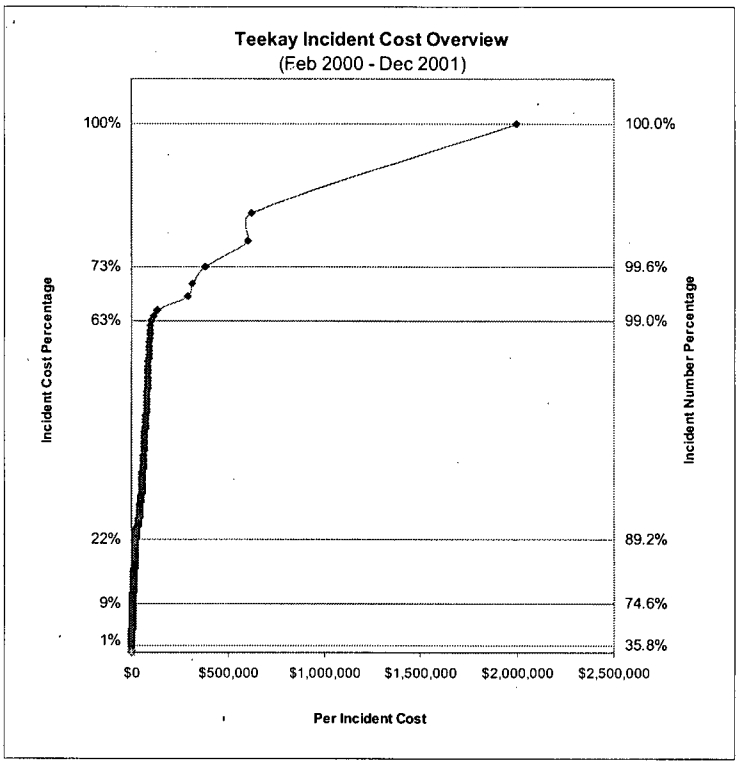

Figure 11: Incident and accident cost overview (artificial data)

For confidentiality, all numbers in the chart are artificial

managerial problems. As for the severest 1% accident, one can never declare that they must fall into the problematic areas where the 99% incidents do, because of the probabilistic nature of accidents. Once one severe accident doesn't fall into the problematic area, its significant financial loss distracts people's attention from the real troublesome area. In this sense, the severest accident is somehow an "outlier".

Hence we need to separately analyze the 99% less severe incidents. Further more, we might be able to predict the severest 1% from the 99% less severe incidents, which will be extremely valuable for Teekay to take preventative strategy.

We also need to carefully think about the relationship between the direct causes and the root causes. Root causes alone don't tell you what to do to correct it. For example, several incidents with the same root cause, let's say "Inadequate Leadership", might have totally

different direct causes, “Poor House Keeping “or " Incorrect Navigation or Ship Handling". Thus when Teekay's managers try to enhance their leadership, they might do quite different things, either to pay more attention on monitoring the housekeeping job or to hone their skills on navigation and ship handling. It is the combination of the direct cause and root cause that leads to practical improvement solution.

Based on the above analysis, we creatively designed the two-layered bubble chart as our analytical tool. The x-axis represents 32 direct causes, and the y-axis represents 8 root causes. At each intersection, a red bubble area represents the aggregate financial loss of incidents and accidents which is due to this direct cause and root cause. You will see the a few big blue bubbles on some intersections. These are the severest accidents. The user inputs the delimit between the severest accidents and the less severe incidents. The reasons for separately analyzing these two kinds of events is as described above in the analysis of Figure 11. We also add auxiliary side bar charts to facilitate reading of the totals along the each direct cause and root cause.

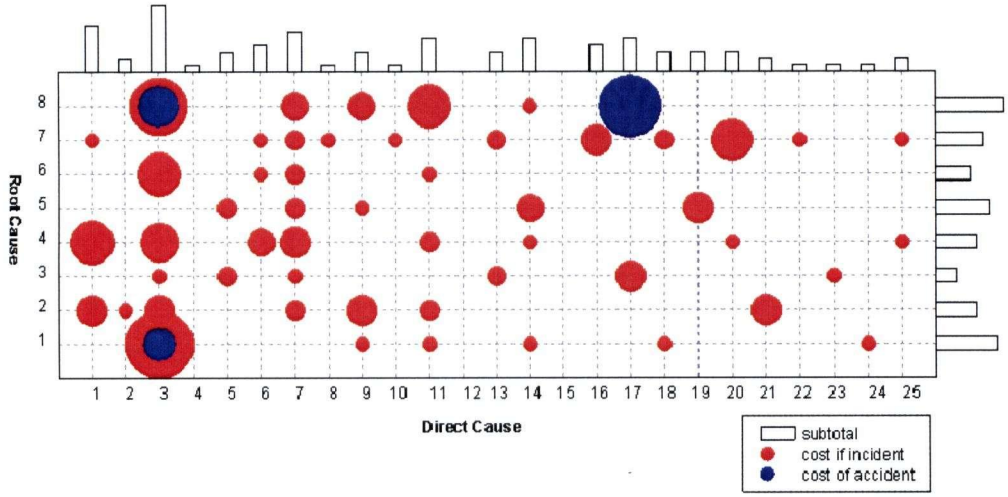

Figure 12: An example of bubble chart (artificial data)

For confidentiality, the labels on x-axis and y-axis are replaced by index, and the data are artificial.

As shown in the Figure 12, "3" is the most outstanding direct cause, which is further due to two root causes, "1" and "8". As people would expect, two severe accidents did happen

at the same intersections. But we also see that the severest accident at the intersection of "8" and "17" was not accompanied with any other incidents. This observation calls for more deliberation. We cannot jump to the conclusion that Teekay need to invest a lot to improve the area where direct cause "17" indicates. It might be equally due to the fact that the operator had suffered from the root cause "8" at the accident time and his misbehavior happened to relate to direct cause "17". We definitely need more investigation why such a severe accident happened. But as indicated by the chart, the real managerial challenge lies at the intersection of "8" and "3", and "1" and "3".

As shown above, the two-layered bubble chart provides the overview of the all incidents and accidents at aggregate level, indicates the relationship between the severest accidents and the majority of incident and accidents, and reveals the investment area to reduce the risk fundamentally.

Another use of bubble chart is to evaluate the risk mitigation effect easily. People would like to see the effect of the last year investment with objective of enhancing leadership. To see this, we may simply put two bubble charts shoulder by shoulder, one for last year and one for this year, and compare the incident cost due to the insufficient leadership. By comparing these two charts, we get the overall view of the changes between these two years. And hopefully we will see less incident cost due to insufficient leadership.

We bear it in mind that a previous-year investment might need more time to make an impact on the company's performance in risk management. Thus we might wait and see the next year's bubble chart. And the correlation among the bubble areas should also be taken into account. The investment in improving leadership might reduce other incident cost as well since the leadership enhancement is sure to positively affect other performance. Moreover, there are various factors other than investment which may drastically affect the risks faced by Teekay, such as unexpected weather, war, route structure change, or other unknown reasons. Finally we realize that the change of bubble area might just come from random effect rather than investment. Considering all these factors, quantifiable or not, we suggest that Teekay managers analyze the changes bubble

by bubble, and actively seek, using their knowledge and experience, the reasons for these changes one by one.

7. Conclusions and Future Work

Our job in risk factor analyses led to several striking findings: there is no significant difference between "0~6" and "7~19" age group vessels in terms of risk exposure; the hull structure makes significant difference, especially, the old designed single hull structure outweighs the interim designs, such as double bottom or double side, though the most updated design, double hull, is the best; the team effect are the most significant risk factor.

The first finding challenges the traditional thinking that old vessels face more risk, which might further affect the life cycle of oil tanker. The second finding might bring significant change in strategy in the accelerating the phase-in of double hull vessels. And the third finding confirms the Teekay managers' experience that human factor is the most important risk factor.

We not only improved the ORCA (Online Root Cause Analyses system) by making some valuable improvements, but also creatively designed dual layered bubble chart to identify long-term risk reduction investment area, and to evaluate the risk mitigation effect. The continuous monitoring chart provides Teekay managers valuable perspectives of the risk dataset and could be used to aid finding incident patterns and take preventive steps.

In future, we'd like to comprehensively evaluate more risk factors, including environmental factors, manning, and trading patterns. We'd like to link the continuous monitoring tool with ORCA, and provide more online functionalities. Finally, we see the potential to integrate the dual layered bubble chart with ORCA, and further develop ORCA system so as to make it a full-featured root cause analysis system.

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