PREDICTING RISK AND HUMAN RELIABILITY: A NEW APPROACH

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Abstract

Learning from experience describes human reliability and skill acquisition, and the resulting theory has been validated by comparison against millions of outcome data from multiple industries and technologies worldwide. The resulting predictions were used to benchmark the classic first generation human reliability methods adopted in probabilistic risk assessments. The learning rate, probabilities and response times are also consistent with the existing psychological models for human learning and error correction. The new approach also implies a finite lower bound probability that is not predicted by empirical statistical distributions that ignore the known and fundamental learning effects

1. Introduction

Risk and Safety are paramount considerations in nuclear technology, and is dominated by the human contribution. Therefore, we have successively introduced and developed a learning theory that naturally includes the human reliability due to individual decision-making and skill acquisition, and hence predicts the system outcomes due to the inevitable error rate, probability, safety culture, uncertainty risk and the associated learning curves as experience is gained. The learning hypothesis states that the rate of reduction of the error rate is proportional to that same rate.

This general theory provide simple model equations that agree with and has been benchmarked against the world's outcome data. Published validation results include literally millions of real accidents, events and outcomes observed in multiple diverse arenas throughout modern society using largely open source data [1, 2, 3]. These include:

a) Industrial outcomes: US (1938-1998) and South Africa (1996-1999) mining injuries and deaths, North Sea oil and gas injuries (1996-2005), and worldwide nitrate fertilizer plant explosions (1970-2005).

b) Transportation events: US airline near misses (1987-1997), railway derailments (1975-200) and deaths (1975-1999), auto deaths (1966-1998), recreational boating deaths (1968-1998), oil spills at sea (1973-2000), and UK shipping losses (1994-2000).

c) Medical systems: world pulmonary deaths (1860-1970), Canada cataract surgery errors (2001-2003), and UK infant cardiac surgery deaths (1984-1999).

d) Technological systems: France nuclear plant errors (1998-1999), US rocket launch failures (1962-2005), Japan nuclear plant shutdowns (1981-1996), North Sea Oil and Gas risk indicators (1996-2006), and US SUV tire failures (1976-2000).

e) Cognitive psychology: independently derived learning rates, laws of practice and response times (RTs), obtained from tens of thousands of test series on individual human subjects [3, 4, 5].

f) For nuclear transients involving operator decision-making, we have already published comparisons to all the existing available Human Error Probability (HEP) data in the published basic simulator based correlation (Time Response correlation (TRC)) [2, 3, 6, 7].

g) For nuclear systems, basic probability of non-response with the data for some 900 transients in actual nuclear power plants, as reported and analyzed by Baumont et al [8], and benchmarked to all the available human reliability analysis (HRA) methods commonly adopted in Probabilistic Safety Analysis (PSA), such as HEART (Human Error Assessment and Reduction Technique) and THERP (Technique of Human Error Rate Prediction) [6]. In addition, the latest actual nuclear station Loss of Offsite Power (LOOP) recovery data have also been shown to agree with the learning hypothesis.

The relevant experience measure was identified and adopted for each case and technological system. For nuclear system transients the experience and decision-making measure is shown to be "time into the transient", and the Minimum Error Rate Equation/Universal Learning Curve (MERE/ULC) probability of non-response, p(ε), was shown to agree with all the data trends. In Figure 1 below we show on a log-log scale the probability of an outcome as a function of experience: the initial decrease is due to the failure rate decreasing with learning; and the much later increase from the inexorable contribution of the non-zero minimum attainable failure rate. In addition, since it has been demonstrated that the learning trend of system outcomes mirrors the human skill acquisition processes: the outcomes are entirely due to the integrated learning process in which the human and system are inseparable.

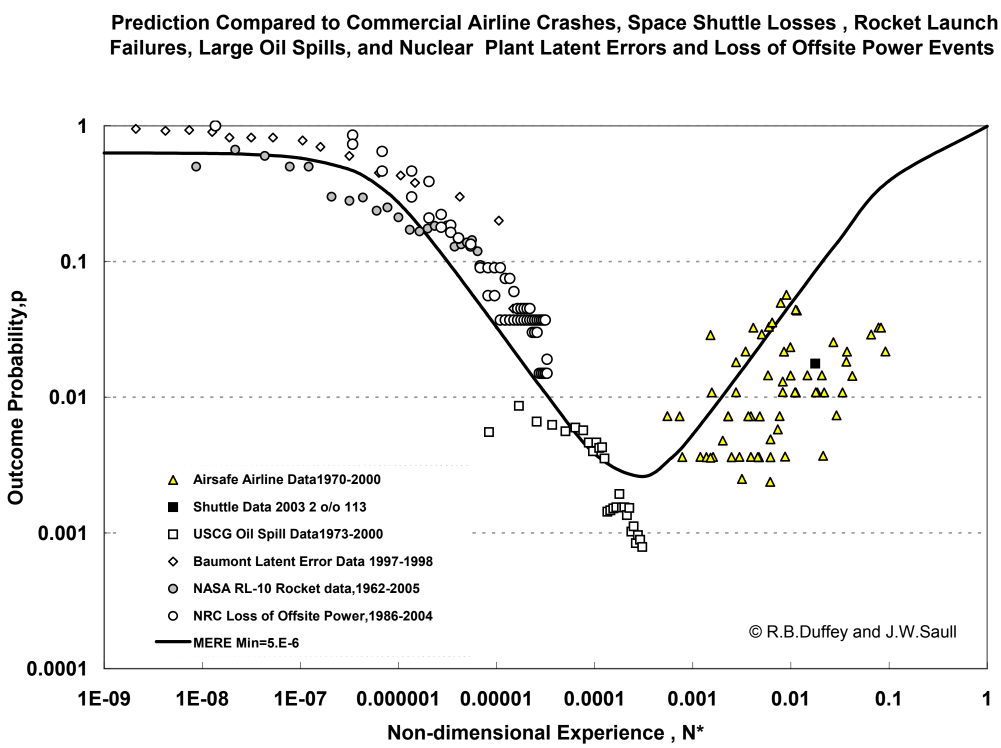

Figure 1: Comparison of reliability prediction to nuclear and other system data (adapted from [6]).

2. Human Error

With this background, we can make several key observations. Our most recent work demonstrates the link to and predicts the HEPs used by HRA models [6].

The present HRA methods (e.g., the first-generation methods) utilise observed task-by-task categorized error probabilities (of commission, omission, cognition etc.), without properly allowing for the known effects of learning and skill acquisition. The influence of experience and knowledge is via different tabulated probability values for a novice or an expert, or for skill, rule or knowledge-based behaviours, based on judgment. Now, in fact the so-called "gold standards" in the cognitive psychology literature are the empirical models for learning known as the Laws of Practice, which show decrease~~s~~ in error rates and RTs with increasing number of trials [3, 4, 5]. In the proposed MERE/ULC method, it is assumed and proven that the HEP, p(ε), is solely as a function of accumulated experience, ε; there is no room for further manipulation of multipliers (i.e., incorporation of the context or skill level). This approach may seem an over-simplification of cognitive aspect in human failure events (HFEs), but it turns out this choice of experience measure also agrees with that adopted in the cognitive psychology literature, where the number of "trials", n_t, during learning becomes simply equivalent to "experience", ε, and the outcome MERE/ULC for systems becomes the same as the psychological ULP for individuals. Previously the HRA community has not validated the HRA methods and HEP results against the huge amount of existing data for individual human skill and knowledge acquisition, available in the cognitive psychology literature, as we have done for the MERE/ULC [3]. Both the observed RT and the measured error rate are dependent solely on the acquired accumulated experience for all the different types of task, and gives rise to the so-called ABC Law of Practice.

The correct view, as taken by the MERE, is that the risk appears as the emergent known outcomes from the entire homo-technological system (HTS), due to the unknown and unobserved actions, decisions and errors of the actual individuals or humans embedded and inseparable within. In effect, the MERE/ULC describes the emergent system learning and trends exhibited by the experience of the collective whole, reflecting how all the individuals within it are also learning, on-the-job and in real time, according to their own experience(s).

3. Benchmark to HRA

Operator actions have to be modeled in PSA. We have also utilized a transparent benchmark and comparison process for HRA that does not overly rely on judgment. The benchmark requirements are stated here first, followed by how the MERE/ULC meets each, as follows [6]:

1. High degree of convergence in task application – MERE/ULC has only one curve to use;

2. Convergence accuracy – MERE/ULC accuracy is solely determined by data validation;

3. Utilize same tasks – MERE/ULC applies equally for any system experience;

4. Examples show convergence – MERE/ULC failure rate and probability accuracy is well within one order of magnitude;

5. Broad HEP range – MERE/ULC natural HEP range is 1,000, from 0.6 down to a natural minimum of $\sim 3.10^{-3}$;

6. Skill, rule and knowledge represented – MERE/ULC handles this via experience;

7. Representative examples – MERE/ULC deals with data for errors and outcomes in and for multiple industries, technologies and systems;

8. Include normal, abnormal and maintenance tasks – MERE/ULC effectively integrates all such tasks in assessing risk by determining outcome probability where so-called "pre-initiators" are already inseparably embedded in the sequence of events.

The agreement between these older, existing HRA methods used in PSA with the new MERE benchmark is extremely encouraging given the simple choices made for the experience measure (in this case time into the transient). The results constitute an independent and additional validation of the Learning Hypothesis. Hence, it clearly shows that we may use the Learning Hypothesis MERE result to determine the *dynamic* HEP in actual transients and events, as well as the outcomes in entire HTS worldwide [6].

Therefore, for estimating the HEP in PSA analysis we recommend adopting the MERE "bathtub" benchmark expression [3, 6] illustrated in Figure 1:

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

where the failure rate with increasing experience is given by,

$$\lambda = \lambda_m + (\lambda_0 - \lambda_m)\exp - k(\tau - \tau_0), \quad (2)$$

where we have, k, the learning rate constant, τ experience in relevant units with some initial value ,τ_0 , and λ_m is the minimum achieved or attainable failure rate.

4. Probability, Risk and Human Reliability

The implications of using this new MERE/ULC (learning) approach for estimating HEP in HRA are profound. From this comparison and analysis as summarized here, we may conclude that within the uncertainties of such an analysis, the required standard HRA HEP models used in PSA can be fitted to the MERE/ULC form derived from the Learning Hypothesis. Conversely, the MERE/ULC probability (the human bathtub) properly represents all the data trends, for diagnosis, decision-making and recovery, and hence can be used in PSA HEP estimation using the correct measure for experience.

Thus we have seamlessly linked all the way from individual human actions and behaviors to the observed outcomes in and for entire systems. We have unified the approach to managing risk and error reduction using the Learning Hypothesis with the same fundamental parameters everywhere being the learning rate constant, k, and the minimum error rate, λ_m. In passing, we note that the fundamental model for human cognition and performance can also be derived based on information theory. The results obtained here are entirely consistent with the Hick-Hyman relation and with statistically-based theories for human learning and the emergence of structure and order as quantified by the Information Entropy [3, 9].

The MERE/ULC results also implies a finite lower bound probability of $p(\varepsilon) > 10^{-3}$, based on the best values derived from all the available data. The initial (novice or starting) probability of ~ 0.6

decreases with accumulated experience and decision-making to a finite minimum of ~ 3.10^{-3} before the effect of the learning is inevitably offset by the inexorably increasing risk exposure, which occurs with large accumulated experience. Clearly the same fundamental learning factors and success motivation is at work, and are reflected in the rapid decrease in errors down the learning curve.

5. Conclusions

We have summarized the results of a new general theory for risk and human reliability. For the first time, we are also able to make and benchmark predictions of the probability of errors and outcomes for any assumed experience interval in any HTS. For *any* transient situation, provided we know or can judge the timeframe available for action, we can estimate the probability of error at any moment or fraction within that interval of risk exposure (to within an uncertainty of a factor of ten) depending on the selected, actual or desired behavior classification.

Learning from experience describes human reliability and skill acquisition, which result in reductions in system error rates, risk and the probability of outcomes. The Learning Hypothesis naturally integrates human and machine reliability, and produces the exponential MERE. The resulting ULC has been validated by comparison against millions of outcome data from multiple industries and technologies worldwide. The comparisons include all the openly available data for both real events and simulator-based transients. The resulting learning rate and probabilities are consistent with the existing psychological models for human learning and error correction, and with the data behind the Laws of Practice. In addition the MERE/ULC results implies a finite lower bound probability of $p(\varepsilon) > 10^{-3}$, based on the best calculations and all the available data, which is not predicted by lognormal and other empirical statistical distributions that ignore known and fundamental learning effects.

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