Managing and Predicting Maritime and Off-shore Risk

R.B. Duffey
Atomic Energy of Canada Limited, Chalk River, Canada

J.W. Saull
International Federation of Airworthiness, East Grinstead, W. Sussex, United Kingdom

ABSTRACT: We wish to predict when an accident or tragedy will occur, and reduce the probability of its occurrence. Maritime accidents, just like all the other crashes and failures, are stochastic in their occurrence. They can seemingly occur as observed outcomes at any instant, without warning. They are due to a combination of human and technological system failures, working together in totally unexpected and/or undetected ways, occurring at some random moment. Massive show the cause is due to an unexpected combination or sequence of human, management, operational, design and training mistakes. Once we know what happened, we can fix the engineering or design failures, and try to obviate the human ones. We utilize reliability theory applied to humans, and show how the events rates and probability in shipping is related to other industries and events through the human involvement. We examine and apply the learning hypothesis to shipping losses and other events at sea, including example Case Studies stretching over some 200 years of: (a) merchant and fishing vessels; (b) oil spills and injuries in off-shore facilities; and (c) insurance claims, inspection rules and premiums. These include major losses and sinkings as well as the more everyday events and injuries. By using good practices and achieving a true learning environment, we can effectively defer the chance of an accident, but not indefinitely. Moreover, by watching our experience and monitoring our rate, understand and predict when we are climbing up the curve. Comparisons of the theory to all available human error data show a reasonable level of accord with the learning hypothesis. The results clearly demonstrate that the loss (human error) probability is dynamic, and may be predicted using the learning hypothesis. The future probability estimate is derivable from its unchanged prior value, based on learning, and thus the past frequency predicts the future probability. The implications for maritime activities is discussed and related to the latest work on managing risk, and the analysis of trends and safety indicators.

1 INTRODUCTION

1.1 *The Universal Learning Curve*

We have developed a general accident theory, so in this paper we emphasize and extract the relevant application to marine shipping. For any technological system with human involvement, like ships and shipping, the basic and sole assumption that we make is the "Learning Hypothesis" as a physical model for human behavior when coupled to a technology (Duffey & Saull 2002, 2008).

Simply and directly, we postulate that humans learn from their mistakes (outcomes) as experience is gained.

Although we make errors all the time, as we move from being novices to acquiring expertise, we should expect to reduce our errors, or at least not make the same ones. Thus, hopefully, we should descend a "Universal Learning Curve" (ULC) like that shown in Figure 1, where our rate of making mistakes decreases as we learn from experience and is exponential in form.
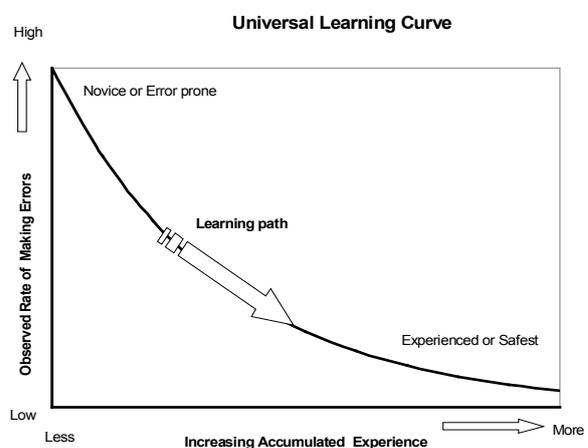

Figure 1. The Learning Hypothesis – as we learn we descend the curve.

The past rate of learning determines our trajectory on the learning path and thus:

- how fast we can descend the curve;
- the rate at which errors occur determines where we are on the curve;
- changes in rate are due to our actions and feedback from learning from our mistakes;
- no reduction in error or outcome rate could mean we have reached the lowest we are able to or that we have not sustained a learning environment; and
- an increase in rate signifies forgetting.

In our book that established the existence of the learning curve (Duffey & Saull 2002), we examined many case studies.

We highlight in this paper the data and information for marine events and their learning trends. We have also found data for oil spills at sea. Since spills are just another accident in a homotechnological system (HTS), namely a ship operated by people, it was interesting to show if the usual everyday marine accidents do exhibit learning. Marine accident outcomes include groundings, collisions, fires and all manner of mishaps. The most recent data we found were on the web in the Annual Report for 2004 of the UK Marine Accident Investigation Board (MAIB, for short, at www.maib.gov.uk). The MAIB responsibility is to examine reported accidents and incidents in detail. The MAIB broke down the accidents by type of ship, being the two broad categories of merchant ships that carry cargo, or fishing vessels that ply their trade in the treacherous waters off the UK islands,

In both types of ship, the number of accidents were given as the usual uninformative list of tabulations by year from 1994 to 2004, together with the total number of ships in that merchant or fishing vessel category, some 1000 and 10,000 vessels respectively. Instinctively we think of fishing as a more dangerous occupation, with manual net handling and deck-work sometimes in rough seas and storms, but surprisingly it turns out not to be the case.
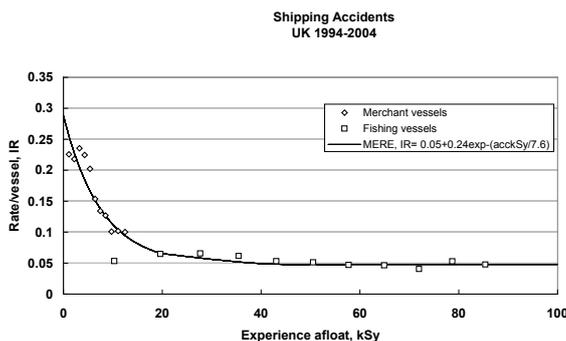

Figure 2. The learning curve for shipping accidents.

We analyzed these accidents by simply replotting the data as the accident rate per vessel versus the thousands of accumulated shipping–years of experience, kSy. By adopting this measure for experience, not only can we plot the data for the two types on the same graph, we also see if we have a clear learning trend emerging. The result is shown by Figure 2, where the line or curve drawn shown is our usual theoretical MERE learning form.

We see immediately that, at least in the UK, the (outcome) accident rate is higher for merchant vessels than fishing boats, but also that learning is evident in the data that fit together on this one plot only if using experience afloat as a basis. The other observation is that the fishing vessels are at the minimum rate per vessel that the merchant vessels are just approaching. Perhaps the past few centuries of fishing experience has lead to that low rate so that, in fact, fishermen and fisherwomen are highly skilled at their craft. The lowest attained rate of ~ 0.05 accidents per vessel corresponds to an hourly rate if afloat all day and working all the time, of:

$$\sim 0.05/(365 \times 24) \sim 5.10^{-6} \text{ per hour} \qquad (1)$$

That is one accident per vessel every 175,000 hours, which is about the least achieved by any HTS or industry anywhere in the world, including the very safe ones like aircraft, nuclear and chemical industries of 100,000 to 200,000 hours. Even allowing for a duty factor afloat for the vessel or crew of 50% or so, or working at sea half the time, it is still of the same order. That last result is by itself simply amazing, and reflects the common factor of the human involvement in HTS. We now examine the learning hypothesis analysis again, but in some more detail.

2 THE RISK OF LOSING A SHIP

We can use data from shipping, as it is a technological system with human involvement that is observed and includes both outcomes and a measure of experience. Shipping losses are an historic data source, as insurers and mariners tracked sinkings; and the human element is the main cause of ship loss, rather than structural defects in the ships themselves.

A large dataset exists for ship losses in the USA, (Berman 1972). We analysed these extraordinary data files, which cover some 10,000 losses (outcomes) over an Observation Range of nearly 200 years from 1800 to 1971. We excluded Acts of War so as to avoid uncontrolled external influences and non–human errors. It is not known how many ships were afloat in total, only which ones sank, and thus became recorded outcomes.

A ship is built in a given year, sails for a while accumulating experience in ship-years afloat, Sy,

and may or may not sink. From some 10,000 ships that were lost, we took a sample of the data only for ships over 500 tons, chosen so that we can compare with modern large commercial losses. In our sample of the data there were a total (N) of 510 losses of the ships.

From the entire set, we show one sample Observation Range in Table 1 for 1850 to 1860, selected arbitrarily from the entire data set. For these loss (outcome) data for 1850 to 1860, 17 ships were lost which had accumulated 265 shipping-years (accSy) of depth of experience before being lost. The losses, $N_i = 17$, are sparsely distributed and apparently random, as we might expect. The entire observation set of 1800 to 1971 can be formed by stacking these incremental observations ranges together for all the observed range and number of outcomes. But this again is only one subset of an array that could stretch over all recorded history, and all human experience - we just happen to not have all that data.

Table 1. Actual Ship Loss Data matrix: A sample outcome observation interval

Year	1850	1851	1852	1853	1854	1855	1856	1857	1858	1859	1860	Sy	accSy	#Losses
1												0	0	0
2		1			1							4	4	2
3				1								3	7	1
4	1											4	11	1
5												0	11	0
6			1			1						12	23	2
7												0	23	0
8												0	23	0
9												0	23	0
10						1						10	33	1
11												0	33	0
12												0	33	0
13		1										13	46	1
14												0	46	0
15												0	46	0
16												0	46	0
17												0	46	0
18												0	46	0
19								1	2			57	103	3
20					1					1		40	143	2
21												0	143	0
22												0	143	0
23												0	143	0
24												0	143	0
25												0	143	0
26												0	143	0
27				1								27	170	1
28												0	170	0
29												0	170	0
30				1								30	200	1
31									1			31	231	1
32												0	231	0
33												0	231	0
34			1									34	265	1
35												0	265	0
36												0	265	0
37												0	265	0
38												0	265	0
39												0	265	0
40												0	265	0
Totals	1	2	2	3	2	2	0	1	3	1	0	265	265	17

The usual time history is given by the sum of the losses for any given year. Thus, for any year, y, there is a loss rate given by summing over all the experience range of losses for that particular observation, j^{th} range year:

$$N_y = \sum_\varepsilon n_i (\varepsilon) \qquad (2)$$

Meanwhile, for a given experience, ε, the total number of losses, N, is given by summing all the losses over the range at a particular experience, as:

$$n_i = \sum_y n_i (\varepsilon) \qquad (3)$$

The sum of the number of Sy at any experience interval is simply given by adding up outcomes:

$$Sy (\varepsilon) = \sum_y (Sy\, n_i (\varepsilon)) \qquad (4)$$

Hence, the accumulated experience in accSy's is as shown from adding the Sy's for all losses:

$$accSy = \sum_\varepsilon (Sy\, n_i (\varepsilon)) \qquad (5)$$

Now we can calculate the outcomes for all the entire Observation Range for 1800-1971. We find the total losses of >500 tonnes are now of course as summed as all outcomes:

$$N_j = \sum_i n_i (\varepsilon) = 510 \qquad (6)$$

and the accumulated experience is summed over the depth of experience:

$$accE = \varepsilon = \sum_j (n_i(\varepsilon)\, Sy) = 11,706\; accSy \qquad (7)$$

So we have confirmed the postulate that we may represent outcomes by a distribution of errors as a function of experience, and where all outcomes are equally likely.

On average, therefore, ships spent an average of $11,706/510 = 23$ years afloat before sinking.

3 SHIPPING LOSS DISTRIBUTION FUNCTIONS

If the losses were truly random in time, then on average the chance is equal that a ship would be lost either side of the middle of the Observation Range, or centered on the date:

$$1800 + (1971 - 1800)/2 = 1885, \qquad (8)$$

and the loss rate distribution should follow a binomial (normal) distribution. The actual distribution of the loss rate data does just that, and data for *the entire Observation Range* is shown in Figure 3, including the 95% confidence bounds.
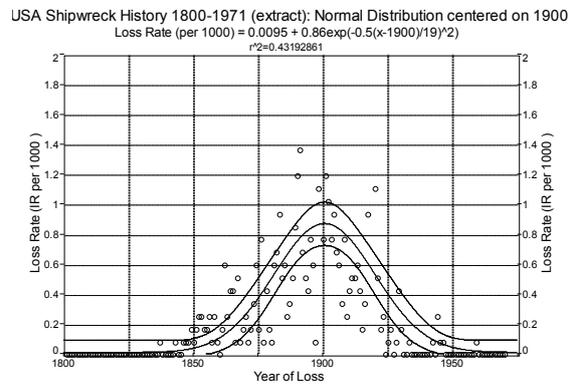

Figure 3. Loss rate fitted with a normal distribution.

The fitted loss rate distribution actually centers on 1900, and is given by:

$$IR(per\ kSy)=0.0095+0.86\ exp\ 0.5((Y-1900)/19)^2 \qquad (9)$$

where 1 kSy = 1000 Sy.

Since the data have a normal distribution, the outcomes are indeed randomly distributed throughout the entire 1800-1971 Range. The standard deviation of 19 Sy and the 95% confidence limits do actually encompass the predicted date of 1885, within the errors of the data sampling and fitting. The most probable loss (outcome) rate is ~ 0.86 per 1000 Sy, which is close to that observed today (~1per kSy) by major loss insurers. The most probable rate has not changed for over 200 years, and the range at 95% confidence is 0.7 – 1 per kSy.

As to the systematic effects of ship-age, it has been characteristic practice to have higher insurance for older ships, implying there risk of loss is greater, and that the outcomes (vessel sinkings, groundings, collisions, etc.) are not random. Older vessels are then *classified* as higher or greater risk. The actual data are shown in Figure 4 for losses in excess of 500 tonnes for two outcome sets spread over two centuries. Clearly, there is little difference between them; and the outcomes are almost normally distributed over the life of the ships with about 40-50 years maximum. The maximum loss fraction peak is at about 15-20 years of ship-life.
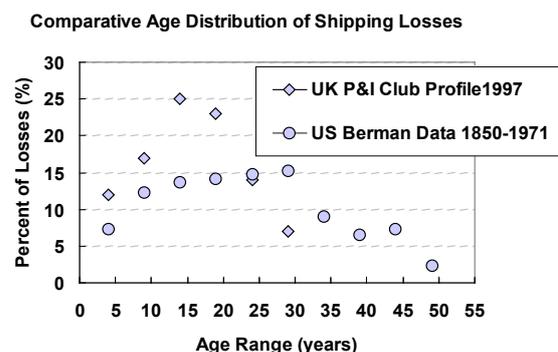

Figure 4. Comparison of shop losses as a function of age.

Now in terms of the influence of accumulated experience, we may plot the loss rate per ship-year versus the accumulated experience in accSy as shown in Figure 5.
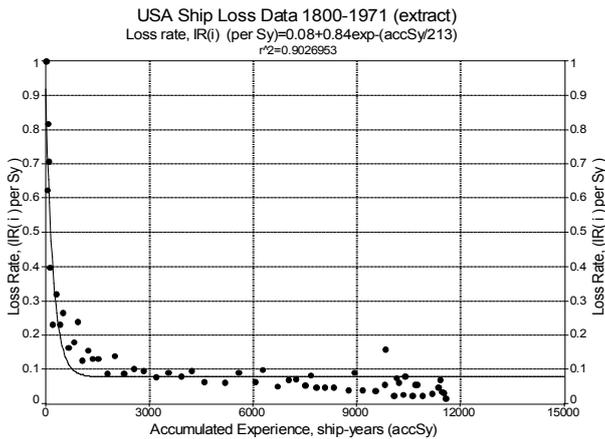

Figure 5. The learning curve for shipping.

The loss rate as a function of the accumulated experience in accSy is then given by a best-fit line of the exponential form derived for the distribution of the total number of microstates:

$$A \approx A_m + A_o\, e^{-\varepsilon/k} \qquad (10)$$

or

$$A \text{ (losses per Sy)} = 0.08 + 0.84\, \exp{-(accSy/213)} \quad (11)$$

This result implies an initial loss rate many times higher than the equilibrium value, and a minimum rate of ~ 0.08 per Sy for those that sank. This is of course telling us that on average the ships that sank lasted for a depth of experience afloat of about (1/0.08) or ~13 Sy, starting off lasting some 10 times less (~1 Sy). It does *not* tell us how long the average ship lasted, including those that were not lost, and indeed this is irrelevant for the moment. We just want to predict the relation between sinking rates and ship lifetimes. On an accumulated rate basis the predicted loss rate is now ~1 per 1000 Sy, illustrating the importance of the data sample size Observation Range for apparently random events.

Thus we have confirmed the postulates that:

– a systematic learning curve exists superimposed on the apparently random losses which we observe as outcomes;
– a relevant measure for accumulated experience and depth of experience can be found (in this case years-afloat); and
– a minimum asymptotic rate does exist, and is derivable from the learning curve.

4 OIL SPILLS AT SEA: TRACKING LEARNING TRENDS

We have provided an initial analysis of importance to the safety and environmental impact of the oil storage and transportation industry, using publically available USA data on oil spills, shipping losses and pipeline accidents, not having access to the oil and gas industry's privately held spill database (Duffey et al 2004).

Spills and accidents can arise in many ways e.g.:

– while filling;
– in storage;
– during transport;
– at process and transfer facilities; plus
– failure of vessels and pipelines.

We would expect significant human involvement in the design, management and operation of all these technological activities, in the piping, pumping, tanks, valves and operations. For handling and storage of (petro) chemicals, the risk of a spill or a loss is also dependent on the human error rate in the transport or storage mode and the accumulated experience with the transport or storage system.
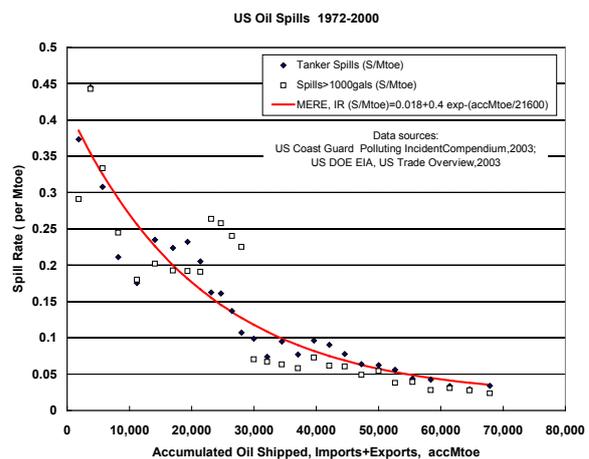

Figure 6. The oil spill learning curve

The US Coast Guard database for oil spills was the most comprehensive we found, but is given in the usual annual format of tables. For shipping spills, in the oil spill database for the observation interval from 1973 to 2000, we found information for 231,000 spill events for the USA, while transporting a total of oil of nearly 68 Btoe, of which 8,700 events were spills of more than 1000 gallons. Assuming there is pressure from the EPA, industry, owners and others to reduce spills rates, then there is a nominally large HTS learning opportunity. We can easily extract the number of spills from such tables and transform it to an experience basis (Duffey & Saull 2008), replacing the list of numbers of outcomes on a purely calendar year reporting basis. The measure for the accumulated experience we took was the total amount of oil being shipped in and out of the USA, which is not given in or by the USGS raw datatables. The US DOE track the oil consumption information and where it comes from for purely

energy analysis purposes. The datatables for crude oil and petroleum products were given in the DOE Petroleum Overview, for 1949-2001, and the details of the calculations we have given elsewhere (Duffey & Saull 2008 in Chapter 8).

The summary result is shown in Figure 6, and follow a clear learning curve, which is also shown fitted to the data.

5 INSURING MODERN LOSSES: THE MOST PROBABLE AND MINIMUM ERROR RATE

Now having established the learning curves and loss rates from historical data, we have also confirmed the results by testing the analysis against other data for modern fleets, where losses for all ships over 500 tonnes were tracked. These include data for modern vessels (Institute of London Underwriters 1988) for losses greater than 500 tonnes for 1972-1998, and for the latest (UK Protection and Indemnity Mutual Insurance Club 2000) Major Claims data from 1976-1999.

In these modern datasets, we also know how many ships were afloat, but the years afloat for each ship were not known (the converse to the Berman dataset). The Observation Ranges were smaller (~ 25 years), but covered the world-wide total losses which are comparable in number.

The data is shown in Figure 7, where we have the loss rate for the ILU dataset for 1972-1998 world-wide is given by, for some 30,000 ships afloat in any Sy, accumulating nearly a million Sy in total, and some 3,000 outcomes (losses) over the 26 year Range:

$$A \approx A_m + A_o\, e^{-\varepsilon/k} \tag{12}$$

or,

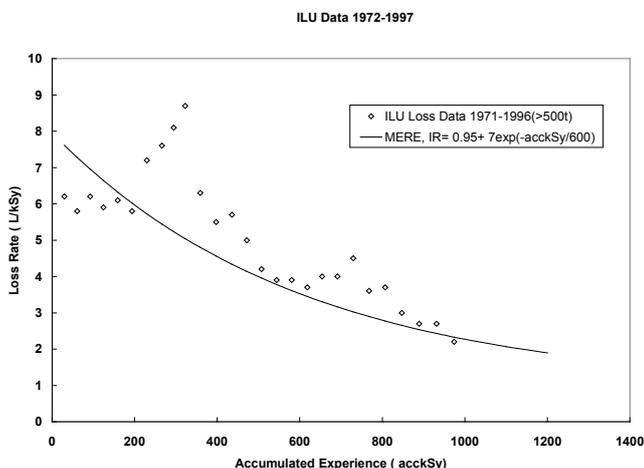$$A \text{ (losses per kSy)} = 0.95 + 7 \exp\text{-}(acckSy/600) \tag{13}$$

Figure 7. Modern Ship Losses

This result shows an asymptotic or minimum loss rate of ~ 0.95 per kS/y for losses > 500 tonnes in 1972-1998 (despite observing nearly 2 /kSy now). We have a similar estimate for the Major Loss data, that is greatest in terms of financial cost, which shows a loss rate of ~1 /kSy (Pomeroy 2001), which is a value consistent with the above analyses.

This lowest predicted minimum rate of ~ 0.95 /kSy is consistent with the most probable rate independently derived from the data for losses only (i.e., 0.86 ± 0.1 per kSy) for 1800-1971. Since the two datasets do not overlap, meeting in 1970, and one is for losses only in the USA and one is for all ships afloat world-wide, we have shown that:

- the minimum error rate predicted for modern ships is close or equivalent to the most probable loss rate for the last 200 years, which if correct also confirms the postulate of the most probable distribution used in deriving the microstates distribution formula;
- the distribution of microstates (manifested as an outcome rate) is apparently independent of technology or date, and is due to the dominant contribution of the human element; and
- the learning curve approach is consistent with the statistical distribution of error states.

6 LEARNING RATES AND EXPERIENCE INTERVALS: THE UNIVERSAL LEARNING CURVE

The two datasets we have studied are at first sight quite distinct, even though both are observed and recorded only for losses greater than 500 tonnes. The observational intervals, the accumulated experience and the number of outcomes are drastically different.

One set (set A) is from 1800 to 1971, and gives a distribution of microstates for only losses for the USA with an experience base of about 10 kSy. The other (set B) extends that set A from 1971 to 1996, but is for the distribution of microstates for losses of all ships world-wide with an experience base of nearly 1000 kSy. Therefore, the depth of experience is quite different. The accumulated experience, $\Sigma n_i \varepsilon_i$, is then quite different for each set, by the same factor of 100. Above, we have shown the learning curve rate constants are also different, being ~ 200 Sy for set A, and ~ 600 kSy for set B, which is a factor of ~ 3000.

So, for these Ranges, the predicted "learning rate ratio" between experience intervals for the losses only in the USA and for the whole world fleet afloat is:

$$\beta_A\, \varepsilon_A,\, /\beta_B\, \varepsilon_B \sim 30 \tag{14}$$

Recall again that dataset A was for all ships afloat world-wide, while dataset B was just for those that

sank in the USA. The ratio above suggests that the experience interval ratio of the USA losses to the world fleet afloat is $(\varepsilon_A/\varepsilon_B) \sim 1/30$ (i.e., 3%), particularly if $\beta_A \sim \beta_B$.

To test that ratio prediction, recall also that for the ILU data in ~ 25 years we had 3000 losses of $\sim 30,000$ ships afloat at any time. That is a loss rate percentage for the whole fleet of order (3000/25) X (100/30000) = 0.4% world-wide. But only a fraction of the world fleet actually sailed and sank near the USA. To determine that fraction, we sought another random sample Observation Range of losses and found an excellent one in the "Atlas of Ship Wrecks and Treasure" (Pickford 1994). Now the Atlas lists about 184 ships sunk off the East, West and Caribbean coasts of the USA between 1540 and 1956 out of a listed sample world-wide of 1400 losses. That is only a fraction of (184/1400) x 100 = 13% of the world's ship losses were in the waters off the USA. We assume that fraction holds for the much later ILU dataset, which was for all ships > 500 tons.

So if just 13% of the ships world-wide sank off the coasts of USA, and only 0.4% of the fleet sank in total around the world, we would have 0.4%/0.13 $\sim$ 3% as the experience interval ratio of only the USA losses to the total world total fleet afloat. Therefore, we have near perfect agreement versus the predicted ratio from the theory of 3% (or a factor of 30).

Given the uncertainties in the calculations, and the vast differences in the datasets, this degree of agreement with the prediction seems almost seems fortuitous and better than might be expected. But the comparison does confirm the general approach and indicate how to compare datasets that possess very different experience bases.

Let us try to test another prediction: if the theory, postulates and analogies are correct the two datasets should both follow the trend predicted by the ULC. We can directly compare the two learning rates for set (A) and set (B) with their very different experience bases by using the non-dimensional formulation of the ULC for correlating data, i.e.,

$$E^* = \exp\text{-}KN^* \quad (15)$$

We correct the learning rate constant for the USA losses only for the ratio of ~ 30 derived above. The actual learning curves give all the needed estimates from the data for A_0 and A_m, which is sufficient to calculate E^* for each microstate. We also have the total experience, ε, necessary to derive the non-dimensional value of N^*. Strictly speaking N^* should be taken as the ratio of experience, ε, to the experience, ε_M, needed or observed to reach the minimum error rate, λ_m, or at least the maximum experience already achieved with the system.

The comparisons of the ULCs suggested by the theory are shown in Figure 8. We have also shown the best-fit correlation to world data, i.e., with K $\sim$ 3,
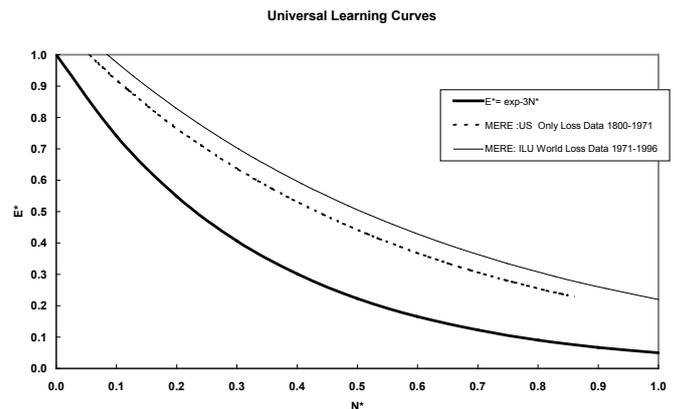
$$E^* = \exp\text{-}3N^* \quad (16)$$

Figure 8. Comparison of trends with the ULC

The value of K $\sim$ 3 was derived from analyzing vast datasets covering millions of error states that included amongst other things (Duffey & Saull 2002, see Figure 1.7 in Chapter 1): USA data for deaths in recreational boating 1960-1998; automobile crashes 1966-1998; railway accidents 1975-1999; coal mining for 1938-1998; plus South African gold and coal mining injuries 1969-1999; UK cardiac surgeries 1984-1999; US oil spills 1969-2001; French latent error data 1998-1999; US commercial aircraft near misses 1987-1997; and also world pulmonary deaths for 1840-1970.

The two other lines, for the US (Berman) losses only and ILU world shipping datasets, are given by the MERE predictions calculated from:

$$E^* = \exp\text{-}KN^* = \exp\text{ - }((1 - A/A_m)/(1-A_0/A_m)) \quad (17)$$

whence

$$A = A_m + (A_o - A_m)e^{-\varepsilon/k} \quad (18)$$

and the values for k, A_m and A_0 are derived directly from those given by the theory and the data. The 213 Sy in the exponent is adjusted for the observational experience interval ratio and becomes k = 213 x 30 = 6390 Sy = 6.4 kSy.

Hence, the only adjustment we have made or needed was to correct the learning rate constant for the differing depths of experience. We justify the factor of ~ 30 simply to bring the experience interval for the losses in the US only data consistently into line with the world experience interval. The remaining differences between the predictions are well within the overall data scatter.

This method thus allows apparently quite disparate datasets to be renormalized and intercompared. The universal learning trends are essentially the

same, and we have validated the overall theoretically predicted trend.

Thus, we have succeeded in not only getting the two very different datasets on the same plot, but in obtaining agreement with the world trend derived from a wide range of totally independent data. Using the non-dimensional variables derived from theory, we have shown that the trends are correct. This agreement is despite the numerical changes being very large, by a factor of ~ 100 in the learning rate ratio and a factor of 1000 in the accumulated experience, as we have discussed above.

7 PRACTICAL APPLICATION: PREDICTING LOSSES AND MANAGING RISK

Data are essential to measuring performance. Note that the shipping error/loss rate is not affected by the massive technology changes in shipping (from sail to steam, from wood to steel) occurring over the last two hundred years. Losses are dominated by human (crew) performance. The overall loss rate (~ one per thousand ship years afloat) enables the prediction of loss probability, which affects both insurance costs and classification. In addition, the learning curve provides the probability of operational error, which is a function of the shipping maneuver or course transient. In principle, the analysis then provides the likelihood of collision, grounding or near misses.

As for other industries and technologies, it would be useful and necessary to have further data maritime continuously collected on actual events, and to develop nautical performance indicators, that can be updated continually for loss and risk assessment purposes. Such an activity is underway for offshore oil and gas fields in the North Sea for both mobile and fixed facilities (Duffey & Skjerve 2008). Such objective measures and indicators enable the presence or absence of learning trends to be discerned, enhancing the management of risk exposure and prediction of losses, and hence would help guide improvements in maritime training, safety and loss control.

8 CONCLUSIONS

We have described a general and consistent theoretical model, however simplified it may be, which describes the rate of outcomes (losses) based on the classic concept of learning from experience. The approach is quantifiable and testable versus the existing data and potentially able to make predictions.

We reconcile the apparently random occurrence of outcomes (accidents and errors) with the observed systematic trend from having a learning environment. We can now explain and predict outcomes, like ship losses, collisions and sinkings, and their apparently random occurrences because the human element component is persistent and large.

We infer that *risk reduction (learning) is proportional to the rate of errors being made, which is derived from the total number of distributions of errors.* We have validated the new theory, and in this paper summarize the use of marine loss and oil spill data as a working example. We analyzed shipping losses over the last two hundred years, which are an example of one such system and a rich data source because insurers and mariners tracked sinkings. Human error is and was the pervasive and main cause of ship loss, rather than structural defects in the ships themselves. The validation results support the basic postulates, and confirm the macroscopic ULC behavior observed for technological systems.

Our new theory offers the prediction and the promise of determining and quantifying the influence of management, regulatory, liability, insurance, legal and other decisions.

REFERENCES

Berman, B.D. 1972. Encyclopaedia of American Shipwrecks, Boston, Mariners Press.

Duffey, R.B. and Saull, J.W. 2002. Know the Risk, First Edition, Boston, Butterworth and Heinemann.

Duffey, R.B., Saull, J.W. and Myers, P. 2004 Learning from Experience: Application to the Analysis of Pipeline and Storage Tank Safety Data and Potential Spill Reduction, Presentation given at National Institute for Storage Tank Management's 7th Annual International Conference in Orlando, Florida, May 12-14.

Duffey, R.B. and Saull, J.W. 2008. *Managing Risk: The Human Element,* West Sussex, UK, John Wiley & Sons Ltd.

Duffey, R.B and Skjerve, A.B., 2008, Risk Trends, Indicators and Learning Rates: A New Case Study of North Sea Oil and Gas, Proceedings ESREL 2008, 17th SRA Conference, Valencia, Spain.

Institute of London Underwriters (ILU) 1988 et seq. Hull Casualty Statistics, data for 1987-1997, International Union of Marine Insurance Conferences (see also http://www.iua.co.uk).

Pickford, N. 1994. The Atlas of Ship Wrecks & Treasure, New York, Dorling Kindersheg Publishing.

Pomeroy, V. 2001. Classification – Adapting and Evolving to Meet Challenges in the New Safety Culture, Safety of Modern Technical Systems, TUV, Saarland Foundation, Germany, p. 281.

UK Protection and Indemnity Mutual Insurance Club 2000. Analysis of Major Claims, London (see http://www.ukpandi.com).