

Predicting and Managing Failures :

Societal and Personal

Risk Perception

ICONE 19

Osaka, Japan

Romney B. Duffey

DSM Associates

October 2011

duffeyrb@gmail.com

(208) 360 5218

Fukushima and Macondo are parallel happenings in two major energy industries with similar themes and consequences

Character: extreme events with large public reaction

Risk and Impacts: all underestimated beforehand

Perceived: major disasters harming environment

Consequence: massive damage to reputation and companies

Reaction: new safety requirements and inspections

Enhanced: emergency preparedness

Implications : widespread

We need to be able to explain data, improve safety, reduce risk and make predictions

Some simple questions to pose and try to answer:

- What is the risk of a major accident ?
 - When technology or designs change how does safety change?
 - What do the past events imply?
 - How can predictions be made ?
 - What risks are tolerable or acceptable?
 - How are these risks to be managed ?
 - How safe are the operating crews?
 - What is a cost effective improvement?
 - What about unknowns?
 - What is the present knowledge?
 - What if anything should be done differently in the future?
 - How can or should the industry operate?
 -
-

Fundamental idea and postulate

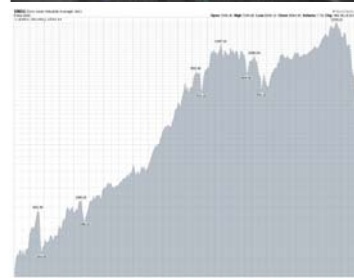
- Risk is caused by uncertainty, and the measure of uncertainty is probability
 - Modern systems and structural failures do not just involve mechanics, components and statistics
 - All modern systems include *people* whose contribution *dominates*, thus making failures *complex*, while barriers will be penetrated
 - To understand and predict failures it is essential to include people: their actions, mistakes, skills, decisions, responses, learning and motivation
 - Therefore, we must explicitly include learned behavior(s) with increasing experience and risk exposure
 - Based on systems outcome data, we developed a unifying *emergent* theory of learning thus avoiding excessive complication
 - Treat all outcomes as occurring with some uncertainty (probability) and hence predictability
 - Also treat rare events, “fat tails” and unknowns as a minimum attainable
 - Aim is to predict and hence manage future risk and their consequences
-

Managing Risk:

Elements of a General Emergent Theory

- All failures include the human contribution, and we all (systems and individuals) follow a learning curve
 - “Rare” events occur or re-occur on average at about the same maximum interval achieved by all other modern systems (universality of failure)
 - It is all about predicting probability, where the “Fat Tail” is due to the human contribution
 - Failure predictions, including rare or unknown events, can be described with the same methods and measures used for all existing and known homo-technological systems
 - With future (increasing) risk exposure/experience, extrapolations of standard statistical, “power laws” and Pareto distributions will grossly under predict risk (missing unknowns, black swans and the risk plateau)
 - The relevant risk exposure and experience measures must be chosen to provide relative predictions of risk (uncertainty) , failure and learning tren
-

What about catastrophic failures: Random? Human? Tolerable? Avoidable? Predictable?



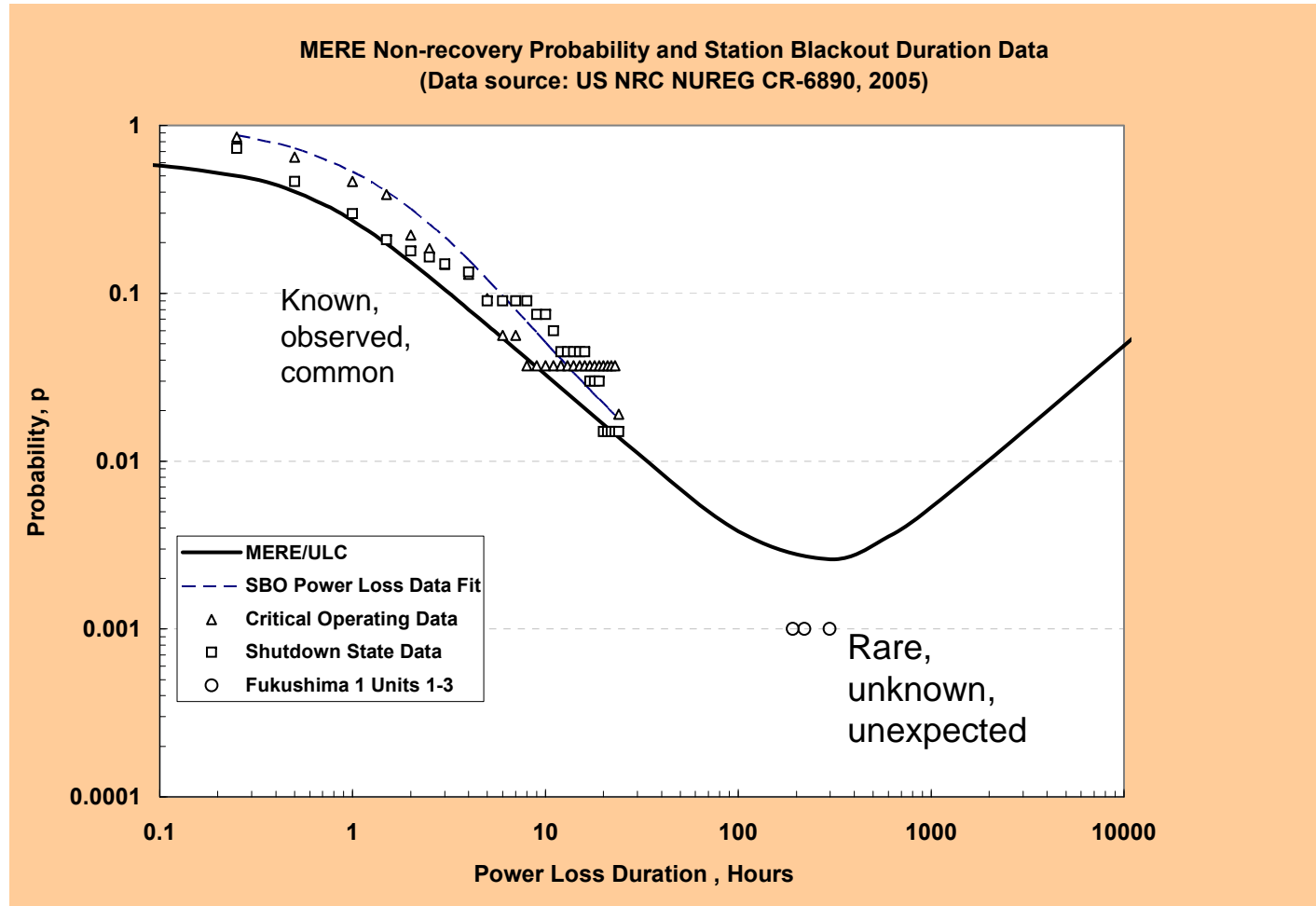
What do such unexpected failures all have in common -apart from costing billions?

All failures include the *inseparable* human element- we design systems to assumed failure modes, safety margins and accident scenarios, with added safety precautions , and then operate them until some unforeseen failure occurs- why are we then surprised?

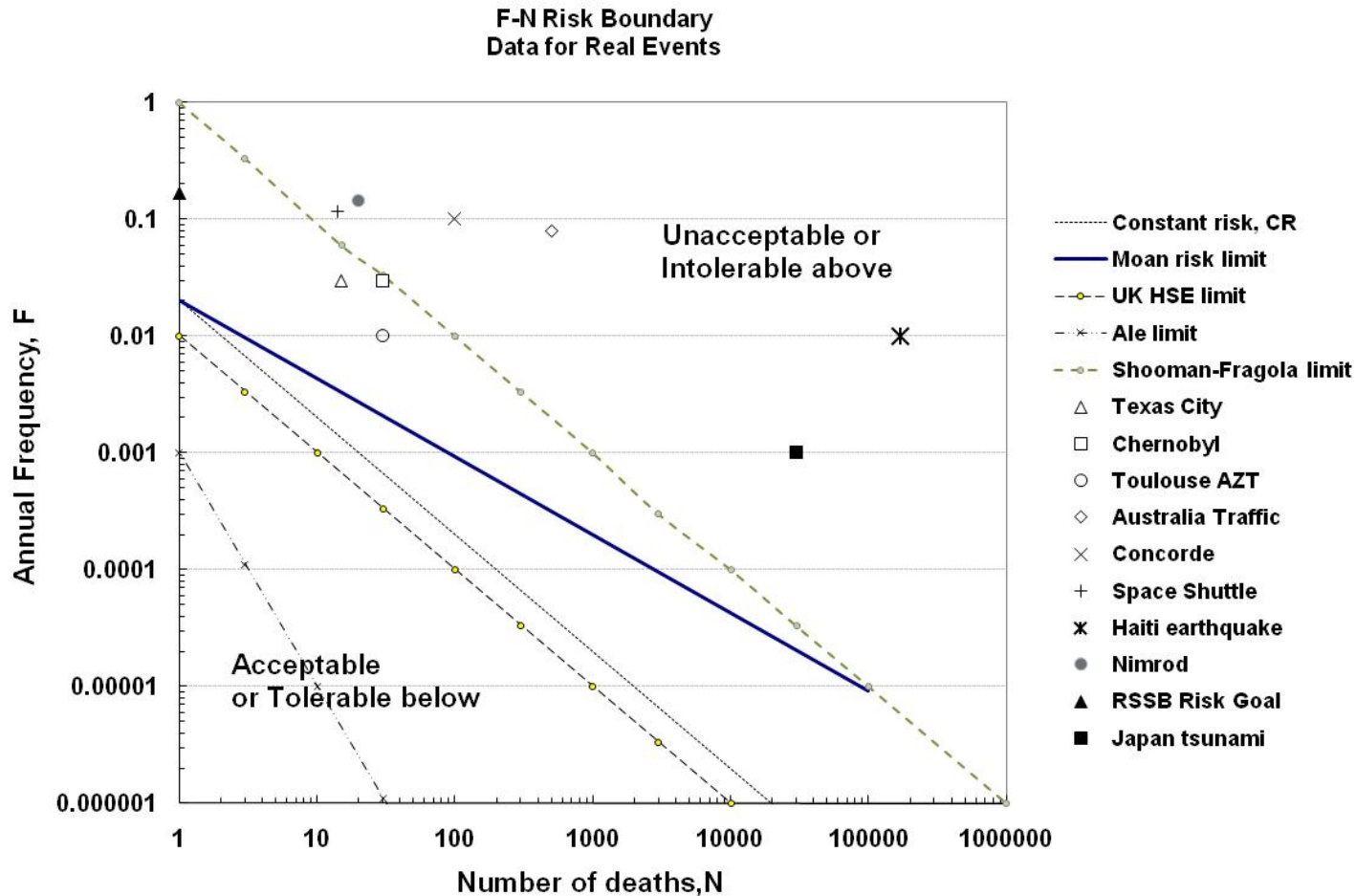
The black balls are observed *outcomes* – what can we learn from the rare and the unexpected?

Risk is measured by our *uncertainty* - the measure of uncertainty is probability

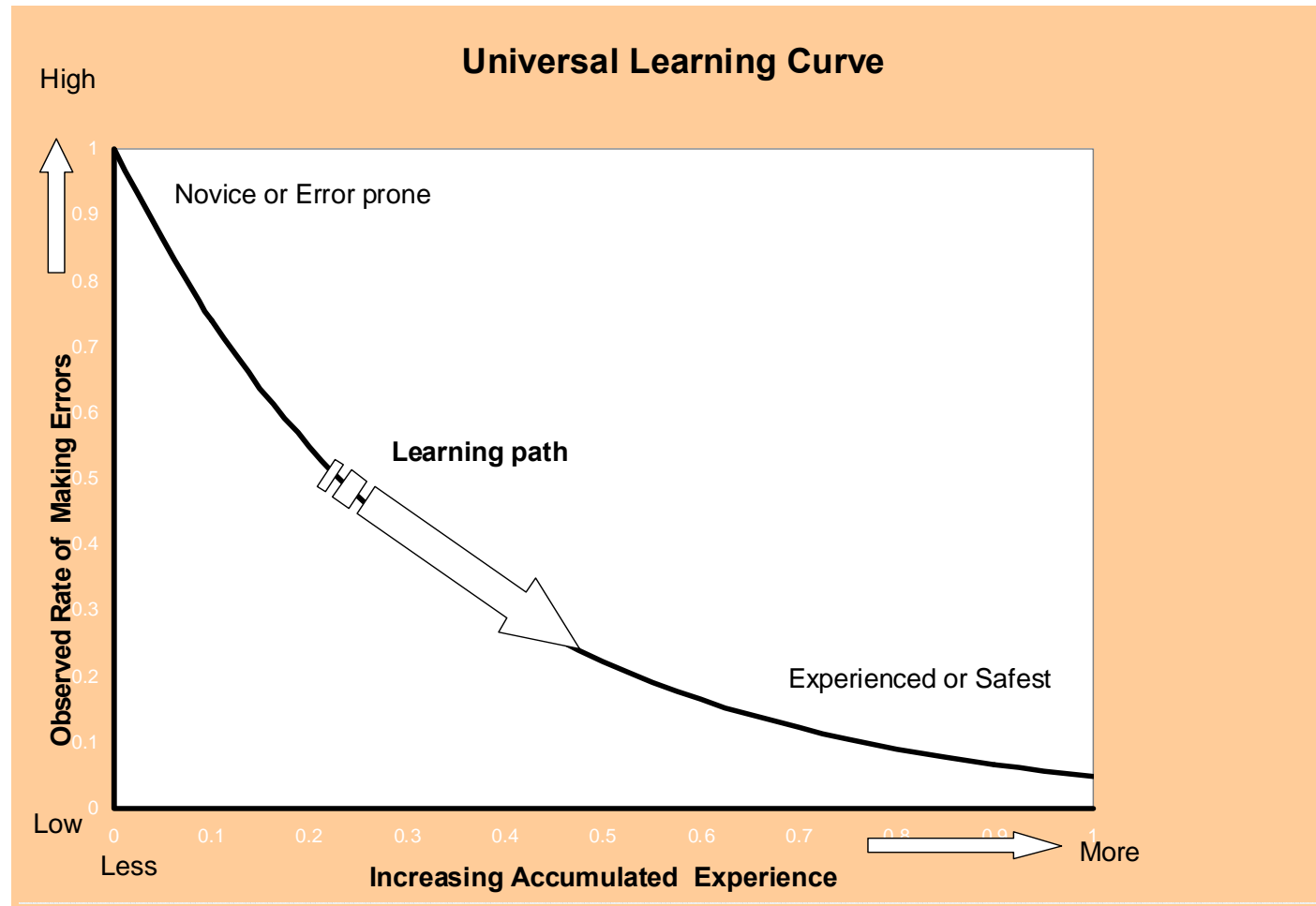
Example for nuclear plant power restoration



Are there “Tolerable Risk” Boundaries ?



We learn from our mistakes as we acquire experience: so we should descend the learning curve



Unknown

Known

The Learning Hypothesis

Human learn from their mistakes, continually correcting errors and their mental “rules” based on experience, as an inseparable part of the total system.

The rate of decrease of the rate of outcomes with experience or risk exposure is taken as proportional to the rate so,

$$\frac{d\lambda(\tau)}{d\tau} \propto \lambda(\tau)$$

With always a finite minimum rate, and a learning constant, k ,

$$\frac{d\lambda(\tau)}{d\tau} = -k (\lambda(\tau) - \lambda_m)$$

Integrating gives the solution to the Minimum Error Rate Equation as a rate that decreases exponentially as,

$$\lambda(\tau) = \lambda_m + (\lambda_0 - \lambda_m)e^{-k\tau}$$

The Paradoxes of Learning Lessons

- Paradox 1**

Without having the events we want to avoid - we cannot learn

- Paradox 2**

All events are preventable - but only afterwards

- Paradox 3**

All events are acceptable to society - until they actually occur

- Paradox 4**

Rare events do not allow prior learning - so surprise us all

Corollary

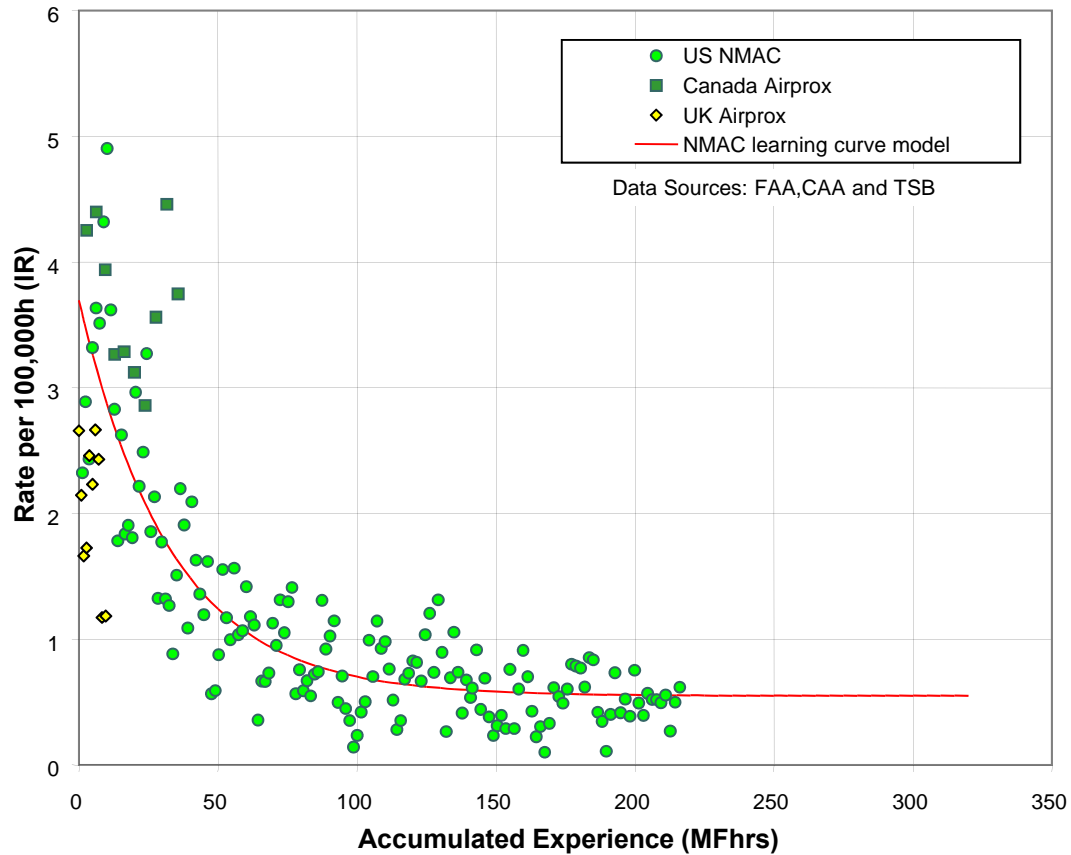
Systems and societies “behave” and reflect the humans learning, rule revising and error correcting within them - but regrettably having no “perfect learning” affects risk perception

Predicting failure: measure for experience and risk exposure varies with the system

| System/ Technology | Experience or Risk Exposure | Outcomes |
|---|---|--|
| Commercial Aircraft | Flight hours | Fatal crashes and Near Misses |
| Offshore Oil Rigs | Production amounts | Spills, fires and explosions |
| Power Grids | Outage duration | Probability and time of non- recovery |
| Rocket Launches | Launch count X Burn time | Launch failure |
| Software/ Procedures | Testing number or time | Faults and errors |
| Manufacturing and Market Share | Production or sales quantity | Product cost or price reduction |

Commercial Aircraft Near Miss Rates

Reported Near Miss Rates
(US 1987-1998 Canada 1989-1998 UK 1990-1999)

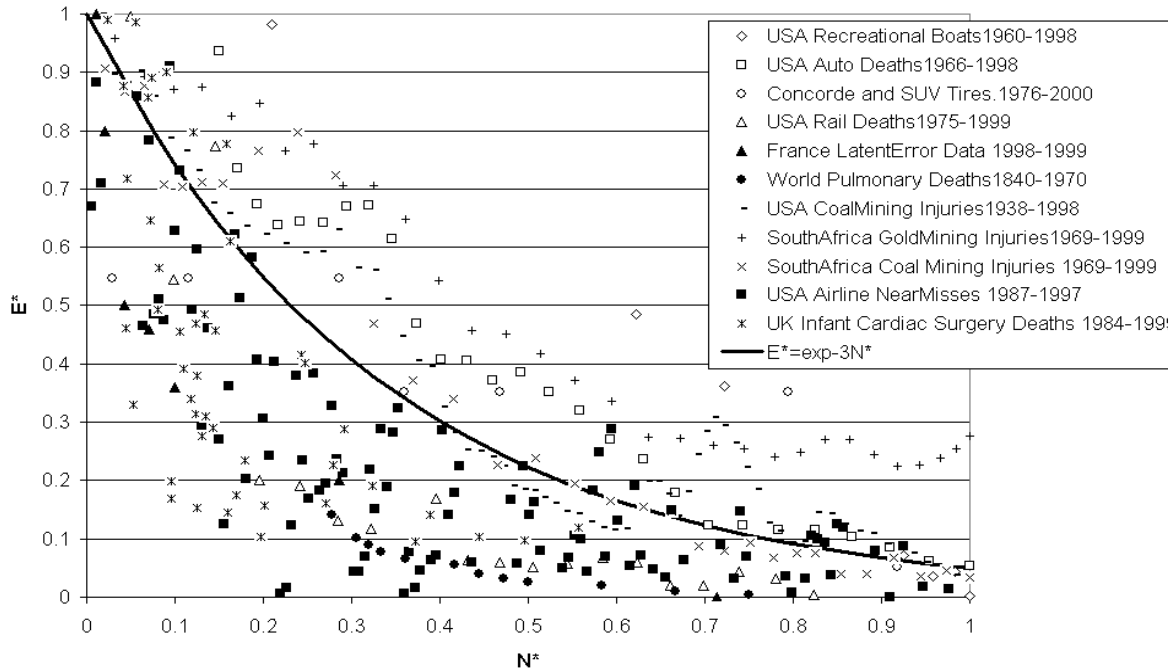


1 per 200,000h

Learning Curve that the Data Show

$$E^* = \exp(-3N^*)$$

Universal Non-Dimensional Learning Curve:
Theoretical Best Fit to Worldwide Error Rates



See paper and references for details and list of systems studied

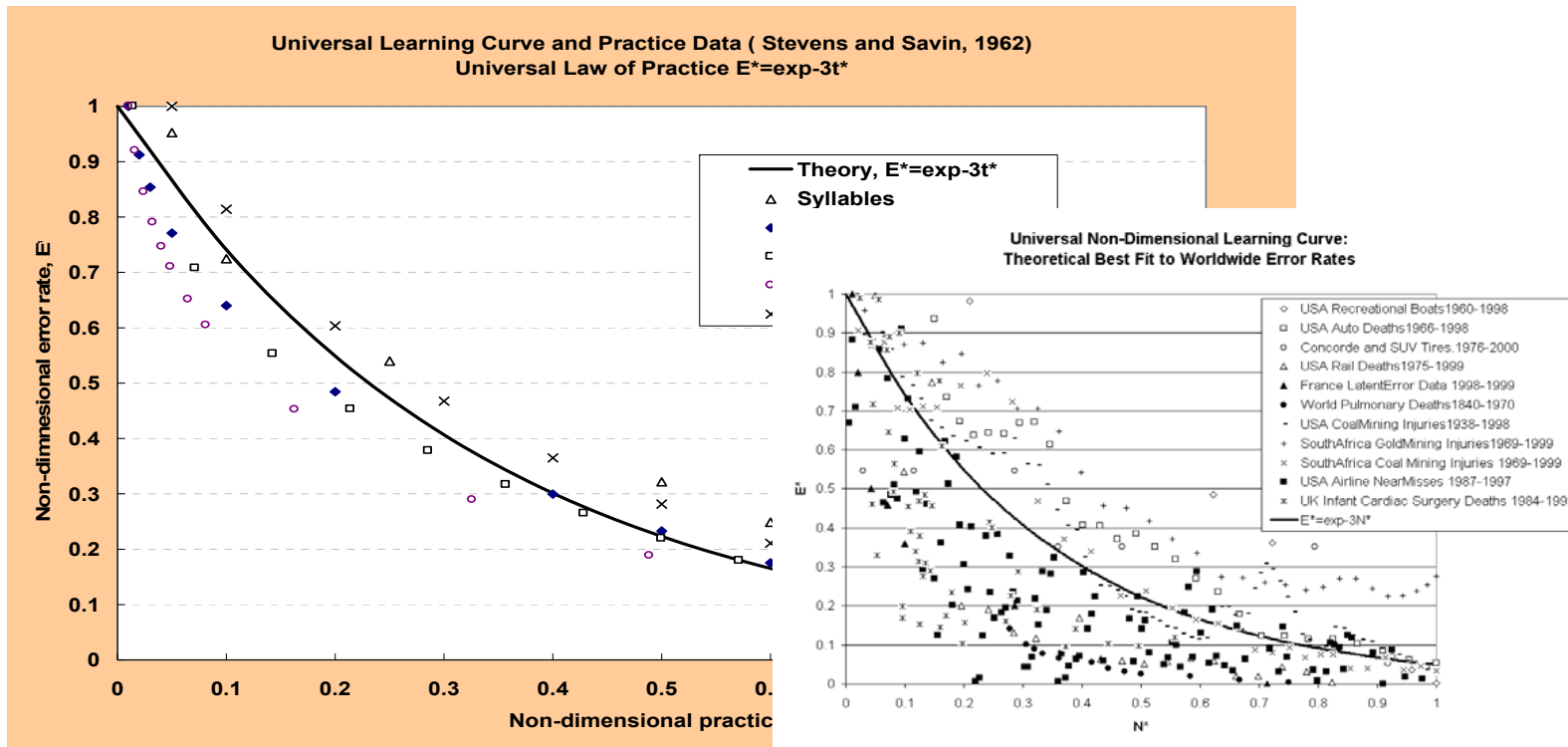
Need surrogate for experience and risk measure

Reflects what we know about our risk exposure and learning

Identical to Laws of Practice, so systems reflect people within them

Validation Comparison: ULC = ULP

Universal Law Equivalence: $E^* = \exp-kt^*$



Therefore, Practice = Experience, and repeated trials, $t \equiv \epsilon$

Hence, external system outcomes reflect individual learning

Best learning constant, $k \sim 3$

Learning from experience: knowing the failure rate, the prior probability of failure uses standard reliability definitions

The *outcome probability* is just the cumulative distribution function, CDF, conventionally written as $F(\tau)$, the fraction that fails by τ , so:

$$p(\tau) \equiv F(\tau) = 1 - \exp - \int \lambda d\tau$$

where the failure rate $\lambda(\tau) = h(\tau) = f(\tau)/R(\tau) = \{1/(1-F)\}dF/d\tau$, where $f(\tau) = dF/d\tau$.

Carrying out the integration from an initial experience, ε_0 , to any interval, ε , we obtain the probability of an outcome as the *double exponential*:

$$p(\tau) = 1 - \exp \{(\lambda_0 - \lambda_m)/k - \lambda_m \tau\}$$

where, from the minimum error rate equation (the MERE), the failure rate is

$$\lambda(\tau) = \lambda_m + (\lambda_0 - \lambda_m) \exp - k\tau$$

Now λ_m is the lowest achievable rate, and $\lambda(\tau_0) = \lambda_0$ at the initial experience, ε_0 , accumulated up to or at the initial outcome(s), and

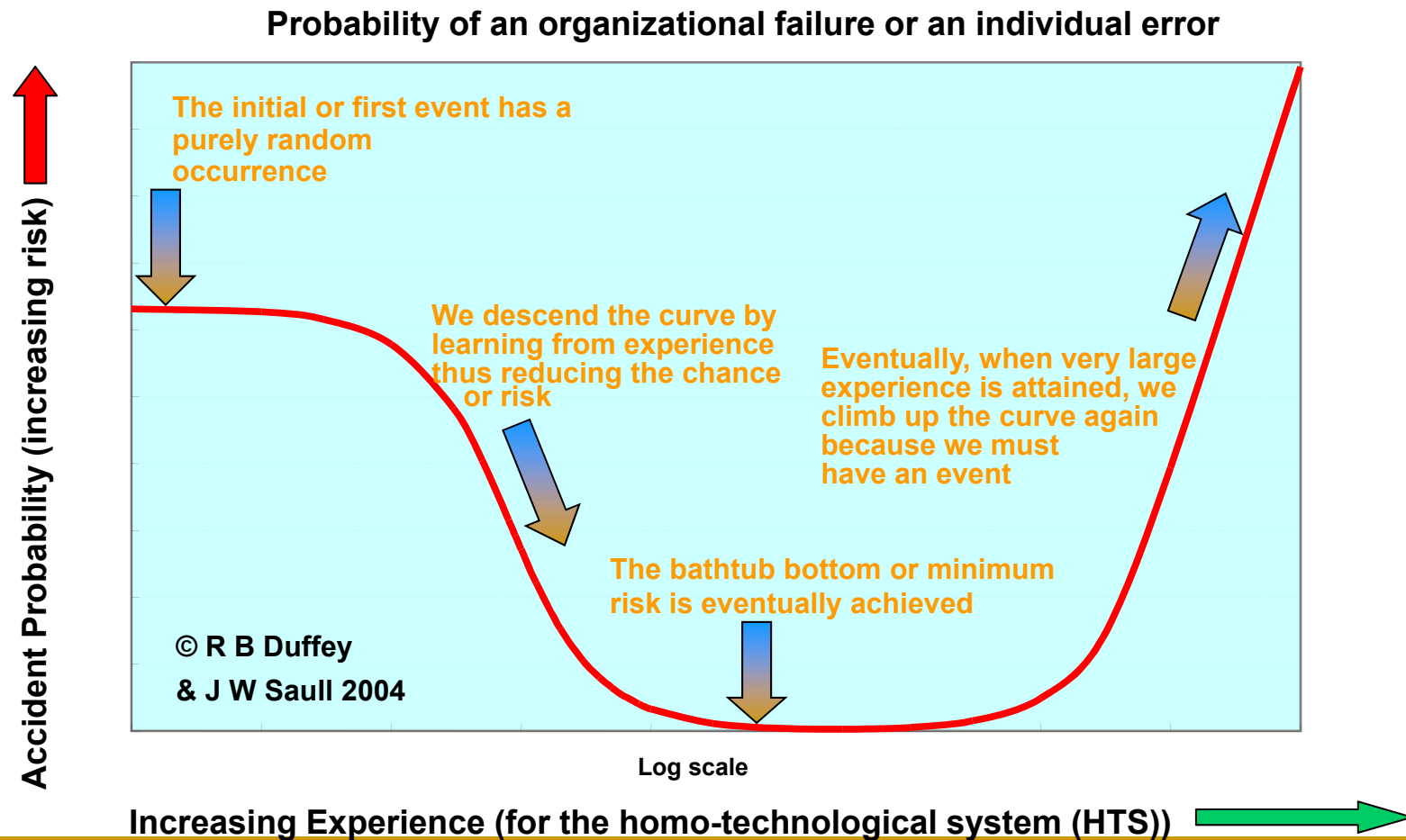
$\lambda_0 = 1/\tau$ for the very first, *rare* or initial outcome, like an inverse “power law”.

In the usual engineering reliability terminology, for n failures out of N total:

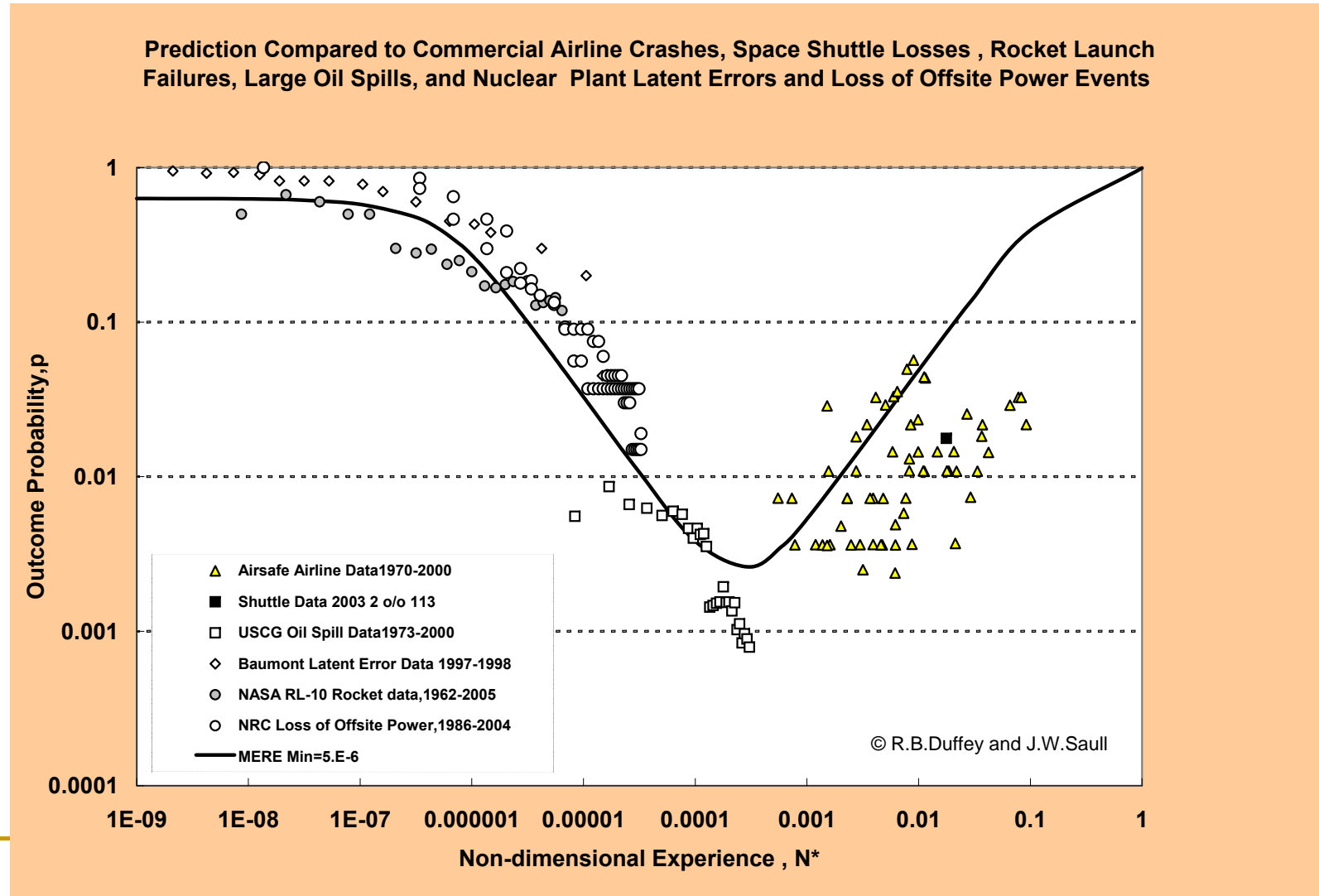
Failure probability, $p(\tau) = (1 - R(\tau)) = \# \text{ failures}/\text{total number} = n/N$, and the frequency is known if n and N are known (and generally N is not known).

The prior learning Human Bathtub

$$p(\tau) = 1 - \exp \left\{ (\lambda - \lambda_m) / k - \lambda_m (\tau - \tau_0) \right\}$$



The data that society has acquired slowly fills the bath tub....



Challenge: Predicting failures with little or no data

Now as experience is gained and learning occurs, the failure rate falls to the minimum achievable, λ_m , and eventually we reach a lifetime probability or service lifetime as the risk exposure measure, $\tau \rightarrow T$.

For illustrative convenience, we take the maximum lifetime, T , as corresponding to an equal 50:50 chance of the certainty of failure or survival. This *half lifetime* is given when $p(T) \sim 0.5$, or

$$p(T) = 1 - \exp - \lambda_m T ,$$

The equal chance of failure or survival then occurs when $\exp - \lambda_m T = 0.5$, or $\lambda_m T = - \ln 0.5 = 0.693$, or at a service half- life or accumulated risk exposure of

$$T \sim 0.69 / \lambda_m$$

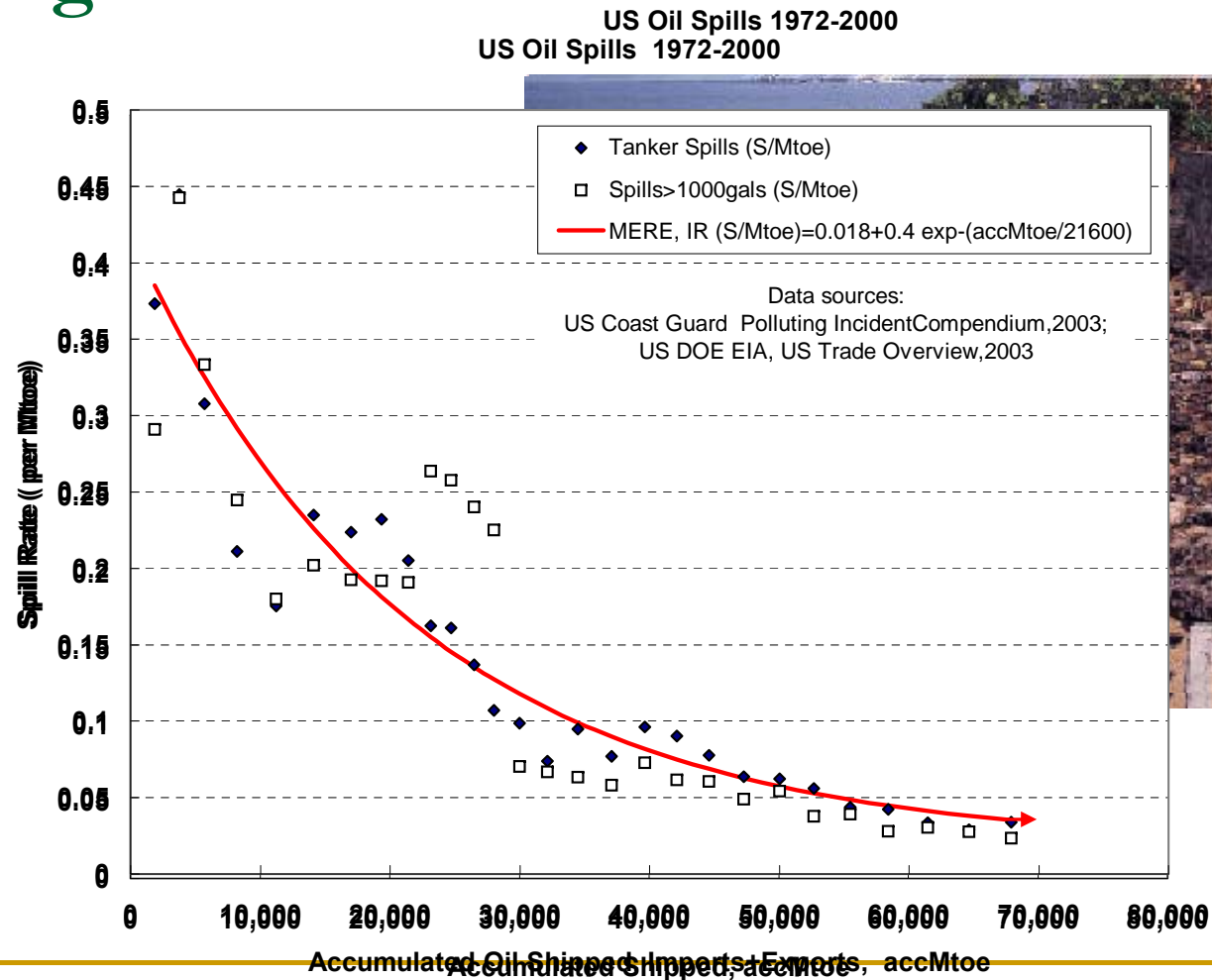
The maximum half lifetime, T , or “likely service life” before failure, is therefore expressed as proportional to the inverse of the minimum attainable failure rate per past unit experience.

So all we have to do is provide a lower bound estimate for the failure rate, λ_m , and if and as additional failure data are gathered, the known achievable or attainable failure rate can always be updated to reflect this additional experience and/or risk exposure.

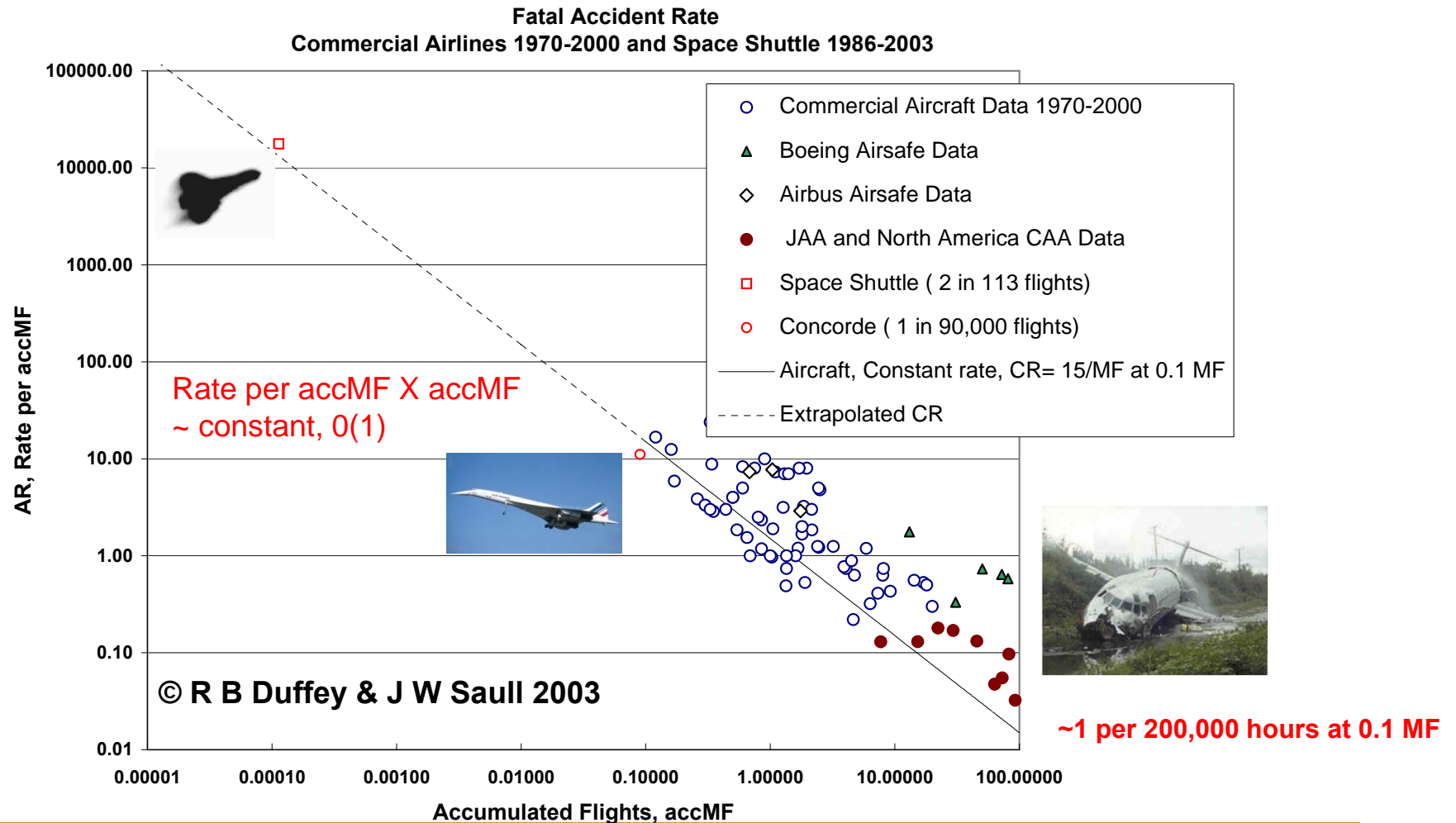
To determine the minimum failure rate, λ_m , we can adopt the classical approach of using data from analogous systems with human involvement.

Because of the common and dominant human contribution, the failure rate of modern systems is *inherently* applicable to other similar systems, and can be used as a basis for prediction based on what we already know..

As we exploit the technology we make mistakes from which we learn: Oil spills at sea follow a learning curve

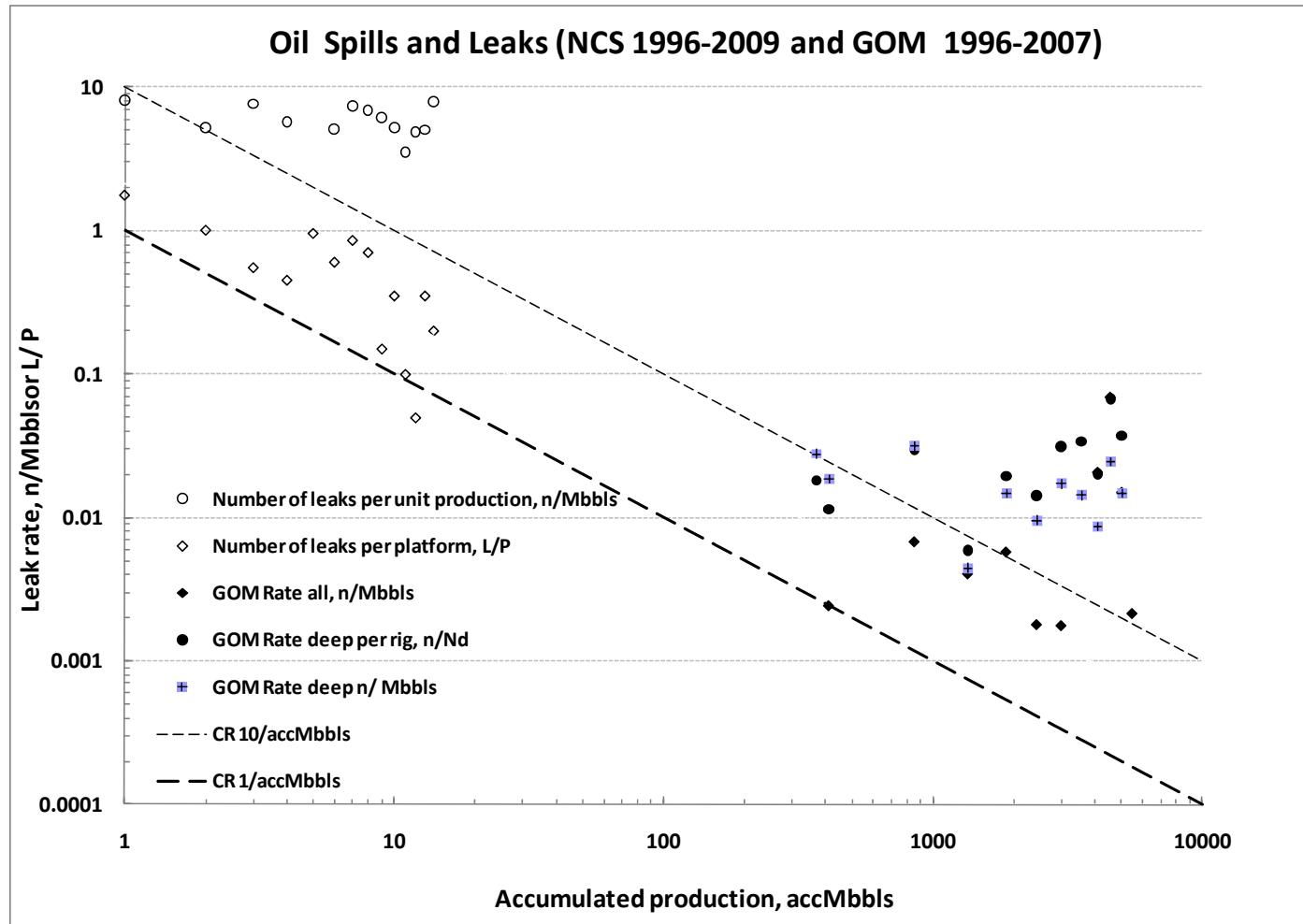


Failure rate for “rare events”: $\lambda(0) = n/\varepsilon$, where $n \sim 1$

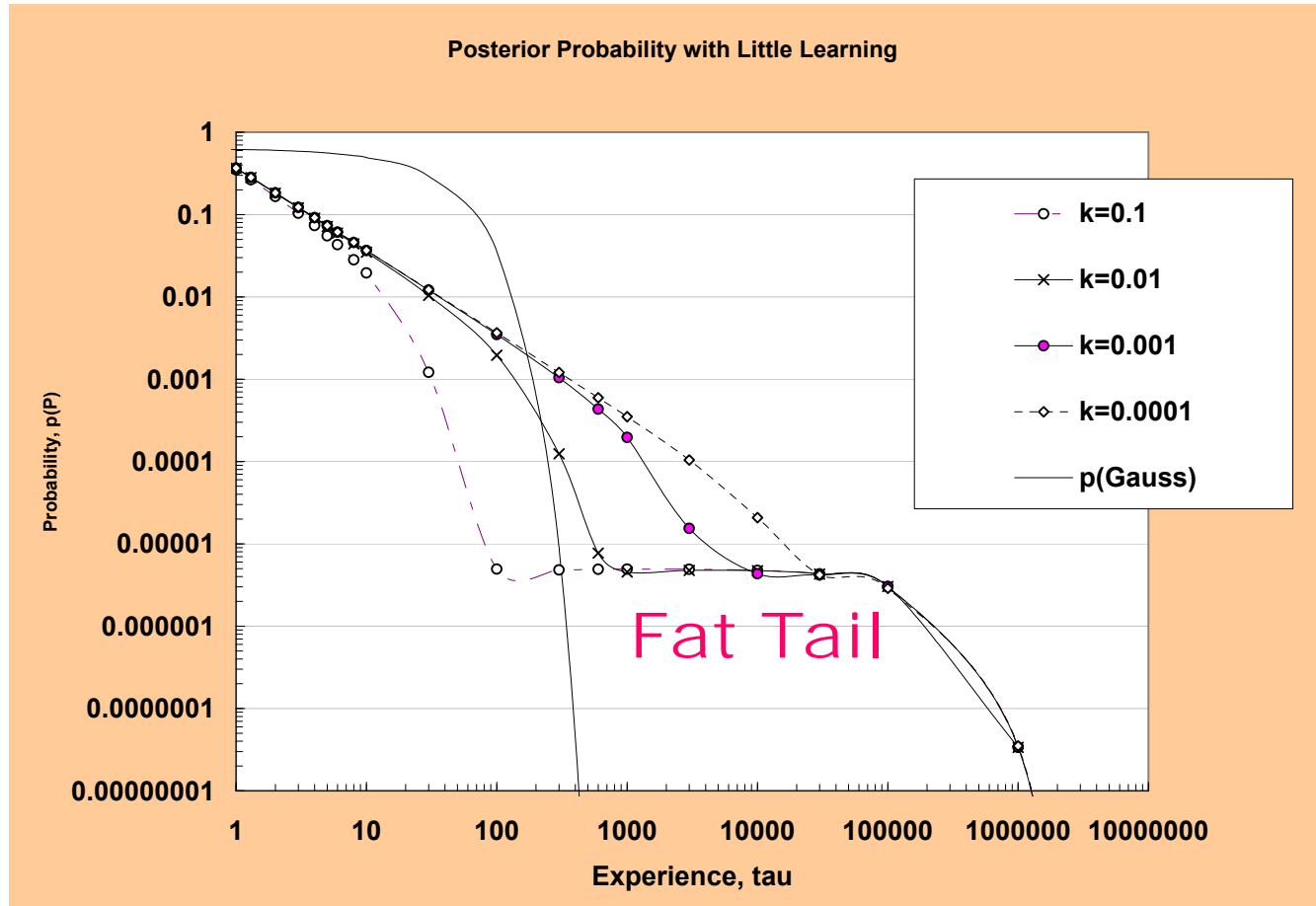


“Best” or lowest minimum rate ~ 0.000005 per risk exposure or experience-hour

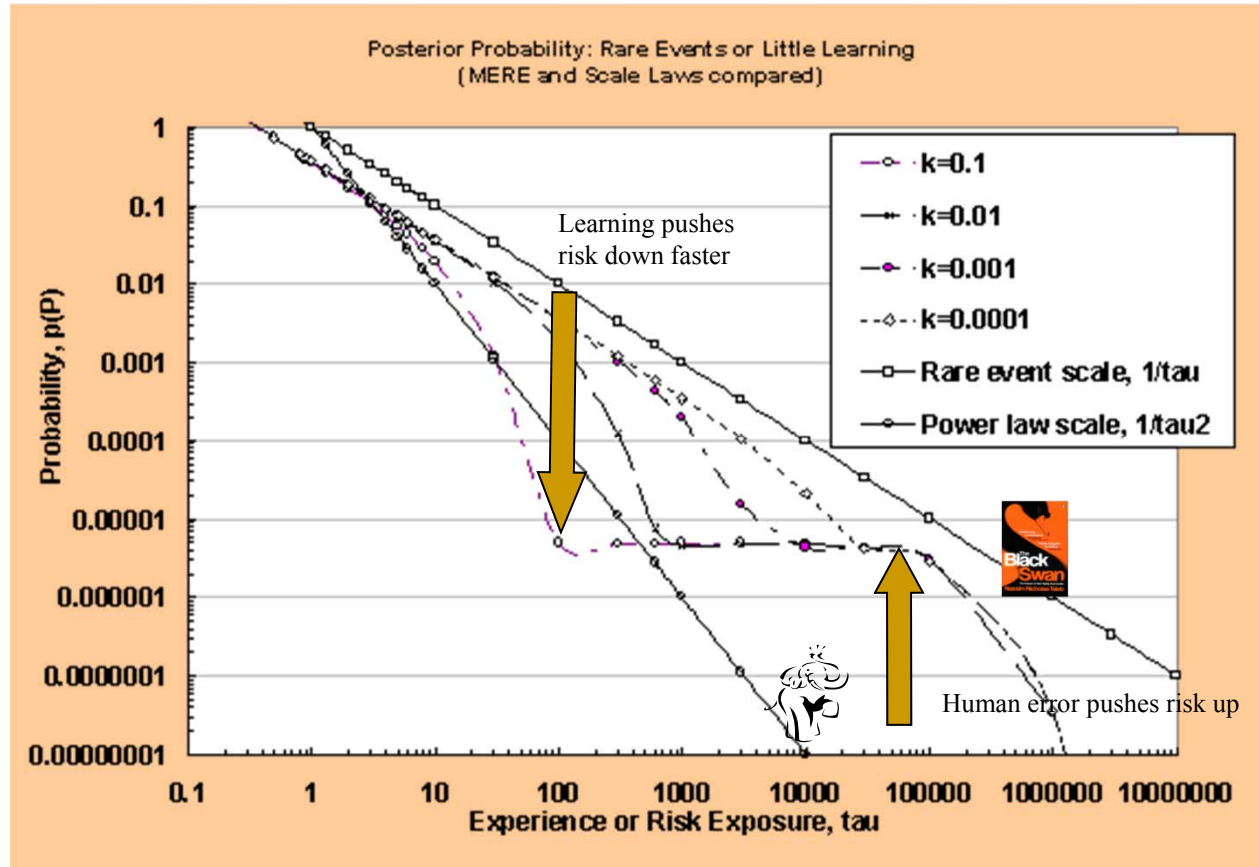
Offshore rigs large leak rate data



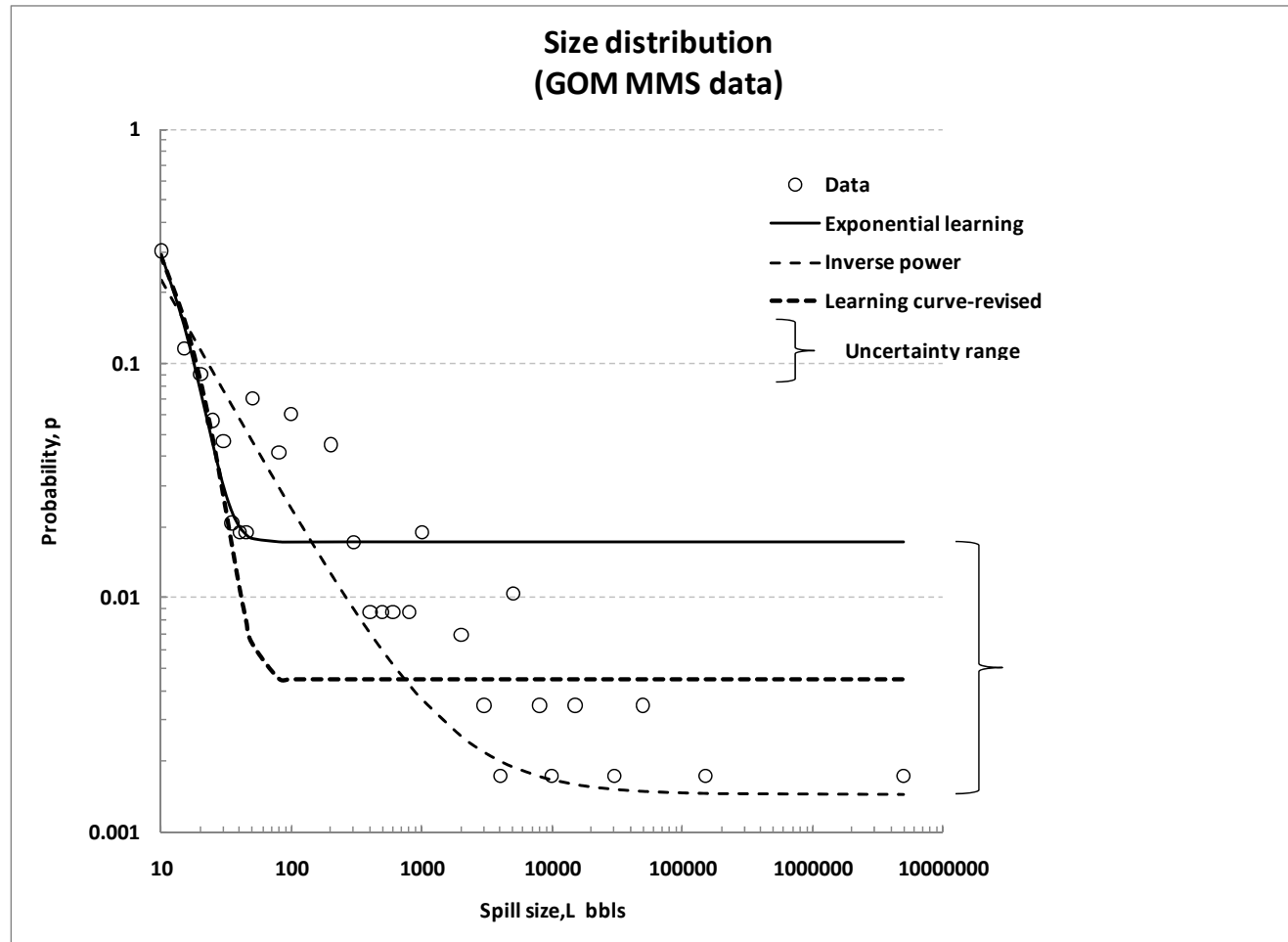
Well known failure of standard distributions to predict the “fat tail”, “black swan” or “rare event”



Future posterior failure probability: learning, not learning, extrapolating Pareto



Deepwater Horizon: Leak or spill probability distribution

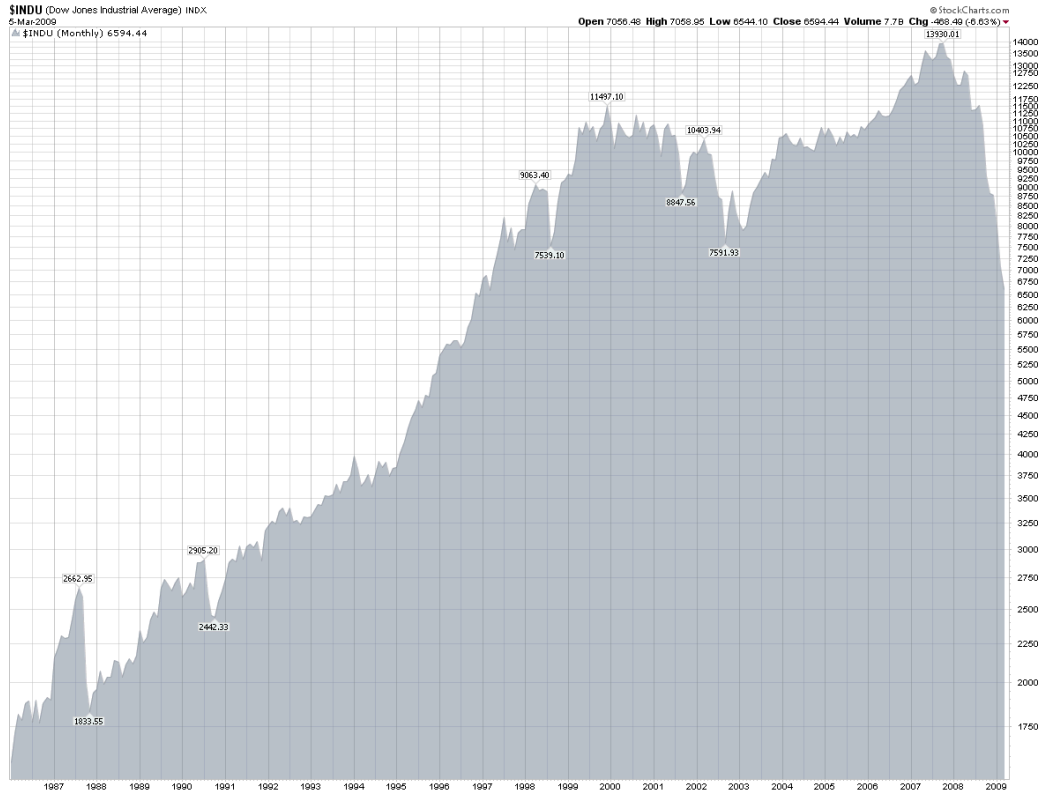


Key Properties of the Information Entropy

$$(H_j = - \sum p_i \ln p_i)$$

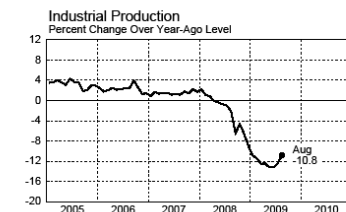
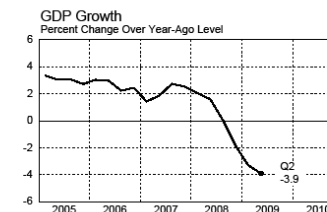
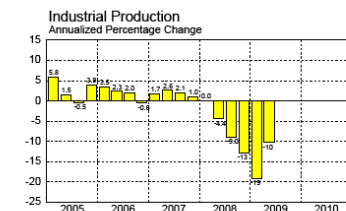
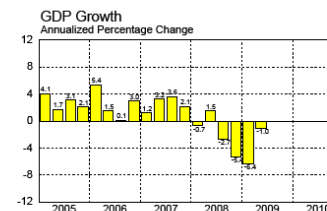
- Fundamental measure of uncertainty and order
 - Enables randomness to be quantified
 - Randomness and fluctuations are essential for order (learning patterns) to emerge – without disorder there is no order
 - Links individual decision making, skill acquisition and learning (ULP) to system outcome “learning curves” (ULC)
 - Provides one objective measure for safety “culture”, and “organizational learning” and/or “resilience”
 - Not easy concept both for many scientists and the public
-

Same impacts of human involvement : Can we predict financial system crises?



**Soros' Principle of Human Fallibility;
Inadequate knowledge of complex systems
Human decisions and risk taking = unexpected results**

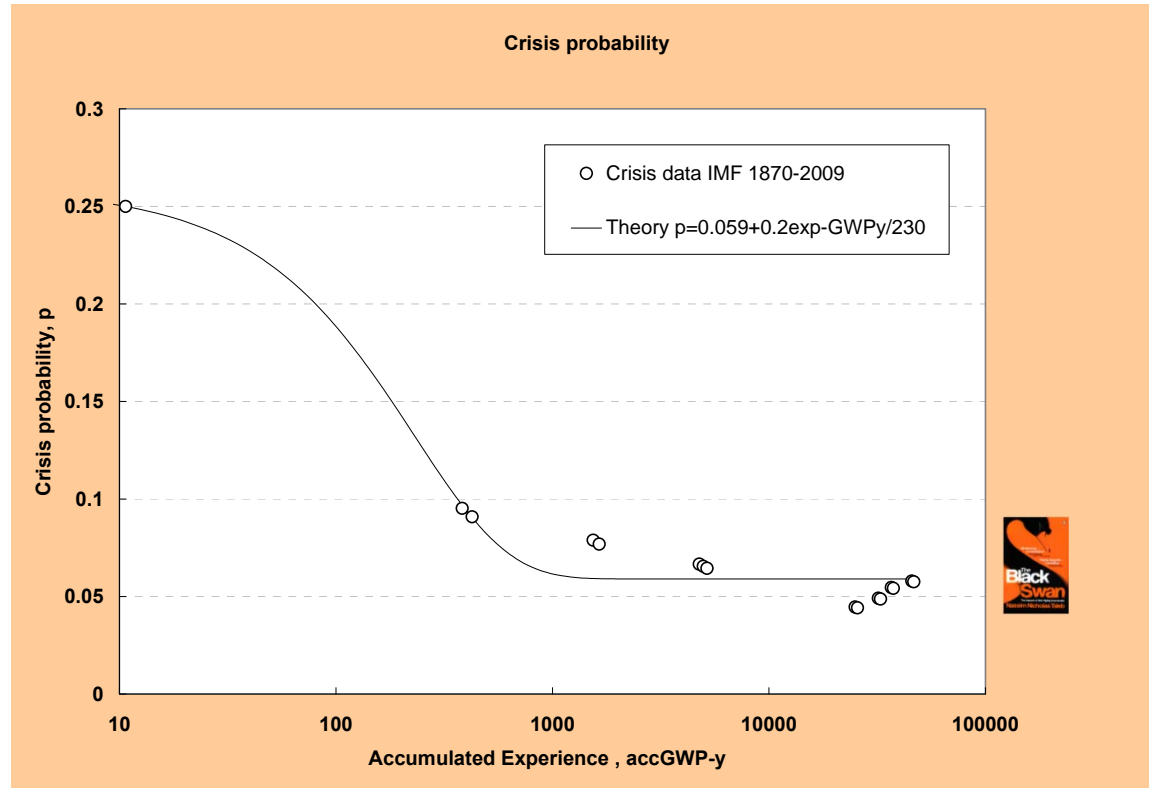
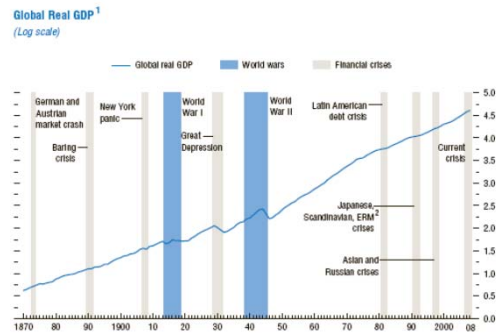
UNITED STATES Output Indicators



Source: Haver

September 18, 2009

Crisis probability as function of global risk exposure



Recall: *average rate is the same as for all other systems*

(one in ~100,000 to 200,000 experience/risk exposure hours)

Planning Technology Advances: or What we know and don't know about Knowns and Unknowns

- *Romney B. Duffey, B.Sc., Ph.D.*
 - March, 2007
-

Unknowns have value too.....

Donald Rumsfeld:

“As we know, there are known knowns.

There are things we know we know.

We also know there are known unknowns.

That is to say we know there are some things we do not know.

But there are also unknown unknowns, the ones we don't know we don't know.”

12 February, 2003



He did not know, but it is just the same problem as
research results....

Perceptions of the Unknown



Nuclear Energy - The Past and Present Unknowns

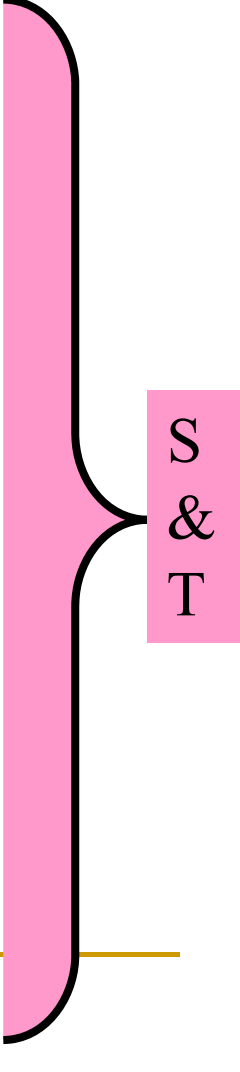
Known Knowns,_m Known Unknowns,_n

| | |
|---|--|
| Theoretical accidents (LOCA....) | Real accidents (Chernobyl, TMI...) |
| Corrosion/erosion | Feeder thinning Davis- Besse vessel |
| Rising GHG emissions | Post-Kyoto plans |
| Refurbished plants | Changing operation |
| Nuclear output | Policy shifts |
| Nuclear “renaissance” | Nuclear reality |
| R&D funding | R&D results |

Nuclear Energy - Some Future Unknowns

Unknown Knowns, M Unknown Unknowns, N

| | |
|---------------------------------------|--|
| New builds | New sites Where ? When? |
| Another BIG accident | Who? What then? |
| New R&D advances | New technology Which? Cost ? Results? |
| Advanced Gen IV plants | How many What? When? |
| Greater efficiency, lower cost | New turbines and cycles How ? |
| Carbon and waste constraints | New global fuel cycles Carbon "price" |
| Changing regulations | Brunel's response Fear and regret.....??? |



S
&
T

Entropy is a subtle concept that *quantifies* uncertainty and complexity: Measures information on what we know about what we do not know, as we learn and are risk exposed in real life

- **“I am purposely avoiding the notion of entropy because the way it is conventionally phrased makes it ill-adapted to the type of randomness we experience in real life”**

Nassim Taleb: “The Black Swan” - notes

- **“Entropy is defined as the amount of information about a system that is still unknown after one has made....measurements on the system”**

Stephen Wolfram (inventor of Mathematica): “A New Kind of Science” p. 44

- **“The only function satisfying the conditions we have imposed on a reasonable measure of the ‘amount of uncertainty’ is $H = -\sum p \ln p$...This suggests that....entropy might have an important place in guiding the strategy of a business man or stock market investor”**

Edwin Jaynes: “Probability Theory” p. 350

- **“Entropy is a measure of the uncertainty and the uncertainty, or entropy, is taken as the measure of the amount of information conveyed by a message from a source”**

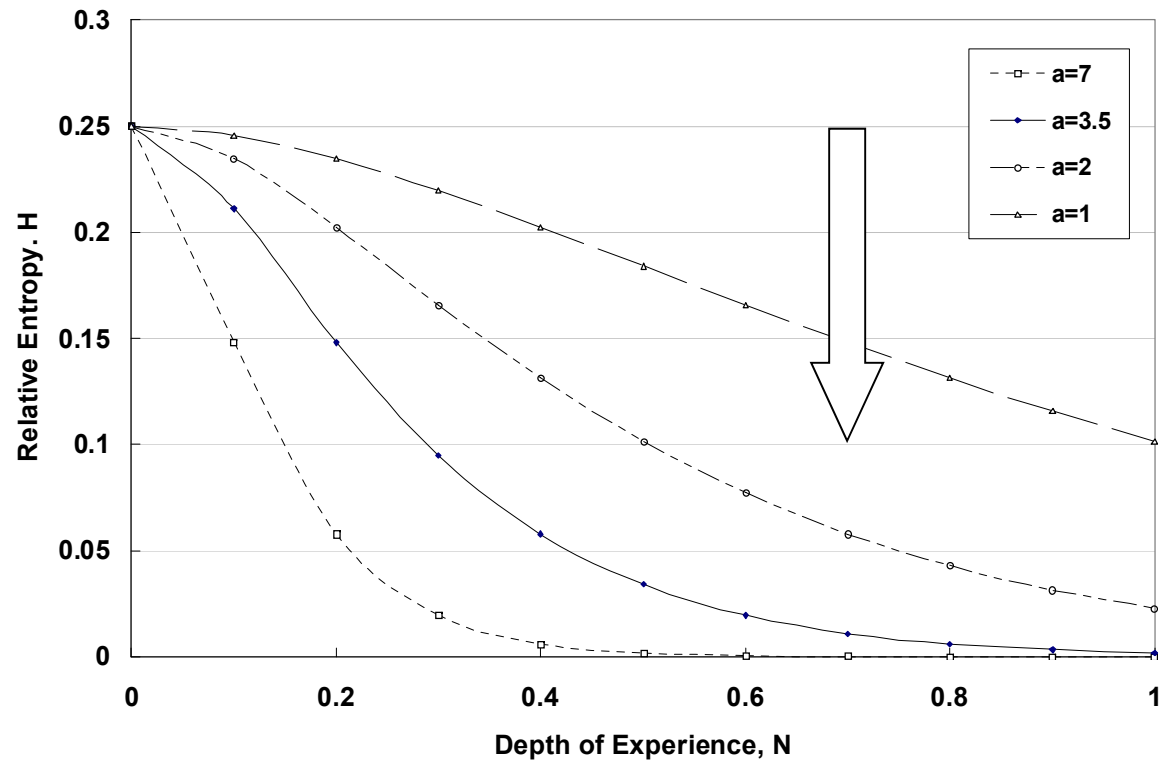
John Pierce: “An Introduction to Information Theory” p. 23

- **“The uncertainty function...a unique measure for the predictability (uncertainty) of a random event which also can be used to compare different kinds of random events”**

~~Walter Greiner, Ludwig Neise and Horst Stocker: “Thermodynamics & Statistical Mechanics”, p. 150~~

Organizational learning increased learning reduces the relative disorder

Information Entropy for Organizational Learning



Learning Lessons:

Reactivity and Cooling

•Chernobyl

Core disassembly by uncontained explosion and radioactive release due to operator error demonstrated need for containment, and of exclusion zone impacts...

Basic public fear was uncontained activity release from explosion due to excess reactivity

•Three Mile island

Core melt due to operator error demonstrated value of containment in limiting releases and the need for enhanced safety systems and training....

Basic public fear was activity release from containment venting after core melt

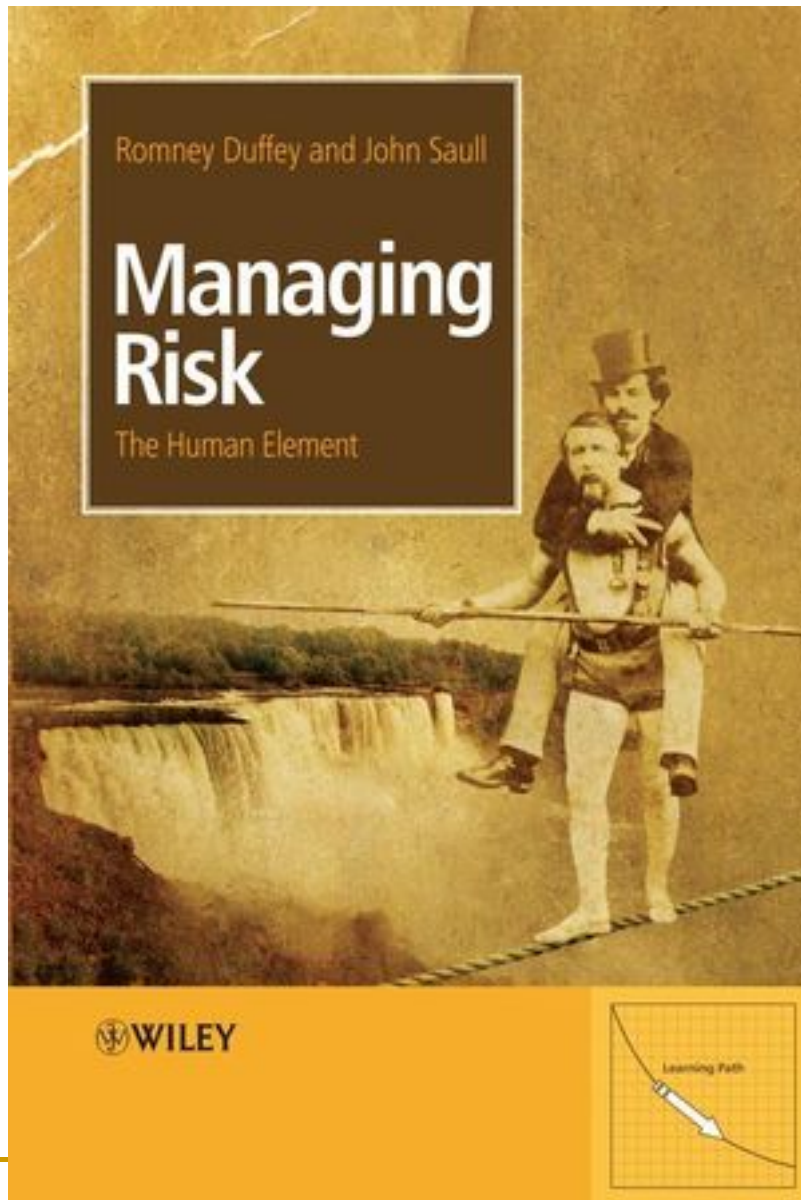
•Fukushima

Core damage due to unprecedented tsunami demonstrated need to cope with “extreme” conditions causing long term loss of total power, flooding damage and loss of active cooling...

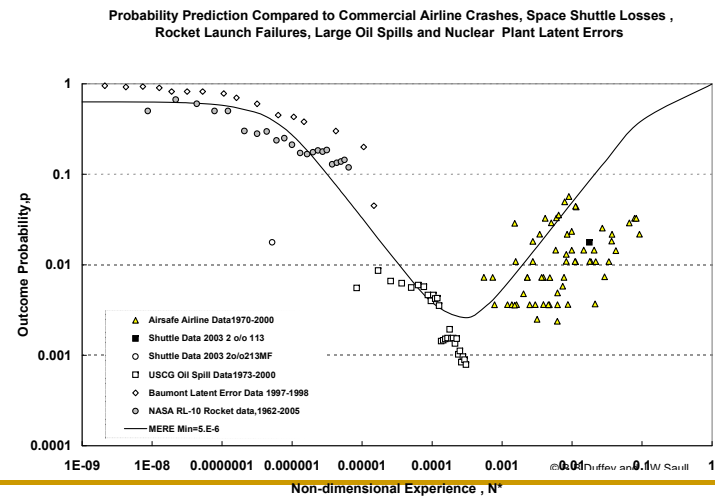
Basic public fear was unknown activity release from lack of long term heat removal

Nuclear Priorities...

- Understand and address the public's fear of radiation
- Reduce the threats and address the fears of nuclear proliferation and terrorism
- Preclude core melt
- Make once-used fuel an asset
- Increase efficiencies and improve economics of nuclear plants
- Make human error a negligible contribution to accidents



- Risk management
- Risk prediction
- Quantifying “safety culture”
- Risk perception
- Collective and individual learning
- Case studies – over twenty
- Latest work: Human error benchmark, power blackouts, financial stability, software reliability



It is not often that we have the opportunity to have an open global discussion about risk, technology development and human error

We are usually just too busy handling our everyday lives, our personal commitments and managing the daily business

But when BIG events happen there is a real opportunity to change behavior, understand mistakes and improve

Unfortunately, admitting mistakes and making change is hard ... personally, professionally , politically and socially

But how we are perceived and trusted is by our willingness to admit our errors and to change...

Change the ways we learn to behave, think, design, operate and respond

Concluding remarks: how to improve safety and risk assessment in the future, knowing what we have learnt from past events

- **Systems and structural failures include the human, so risk and safety predictions should include human error, decision making and learning effects, including management and corporate attitudes**
- **Risk and failure predictions can use the methods and measures used for all existing homo-technological systems**
- **With future (increasing) risk exposure/experience, extrapolations of standard statistical, “power laws” and Pareto distributions can under predict the key human contribution to the risk plateau (missing unknowns, “fat tails”, and black swans)**
- **The relevant risk exposure and experience measures must be chosen to provide absolute predictions of risk (uncertainty) , failure and learning trends**
- **Introducing new technology (automation, intelligent software, new materials..) and novel approaches (safety management , risk assessment, “smart” systems...) involves risk that must be measured.**
- **The fundamental issue then is how fast and well we learn from our experience.**
- **The safest industries have the toughest task**