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Incorporating management and organisational factors into probabilistic safety assessment

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This paper is concerned with how management and organisational influences can be factored into risk assessments. A case study from the rail transportation sector illustrates how organisational factors can act as high level influences which are manifest as operational errors giving rise to major accidents. A model is proposed which describes the interrelationships between management influences, immediate causes and operational errors. This model can be used for organisational auditing, monitoring and system design. A strategy is described for collecting data from an existing organisation to develop a specific form of the generic model. The final issue addressed is the use of the model to quantify the effects of organisational influences on risk arising from human error. A numerical case study is provided to illustrate the approach.

1 INTRODUCTION

There is currently considerable interest in the question of how the effects of management and organisational variables can be incorporated into probabilistic safety assessment. Studies of major accidents from a variety of industries, e.g. the Challenger Space Shuttle, Exxon Valdez, Piper Alpha, Three Mile Island, Chernobyl, indicate that they rarely arise from random failures of hardware as modelled by classical reliability theory. Usually the disaster arises from a combination of active and latent human errors in areas such as design, operations and maintenance.

The characteristic of latent errors is that they do not immediately degrade the functioning of the system, but in combination with other events, which may be active human errors or other random events in the environment, they give rise to a catastrophic failure. Two categories of latent errors can be identified: operational and organisational. Typical operational latent errors include maintenance errors, which may make critical systems unavailable or leave the system in a vulnerable state. Organisational latent errors include design errors, which give rise to intrinsically unsafe systems, and management or policy errors, which create conditions which induce active human errors. The latent failure concept is discussed more fully by Reason [1] and Wagenaar *et al*[2]

As a first approximation, it is convenient to model accident causation as a process involving three levels. This model will be illustrated with reference to an actual railway accident which occurred in the United Kingdom in 1988. This was the Clapham Junction disaster, which arose as a result of wiring errors made on a relay controlling signals. Because of the errors, signal failures occurred which led to a train collision in which 21 people died. The pattern of causation for this accident is illustrated in Figs 1 and 2.

The combination of latent, active and recovery errors that gave rise to the disaster are set out on the left of Fig. 1 and are detailed in Table 1. When other wiring systems were examined after the accident, similar wiring errors were observed in many cases, suggesting that the conditions which induced the failures were systemic in nature. The factors to the right of Fig. 1 are the major. (but by no means all) immediate influences (or error-inducing factors) which determined the likelihood of the active, latent and recovery errors implicated in the accident. Figure 1 illustrates the many-to-many nature of the patterns of influences between the immediate causes and the errors.

In Fig. 2, the third level of the causal network is illustrated, where some of the higher level policy factors influence the lower level error-inducing factors

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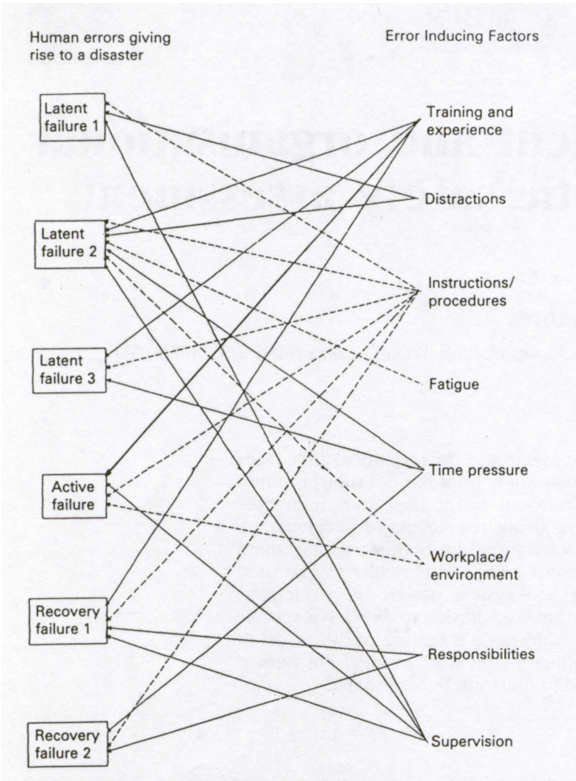

Fig 1: Relationship between error-inducing factors and error for a major disaster

by a similar many-to-many pattern of influences. Even this rather complex picture is a simplification of the real situation, where there may also be interactions between factors at the same level (e.g. safety policy and safety culture). In addition, other more global factors such as the general economic situation, and the prevailing political philosophy may also have an impact on the policy levels.

In our experience in investigating serious accidents, the level of complexity that is depicted above is typical of that encountered in systems with potential for major disasters in industries such as nuclear power, chemical processing, transport systems and aerospace. Given this complexity, it may be questioned if even a qualitative modelling of potential failures is possible, let alone any attempt to quantify these probabilities for incorporation in risk assessments. In our opinion, these objectives are achievable, even thought considerable work will be necessary to fully develop a comprehensive assessment methodology. However, a variety of techniques have already been developed and applied, which can be combined to form the basis for this methodology. In the following sections both the qualitative and quantitative aspects of the methodology will be described, and a worked example will be provided.

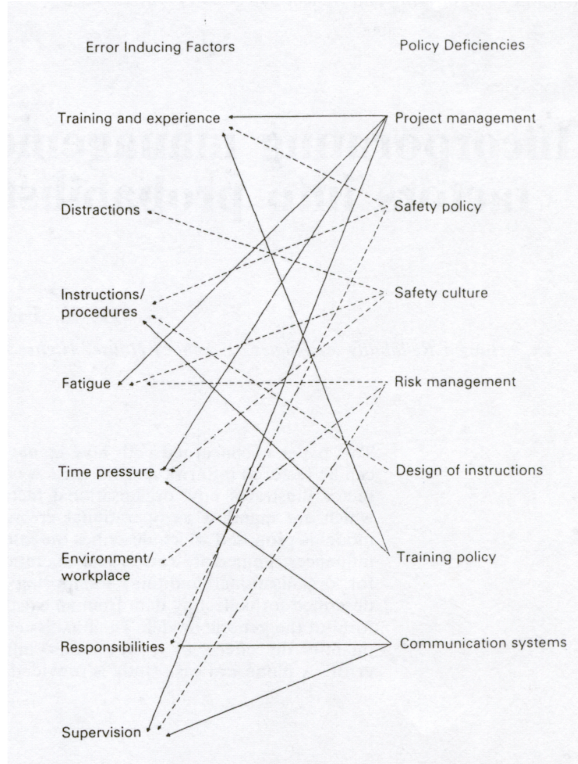

Fig. 2. Relationship between policy deficiencies and error-inducing factors for a disaster .

Table I. Errors contributing to the Clapham J unction disaster (see Fig. I)

Latent error 1	Technician removes old wire from relay terminals to install new connections but fails to insulate the ends of the old wire.
Latent error 2	Technician fails to disconnect the old wire at the power supply end.
Latent error 3	Technician fails to bend back old wire clear of relay terminals.
Recovery error 1	Supervisor fails to carry out specified wiring checks therefore errors not detected.
Active error	Technician works on adjacent relay two weeks later. It is assumed that he disturbed the old live wire and it was left in contact with the relay terminals, giving rise to signal irregularities that eventually caused the accident.
Recovery error 2	Irregular signals noticed by drivers prior to the accident but *not* reported be- cause of time pressure.

2 QUALITATIVE MODELLING OF RISK IN MAJOR HAZARD SYSTEMS

When an accident such as Chernobyl, Exxon Valdez or Clapham Junction is analysed in depth it appears at first to be unique. However, certain generic features of such accidents are apparent when a large number of cases are examined. Figure 3 is intended to indicate, in a simplified manner, how such a generic model might be represented. The generic model is called MACHINE (Model of Accident Causation using Hierarchical Influence Network). The direct causes of all accidents are combinations of human errors, hardware failures and external events. In Fig. 3 these are broken down in more detail. Active, latent and recovery errors have already been discussed. In the case of hardware fail4res, these can be categorized under two headings. Random failures are the normal failures considered by reliability models, e.g. due to the anticipated processes of wear. Extensive data are available on the distribution of such failures from testing and other sources. Human-induced failures comprise two subcategories, those due to human actions in areas such as assembly, testing and maintenance, and those due to inherent design errors which give rise to unpredicted failure modes or reduced life cycle. As all reliability engineers will be aware, most failure rates for components derived from field data actually include contributions from human- induced failures. To this extent, such data are not intrinsic properties of the components, but are dependent on the human influences (management, organisational) in the systems where the components are employed.

The third major class of direct causes are external events. These events are the characteristics of the environment in which the system operates. Typical external events considered in PSAs include seismic, geological, and other natural phenomena and collisions from aircraft and other objects, depending on the system. Such events are considered to be independent of any human influence within the boundaries of the system being analysed, although the risk management policy is expected to ensure that adequate defences are available against external events which constitute significant threats to the system.

The first level influences in Fig. 3 are intended to represent typical factors which have a direct effect on the likelihood of occurrence of the immediate causes of the accident. In the diagram, those influences that impinge on the human causes of failures are described more extensively. However, the large number of influences on the human causes of hardware failures should be noted. For completeness, all of the interconnections between the immediate causes and the first level causal factors are represented. In practice, the strengths of these influences will vary considerably, and thus it may only

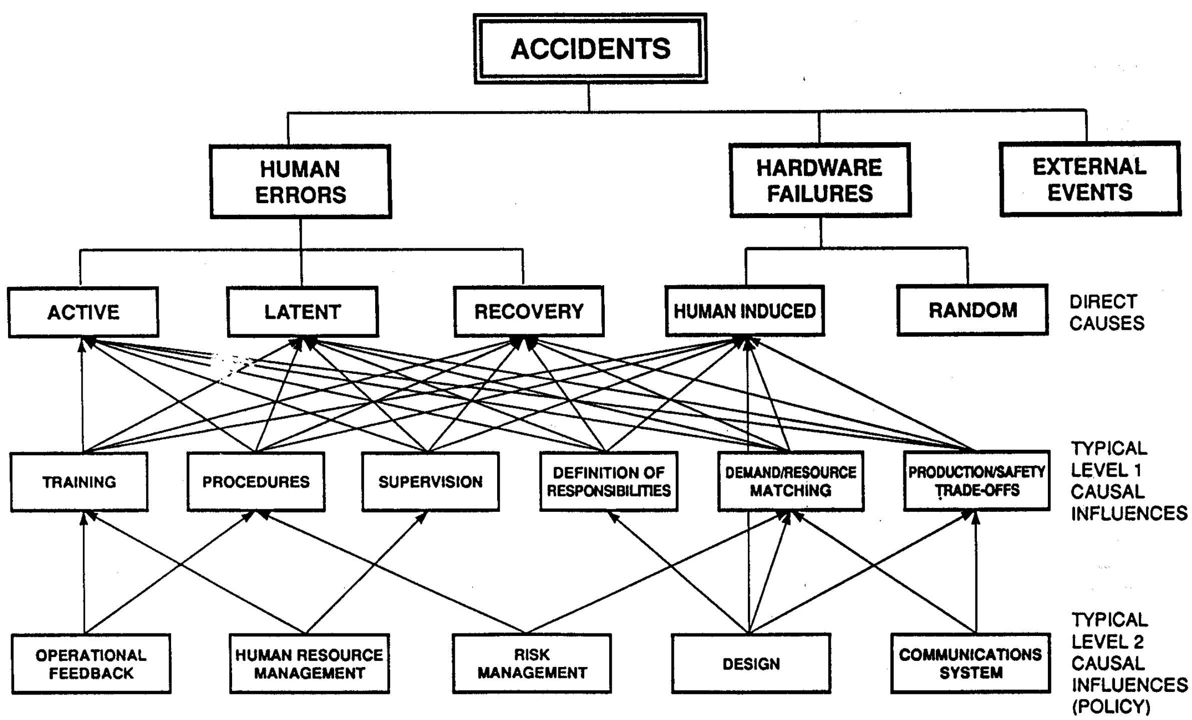

Fig. 3. Generic model of accident causation.

be necessary to model a few highly significant influences.

The second level influences represent typical policy level factors which determine the likelihood that the first level influences will be negative or positive. In many cases there will be intermediate levels between those indicated in the model. As indicated by Reason1 and Wagenaar *et al.,2* there will be managers who interpret and implement the directives from the policy level, and who will be directly responsible for the states of the first level causal influences. However, for the sake of clarity, these influences have been omitted from the representation in Fig. 3.

The model, although obviously incomplete at this stage, could easily be extended to accommodate additional influences and levels so that it constituted a comprehensive generic model of accident causation. A particular advantage of the model is that it captures the complexity of the interactions between influences and is capable of explicitly evaluating the higher level common causes which cascade down through the system to modify the likelihood of specific errors and system failures at the operational level. A further advantage of this structure is that it can be applied directly to qualitative and quantitative assessments of risk in practical PSA analysis, as will be discussed in later sections.

3 PRACTICAL APPLICATION OF THE MODEL

There are many potential practical applications of the model described in the previous section. If it is sufficiently comprehensive, and captures the various levels of influences that actually determine the likelihood of accidents, then it could provide the basis for an auditing tool which could be used by both companies and regulators. If a set of indicators were developed that could be applied to evaluate significant factors in the pattern of influences (e.g. those factors which had a major influence on a number of lower level factors), then the risk potential of the system could be assessed by carrying out a detailed evaluation of these influences using pre-defined criteria. This process could be regarded as a form of on-line monitoring to ensure that the integrity of the system was being maintained. Another potential application would be during the design and development of new systems, to ensure that organisational influences with particular significance were addressed explicitly as part of the organisational design. The other major application area of such a model would be in ensuring that quantitative risk assessments take into account the effects of the network of influences identified by the model. As will be described in later sections, the model can be applied directly to incorporating the effects of management and organisational variables in the quantification of both human and hardware failures.

4 IMPLEMENTATION ISSUES

There are a number of significant problems involved in developing the concept described in the previous sections into a practical tool. The major question is how causal influence models can be set up which represent the actual networks of influences found in real systems. The influences depicted in Fig. 3, derived from our own accident studies, seem to cover a large proportion of the major factors at level 1 of the model. Data from Groeneweg *et al.3* suggest a very similar set of influences (which they call General Failure Types) derived from extensive studies of offshore oil installations and chemical case studies. This would appear to confirm the validity of the overall concept. With regard to the interdependencies between influences at different levels, in the generic model it is assumed that all of the first level influences have some influence on the direct causes of failures. The influence of the policy factors on the first level factors are specific in some cases (e.g. communications systems), and generic in others (e.g. human resource management).

In order to tailor the generic model for a specific system a number of requirements are necessary. The first of these is an elicitation technique to capture from individuals in the organisation the detailed structures of influences that could result or have resulted in accidents. This type of information requires inputs from teams of individuals from all levels in the organisation, to ensure that the interrelationships between influences at different levels are captured. The obvious first source of information is accident investigations. However , evaluations of near-misses would also constitute a significant source of data.

In addition to the elicitation process, some form of representation of the influences is required which is compatible with the generic model of Fig. 3. Fortunately, both the elicitation and representation requirements are satisfied by a system which has already been developed for another purpose. This system has the additional advantage that it lends itself to the subsequent quantification of the effects of the various influences identified.

s THE INFLUENCE MODELLING AND ASSESSMENT SYSTEM (IMAS)

IMAS was originally developed by Human Reliability Associates and the London School of Economics

(Ref. 4) as a method for eliciting the diagnostic models held by nuclear power plant operators when responding to emergencies. Essentially, the diagnostic model is elicited by means of an interactive computer program, which represents the model in the form of a network comprising three entities:

(a) Events are occurrences that are causally connected to other events or nodes in the network. For example the event 'Leak in a steam generator' can lead to the event 'Radioactivity in the secondary circuit'.
(b) Linkages are patterns of connections between events that are causally related. In the original IMAS system, two types of linkage were defined: *leads to* and *stems from.*
(c) Indicators are information sources which can be directly observed by the operator, which indicate states or events which cannot be accessed directly. For example, the event 'Radioactivity in the secondary circuit' is *indicated by* a radiation alarm in the control room.

This structure can readily be applied to the MACHINE accident causation influence network. Instead of events that causally lead to other events, the nodes in this case are states that influence other states, which in turn influence the likelihood of events such as active or latent errors or hardware failures. As will be discussed later, these links are probabilistic in nature. Thus, the existence of a good human resource management policy will increase the probability that there will be an adequate match between demands and resources, and effective training. However, the existence of the good human resource policy does not *guarantee* that resources will be matched or training optimized. This is because other influences, e.g. feedback from operational experience, may impinge on resource matching and training. Another point to bear in mind is that the generic model is what Phillips *et als* refer to as a 'requisite' model. This means that it does not attempt to capture *every* interrelationship but only those which are necessary to provide a usable model for the purpose at hand. Thus there may be other influences, e.g. the culture at the workplace, which influence the effectiveness of training, which are not included in the model.
Some points about the elicitation process have already been mentioned, i.e. the need for a broad range of individuals to be represented in the elicitation team. Another requirement is that the interactive session is led by an experienced facilitator who is aware of group dynamics and ensures that the session is not dominated by assertive individuals. Ideally, the model should be built up over a period of time by considering near-misses as well as accidents. Near-misses will be much more frequent than accidents, and just as useful in supplying information to build up the structure of. the model.
The indicators in the IMAS system have their counterpart in MACHINE in terms of scales which define measurable variables used to assess the state of the factors in the influence network. Thus, the indicator for operational feedback would be a numerical scale defining at one end the observable attributes of an optimal operational feedback system (e.g. ownership by operators, provision of job aids to assist in determining root causes, direct communication of summary results to policy makers at regular intervals) and at the other end the characteristics of a poor or ineffective operational feedback system (e.g. no consideration of causation, no active participation by workforce, no feedback of results to policy makers). Indicators allow a numerical score to be assigned to the influences. These numerical scores have a number of applications. A-t a simple level, they can be aggregated to give an overall indication of the 'health' of the system. A similar procedure has been described by Groeneweg *et al.3* in the context of offshore operators. However, the MACHINE approach allows a more comprehensive audit, since it addresses second level organisational factors as well as direct level causative influences.

6 USING MACHINE FOR THE QUANTIFICATION OF MANAGEMENT INFLUENCES

The network representation of accident causation used in MACHINE lends itself readily to incorporating management influences into PSA assessments. The resources required to do this are significant, but this is an unavoidable consequence of the complexity of the relationships between management policy variables and direct causative influences.
The MACHINE influence network is isomorphic with the Influence Diagram approach which was first applied to human reliability assessment by myself and my colleagues at the London School of Economics (Ref. 5). In order to illustrate directly how the MACHINE model described in previous sections can be applied to PSA assessment, a simplified analysis of certain aspects of a general accident situation will be presented. It should be emphasized that the numerical values used in this example are purely for illustrative purposes. Space constraints preclude a detailed description of the Influence Diagram methodology. However, further information is available in Phillips *et al.* , 5 and the main features of the approach will be illustrated in the following example.

6.1 An illustrative example of quantification for PSA using MACHINE and Influence Diagrams

In this example, we shall perform the analysis of the human errors in a typical accident scenario. The error probability calculated in this example is global and includes active, latent and recovery errors. Only a subset of the influences will be presented. However , the application to a more complex analysis is a simple extension to that presented here. It is also worth pointing out that the analysis could easily be extended to include the human influences on hardware failures, as set out in Fig. 3. The example illustrates how the probability of operator errors might have been assessed prior to the accident occurring, by evaluating the effects of level and level 2 factors.

The Influence Diagram for operator errors is given in Fig. 4. The main level I factors influencing the probability of error are quality of training, availability of effective operating instructions and time pressure on the operator. Two factors are specified as influencing the quality of training. These are the extent to which task analysis was employed to generate the training specification, and the use of feedback to modify the existing training regime in the light of operational experience. The availability of effective operating instructions is modeled as being dependent upon two policy factors. The first of these is the policy for developing instructions, which ensures that procedures are kept up to date, and are designed according to accepted standards. The other policy factor is project management, since this influences the early definition of work required, so that appropriate instructions will be available at the workplace when required.

Project management also influences the likelihood that staffing levels will be adequate for the tasks required. This latter factor, together with the extent to which appropriate jobs are assigned to individuals, and the complexity of the jobs, all influence the level of time pressure likely to be felt by the operator .

6.2 Commentary on the calculations

The information required to perform the numerical calculations for the Influence Diagram is provided in the Appendix. In this section, a commentary on these calculations will be provided. In calculation Al, the assessment team is asked to evaluate the evidence that feedback from operational experience is used to develop training. In order to make this evaluation, they will be provided with an 'indicator' in the form of a scale specifying the nature of the evidence that should be taken into account. For example, the end of the scale defining the ideal situation would include conditions such as: 'Results from operational ex-

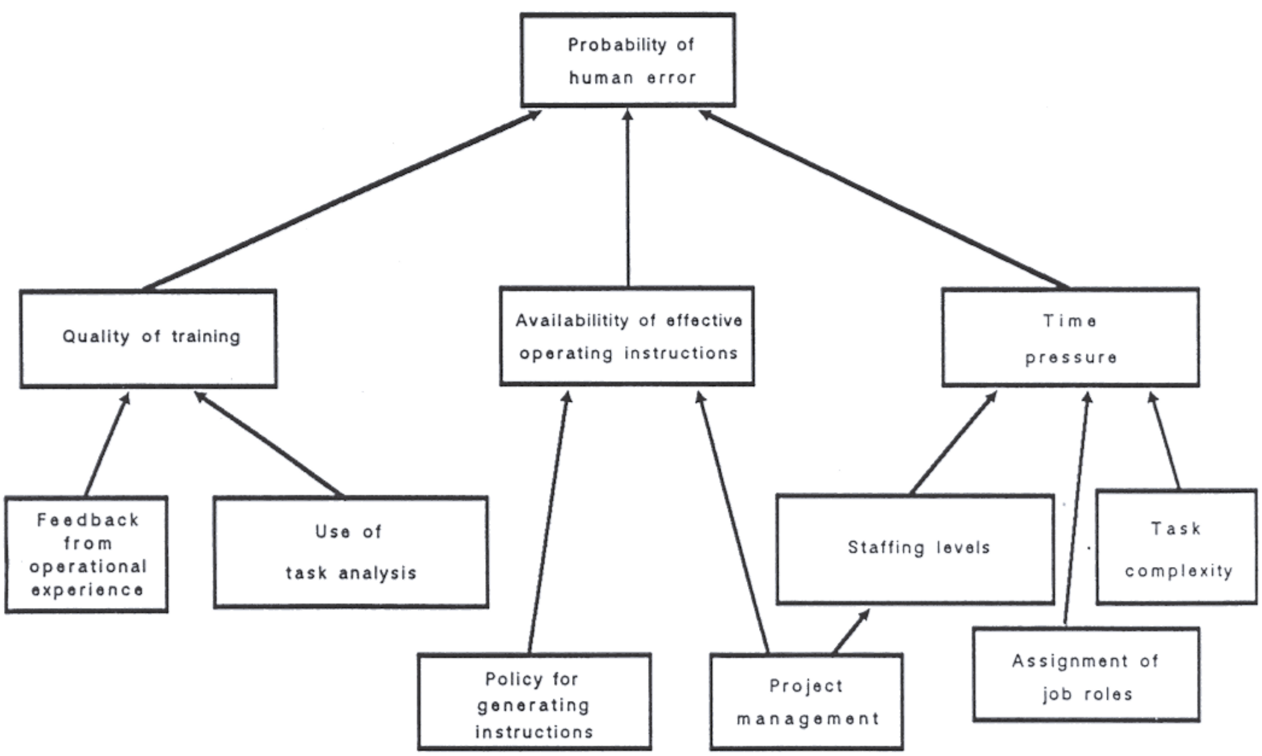

Fig. 4. Influence Diagram

perience fed directly to the training department', and 'Evidence that training regime is modified as a result of feedback'. The other end of the scale would describe the worst case situation, for example 'No feedback from operational experience into training'. In the example cited, the evidence strongly indicates that feedback is not used effectively in developing training. It should be noted that the quantities 0.2 and 0.8 are not strictly speaking probabilities, but actually assessments of the weight of evidence regarding the variable being assessed. They can, however, be treated as probabilities for the purpose of calculations.

Calculation A2 contains a similar assessment to Al but for the use of task analysis. As illustrated in A3, the assessment team is then asked to evaluate the weight of evidence that the quality of training will be high (or low) given various combinations of the influencing factors feedback and use of task analysis. Of course, such evaluations are difficult to make. However, they utilise whatever expert knowledge is possessed by the evaluation team, and factor this into the analysis. They also allow the assessors to factor into their evaluations any interactions between factors. For example, the combined effects of poor feedback and non-use of task analysis may degrade the quality of training more strongly than either influence in isolation. Each of the conditional assessments is then weighted by the results of stages Al and A2 and the products added together to give an estimate of the unconditional probability that the training is adequate.

Similar assessments are performed to evaluate the probability that effective operating instructions are available (A6) that staffing levels are adequate (A9) and that time pressure will be high or low (AlO). In this last case, since three influences impact upon time pressure, eight joint assessments need to be made.

Although these combined assessments are arduous, it should be noted that the evaluations of the effects of combinations of influences may be regarded as applicable across a range of systems, and hence would only need to be performed once for a generic model. The system specific evaluations would then be the simpler level 2 assessments set out in Al, A2, A4, AS, A7 and A8. As discussed earlier, guidance for performing these assessments could be provided by the use of indicator scales delineating the conditions for the least and most favourable ends of the scales. Similar scales can be used to make direct evaluations of the level 1 influences, if the assessments described earlier are judged to be too difficult. Even if the full assessments are made, it is useful to compare these with the indirect assessments to check convergence.

The final stage of the procedure is to generate an overall unconditional probability of human error (All). This is achieved by assigning probabilities of error to combinations of the three first level

influences: quality of training, availability of operating instructions and time pressure. These conditional probabilities are generic, in that they could apply to any system. They are made specific to the situation under consideration by multiplying them by the assessed probabilities of the level 1 influences, as derived from the earlier analyses. These products are then summed to give the overall unconditional probability of error occurrence in the situation being evaluated.

The assignment of probabilities is problematic, given the known difficulties in obtaining empirical data. If these assessments are made using absolute probability judgment (see Ref. 6), the assessors are able to modify the probabilities to reflect any perceived interactions between combinations of level 1 influences. If this requirement is not critical, then other quantification methods can be employed to evaluate the required intermediate probabilities.

The Success Likelihood Index Method (SLIM) (Ref. 7) is particularly suitable for this, since it evaluates probabilities as a function of variations in Performance Influencing Factors which correspond to the level 1 factors used in this example. Each of the eight conditions in All can be treated as a separate task for evaluation by SLIM, using common weights for each factor across all conditions, but differing ratings to reflect the differing conditions in each case. SLIM requires calibration data to be supplied for the two end-point conditions, but this is considerably less onerous than evaluating probabilities for all conditions. Another source of probabilities to include in All would be laboratory experiments where the first level influencing factors were varied systematically.

7 CONCLUSIONS

The modelling approach described in this paper , although at an early stage of its development, has the potential to address both qualitative and quantitative aspects of assessment of the human contribution to risk within the same framework. The MACHINE model can be used as the basis for an audit tool to monitor the organisational and management factors that impinge on risk, as well as the more direct causal factors that determine human and hardware failure probabilities. The next stage of development of MACHINE is to embark upon a series of field studies to determine if the provisional influencing factors assigned to the model are truly generic in nature, or if the factors vary within different industries. The numerical applications of the model need to be investigated by performing independent evaluations of the same plant to check for convergence, and ultimately to attempt external validation of the

model's predictions by comparisons with human and hardware near miss and error rate data from operating plants.

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APPENDIX: INFLUENCE DIAGRAM CALCULATIONS

At What is the weight of evidence for use of feedback from operational experience in developing training?

Good	*Poor*
0.2	0.8

A2 What is the weight or evidence or use or task analysis in developing training?

Used	*Not used*
0.2	0.8

A3 For quality of training:

If feedback then weight of is	and task analysis evidence that is	Quality of Training is High	Low	Joint weights (feedback x task analysis)
Good	Used	0.95	0.05	0.04 = (0.2 x 0.2)
Good	Not used	0.80	0.20	0.16 = (0.2 x 0.8)
Poor	Used	0.15	0.85	0.16 = (0.8 x 0.2)
Poor	Not used	0.10	0.90	0.64 = (0.8 x 0.8)

Unconditional Probability (weighted sum) that Quality of Training is

High	Low
0.254	0.746
0.25	0.75 (rounded)

A4 What is the weight of evidence that policy for generating instructions is:

Effective?	Ineffective?
0.3	0.7

A5 What is the weight of evidence that project management is:

Effective?	Ineffective?
0.1	0.9

A6 For availability of effective operating instructions:

If Policy for generating and instructions is	Project in management is	then weight of evidence that good operating instructions are		Joint weights (Policy x Project Management)
		Available	Not available	
Effective	Effective	0.90	0.1	0.03=(0.3x0.1)
Effective	Ineffective	0.60	0.40	0.27=(0.3x0.9)
Ineffective	Effective	0.50	0.50	0.07=(0.7x0.1)
Ineffective	Ineffective	0.05	0.95	0.63=(0.7x0.9)

Unconditional Probability (weighted sum) that effective operating instructions are

Available	Not available
0.255	0.744
0.26	0.74 (rounded)

A 7 What is the weight of evidence for assignment of job roles?

Good	Poor
0.5	0.5

A8 What is the weight of evidence for task complexity?

High	Low
0.6	0.4

A9 Staffing levels

If *Project management is*	then *weight of evidence for staffing levels being*		Weights (Project Management)
	Adequate	*Inadequate*	
Effective	**0.6**	0.2	0.1
Ineffective	0.4	0.8	0.9

Unconditional Probability (weighted sum) that staffing levels are

Adequate	Inadequate
0.24	0.76
0.2	0.8 (rounded)

Al0 For Time Pressure:

If Staffing and levels are	Assignment of job roles is	and Task complexity is	then weight of evidence for Time Pressure being		Weights
			Low	High	(Staffing Job x levels roles x Task complexity)
Adequate	Good	Low	0-95	0.05 0':70 0.10 0.75	0-072 = (0-24 x 0-5 x 0.6)
Adequate	Good	High	0.30		0-048 = (0.24 x 0.5 x 0-4)
Adequate	Poor	Low	0.90		0-072 = (0.24 x 0-5 x 0.6)

Adequate	Poor	High	0.25	0-048 = (0.24 x 0-5 x 0.4)

AlO (continued) For time pressure:

If *Staffing* and *levels are*	*Assignment of job roles is*	and *Task complexity is*	then *weight of evidence for Time Pressure being*		Weights
			Low	*High*	*Weights (Staffing Job Task levels* x *roles* x *complexity)*
Inadequate	Good	Low	0.50	0.50	0.23 = (0.76 x 0.5 x 0.6)
Inadequate	Good	High	0.20	0.80	0.15 = (0.76 x 0.5 x 0.4)
Inadequate	Poor	Low	0.40	0.60	0.23 = (0.76 x 0.5 x 0.6)
Inadequate	Poor	High	0.01	0.99	0.15 = (0.76 x 0.5 x 0.4)

Unconditional Probability (weighted sum) that time pressure is

High	***Low***
0.3981	0.6019
0.40	0.60 (rounded)

A11 For the task modeled:

If *quality of* and *training is*	*effective operating instructions are*	and *Time pressure is*	then *the probability of*		*Joint Probabilities (Quality of Operating Time training* X *instructions* X *pressure).*
			Success	*Failure*	
High	Available	Low	0-9999	0.0001	0.0390 = (0.25 x 0.26 x 0.60)
High	Available	High	0-9995	0.0005	0.0258 = (0.25 x 0.26 x 0.40)
High	Not available	Low	0.9992	0.0008	0.1137 = (0.25 x 0.74 x 0.60)
High	Not available	High	0.999	0.0010	0.0752 = (0.25 x 0.74 x 0.40)
Low	Available	Low	0.999	0.0010	0.1145 = (0.75 x 0.26 x 0.60)
Low	Available	High	0.993	0.0070	0.076 = (0.75 x 0.26 x 0.40)
Low	Not available	Low	0.991	0.0090	0.3341 = (0.75 x 0.74 x 0.60)
Low	Not available	High	0.990	0.0100	0.2209 = (0.75 x 0.74 x 0.40)

Assessed Unconditional Probability of overall task success or failure

(CALCULATED AS THE SUMS OF THE PRODUCTS OF EACH SUCCESS AND FAILURE PROBABILITY WITH THE CORRESPONDING JOINT PROBABILITIES)

Success	*Failure*
0-994	0.006 **(rounded)**