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Human Error assessment in complex Socio-Technical systems – System Dynamics versus Bayesian Belief Network

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Abstract

Due to the complex interactions that appear between the actors (humans, computers) of complex socio-technical systems the reliability issue of the human complement in such systems is very important. Predicting human error in the context of human-machine or human-human interaction reveals important information concerning the reliability of the whole systems. In order to prevent accidents in such systems it is important to assess the implication of human error during the early stages of system requirements.

This paper compares the advantages and deficiencies of System Dynamics and Bayesian Belief network methodologies in assessing the reliability issue of complex socio-technical systems. The BBN approach employs probabilistic relationships between influences in order to reason about uncertainty where System Dynamics on the other hand concentrate upon the interconnections of the various components and the influences between each other, expressed in a loop structure.

In both methodologies a taxonomy framework of influences that contribute to human error is applied. Components of the taxonomy are represented in a causal effect diagram. The diagram is represented in System Dynamics and BBN formats which quantifies error influences arising from *user knowledge*, *ability*, and *task environment*, combined with factors describing the *complexity of user action* and *user interface quality* in scenarios of projected system usage. The models predict the different types of errors (slips and mistakes) in complex socio-technical systems.

"What if" scenarios concentrate on representing critical conditions in a system that are more prone to human error. These are subsequently transformed into a sequence of scenario threads that enable the evaluation of BBN and SD models, taking into consideration the properties of humans, machines and the environment in which they reside.

Introduction

Due to the complex interactions that appear between the actors (humans, computers) of complex socio-technical systems the reliability issue of the human complement in such systems is very important. Predicting human error in the context of human-machine or human-human interaction reveals important information concerning the reliability of the whole system. In order to prevent accidents in such systems it is important to assess the implication of human error during the early stages of system requirements.

This paper compares the advantages and deficiencies of System Dynamics and Bayesian Belief network methodologies in assessing the reliability issue of complex socio-technical systems.

Socio-technical Systems and the reliability issue

The complex nature of socio-technical systems designs necessitates their evaluation against the reliability issue prior to becoming fully operational. This is important in order to avoid unnecessary accidents. According to Reason [Reason, 1990] human error was the main cause of accidents during the last decade. Therefore assessing the level of human error in such systems in the early stages of their design is a wise option.

Socio-technical systems designs must be planned in a way that opposes humans from performing erroneous actions. This can only be achieved if we investigate the various types of errors and their causes. Human error has an overall effect on the overall system's performance, due to the influence on fatigue and stress levels of individuals. Therefore, systems that can manage to minimise human error are less prone to accidents. The next section introduces the notion of human error and the various types in which it is classified.

Human Error

According to Reason [Reason, 1990] human error is defined as, "all the occasions in which a planned sequence of mental or physical activities fails to achieve its intended outcome, and when these failures can not be attributed to the invention of some change agency."

Reason, distinguishes between two different types of error: *slips* and *mistake*s. Slips (and lapses) are skill-based errors that happen when an action is incorrectly performed, frequently during familiar work requiring little attention. In our view, tasks of physical complexity, such as complex manipulations involving precise movements and detailed co-ordination are more prone to slip-errors. Mistakes, on the other hand, are either rule-based or knowledge-based errors and associated with problem solving. Rule-based mistakes can occur by the application of "bad" rules or the misapplication of "good" rules; knowledge-bound mistakes are rooted in bounded rationality, incomplete or inaccurate knowledge. In this paper, tasks of high cognitive complexity are considered more prone to mistake-errors.

The classification by Rasmussen [Rasmussen, 1982] of knowledge, rule, and skill-based errors is widely quoted by Reason and others. A "knowledge" error, referred to as a mistake, occurs from inadequate or incorrect information. If the information is correct, but the wrong method of application is chosen, a "rule" error occurs, termed a "lapse." In medicine, an example of such an error would be an incorrect diagnosis. Finally, the plan may be good, but the performance is faulty, often from distraction or inattention. This is a skill-based error, termed a "slip." Skill-based errors are the most frequent and are also most often detected by the individual (60% of time). The rule-based errors are less common and are also less often recognised (27% of time) by the individual. The most uncommon are the knowledge-based, recognised infrequently by the individual (about 11% of time). In general, an individual detects about three of four errors. The remainder must be detected by appropriate designs in the system, termed "forcing functions," or by supervision.

A taxonomy of *influencing factors* [Sutcliffe et al, 1998] that describe the necessary preconditions for errors to occur is grouped into four categories:

- Environmental conditions,
- Management and organisational factors,
- Task/domain factors and
- User/personnel qualities.

Each affects different human internal variables such as fatigue, stress, workload and motivation. These in turn, affect the probability of human errors, manifest as slips and mistakes (knowledge based and rule based errors).

Domain facts that describe the working environment, the people who will operate, control and manage the system are used to capture domain-specific influencing factors. Such “domain scenarios” can either be taken from real-life by observations or by interviewing the users, or postulated to cover a variety of organisational and work situations that may occur in the domain. Some of these factors can be measured objectively by using psychological questionnaires. For instance general ability and accuracy/concentration can be measured by intelligence aptitude scales, decision making and judgement by locus of control scales, whilst domain and task knowledge can be measured by creating simple tests for a specific task/domain. The main implications of the personnel factors are for personnel selection and training while generic requirements indicate the need for computer based intelligent assistants, critics, and aide memoir information displays.

Bayesian Belief Networks (BBNs)

BBNs as a means of combining the influencing factors into a more formal and predictive model of human error. BBNs are graphical networks that represent probabilistic relationships between variables. They offer decision support for probabilistic reasoning in the presence of uncertainty and combine the advantages of an intuitive representation with a sound mathematical basis in Bayesian probability [Pearl, 1988]. BBNs are useful for inferring the probabilities of events which have not as yet, been observed, on the basis of observations or other evidence that have a causal relationship to the event in question. For example, a doctor might have observed a variety of symptoms in his/her patient. Using a BBN, s/he can determine the probabilities that these symptoms are caused by each of the several possible alternative diseases, and hence further complications that might arise.

BBNs have become increasingly popular as a means of predictive, probabilistic reasoning [Fenton 1999]. Although the underlying notions of Bayesian probability theory and propagation have been around for some time, it is only recently that efficient algorithms, as well as the tools to implement them, have enabled realistically sized problems to be solved. BBN technology is now used in systems for medical and mechanical failure diagnosis and, for example, underpins the interactive printer fault diagnostic system on the Microsoft Web site [Fenton 1999].

A BBN is constructed of *nodes* and *arcs*. The nodes represent variables, and the arcs represent (usually causal) relationships between variables. The example in Figure 1 is a fragment of the net described in further detail in the proceeding section. It shows the external environmental conditions that influence the fatigue and stress levels of individuals on a military vessel. This is expressed as a variable that is affected causally by two factors: (1) the sea state and (2) the visibility. Variables with either a finite or an infinite number of states are possible in a BBN, so the choice of measurement scale is left to the analyst’s discretion. For this case study we have assigned these variables to one of the three possible states: *high*, *medium*, or *low*.

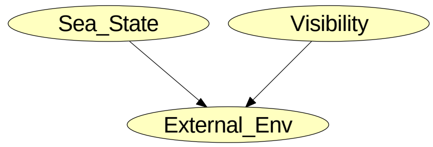

Figure 1

In the above example, if we know that the sea state is high (bad) and the visibility is low then the overall probability of the external environment to be high (bad influence to individuals) is greater. In the BBN we model this by completing a node probability table (NPT). Table 1 shows the NPT for the external environment variable.

	Sea State	High			Medium			Low		
	Visibility	High	Med	Low	High	Med	Low	High	Med	Low
External Environment	High	0.33	0.75	1	0.2	0.5	0.75	0	0.25	0.6
	Medium	0.34	0.25	0	0.2	0.3	0.2	0	0.35	0.3
	Low	0.33	0	0	0.6	0.2	0.05	1	0.4	0.1

Table 1Node Probability Table

Nodes with incoming arcs are associated with a table of conditional probabilities as shown in Table 1. Each arc and table of conditional probabilities represent knowledge about one node that is useful for predictions about another node. Hence in Table 1, column 1 the requirements engineer has asserted that if the Sea state is high (bad) and the Visibility is low then the probability of the external environment being high (bad) is 1, with zero probabilities of being medium and low.

Table 1 is configured by estimating the probabilities for the output variables by an exhaustive pair wise combination of the input variables. BBNs can accommodate both probabilities based on subjective judgments (elicited from domain experts) and, probabilities based on objective data.

When the net and NPTs have been completed, Bayes theorem is used to calculate the probability of each state of each node in the net. The result of this calculation is a probability distribution for the states according to each node. Then, if evidence is available to determine the states of particular nodes from particular scenarios, the values entered are propagated through the network, updating the values of other nodes.

BBN approach to HE

The generic model of influencing factors that give rise to human error is illustrated in Figure 2. Four groups of factors (environmental conditions, management/organisational factors, user / personnel qualities and task / domain characteristics) are considered the main influences of human error. Environmental context is influenced by the external and internal environmental conditions. Consequently the environmental context variable has an indirect influence to individual’s ability through increasing the fatigue and stress levels. Individuals ability however has a direct effect to knowledge and rule based errors. Domain characteristics on the other hand are model through task complexity and functional User Interface (UI) design.

Organisational factors (Management culture, incentives) have a direct effect on individuals motivation. Finally individuals characteristics such as domain and task knowledge have a direct effect to Rule-Based (RB) and knowledge-based (KB) errors. Slips are mainly influenced by the UI, the constrains (time constrains, destructions) and individuals dedication.

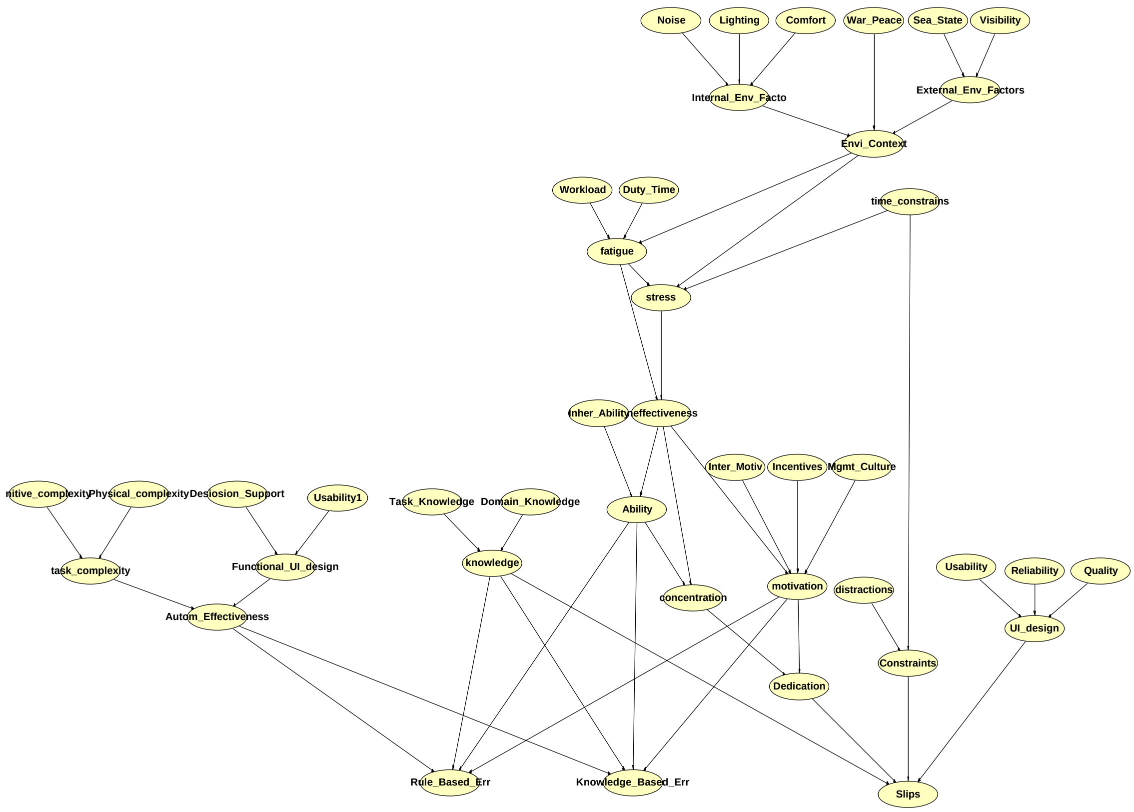

Figure 2 BBN diagram for Human Error assessment

System Dynamics approach to Human Error

System Dynamics employs a different approach to modelling human error. Instead of focusing on the probability of an error to occur system dynamics concentrates on the projection of the current system state into the future based on the interconnections between its elements. Causal loop diagrams is the first step in evaluating system behavior. They show the interrelations between system variables and expose feedback loops within individual systems, and between adjoining systems. They are developed by gathering variables, and then correlating the variables with one another as causally related pairs where one member acts as an independent variable, and the other as a dependent variable.

The causal effect diagram that corresponds to human error prediction is shown in figure 3. Again the four main groups of factors that influence the human error are identical to the BBN model. The main feedback loop of this model incorporates workload, fatigue, stress, motivation and the three types of errors. The loop is initiated by the increase of workload from the three types of errors. This subsequently influences the fatigue level of individuals, which in turn increases the level of stress. However stress has a negative effect upon motivation and individual's ability, which in turn increases human error occurrence; this constitute a reinforcing loop.

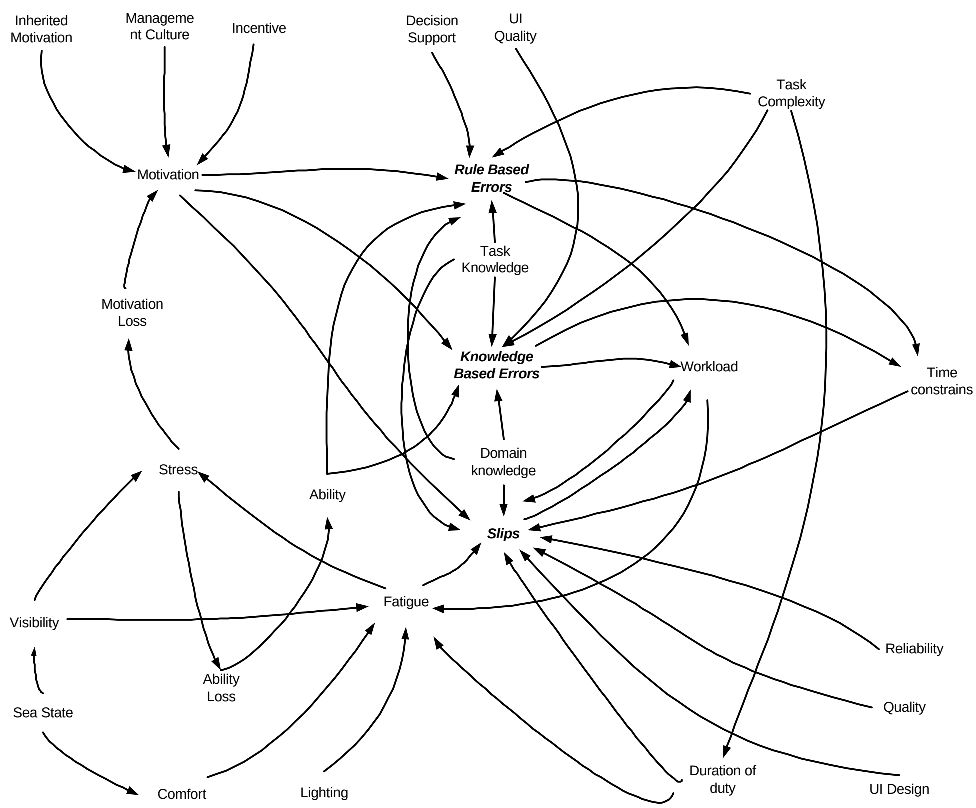

Figure 3- Causal effect diagram for Human Error assessment

System Dynamics Versus BBN in Human Error assessment

Comparing the two methodologies in modelling and assessing human error in socio-technical systems, the following conclusions have been drawn:

Both methodologies suffer from the black box syndrome - increasing the complexity of the model results in decreasing its comprehensibility by practising managers. In order to overcome this problem we can decompose the models into smaller sub models that are more manageable.

System dynamics is based on a more natural way of reasoning about a problem which is based on the feedback loop structure. BBN on the other hand is based on the probabilistic propagation of influences between the entities of a system. However, as the model's complexity increases system dynamics comprehensibility is declining in a more radical fashion than the BBN models. On the other hand the population of the BBN's node probability table constitutes a very tedious and time consuming task once the complexity in increased.

System dynamics study the impact of delay on systemic behaviour. Specifically, what are the implications when a cause takes a long time to exert its effect, and when cause

and effect are physically far apart. BBN is lacking this notion of delayed influences. Influences are propagated to subsequent notes without any intermediate delay. However, there are situations where the delay is a necessary component of a model (i.e. there is not an immediate change in the stress level of individuals, most of the times stress is expressed in an exponential fashion).
BBN might be more appropriate in estimating the probability of an error in certain situations, however these results provide limited benefits due to the lack of the time dimension. The model warns that the system might have a reliability problem but it does not clarify the point in time that this will occur, this might be in ten seconds, minutes, hours, days or even years. As a result a proposed system design might be in favour to alternative designs even if this might suffer by low reliability at some point in the future. This is because the reliability problem might appear long after the expected life span of the system. Therefore if the proposed design is also in favour of cost then it would be preferred over a more expensive design which is expected to be reliable throughout its life span.

BBN can provide the user with a probability that a certain event might occur in the system. The reasoning however and the propagation of the probabilities between the various notes of the model is based on very fine threads of a possible system scenario. In order to gain any real output from a BBN model we need to run the model iteratively for a number of times while changing the values of the models key notes. Metaphorically speaking, by following this approach we are trying to predict an image that is covered behind a peace of black cloth by poking the cloth with tiny holes. Each hole corresponds to a run in the BBN model. In order however to find what is actually behind the cloth (the real problem) we keep poking the cloth in a not methodological fashion. Since it would be impossible to open holes in the whole cloth we might never identify the real cause of a problem. System dynamics however adopts a more methodical approach to this problem.

Conclusions

Despite their strengths both methodologies suffer from a number of disadvantages. Both suffer from the black box syndrome. In order to overcome this problem, several attempts were made in abstracting the models into a number of smaller and more comprehensible ones that interact with each other.

BBN model constitute a more practical way to model human error propagation in complex socio-technical systems, because the granularity level (variables states) of the model variables is controlled by the modeller. On the other hand, system dynamics (due to their continuous simulation nature) enable the investigation of system variables at all levels of granularity, characteristically enabling the visualisation of broader system behaviour.

To sum up system dynamics is a more favourite methodology in modelling the effect of human error in socio-technical systems reliability. This is due to the fact that these systems are composed of elements that are dynamically changing according to various conditions (influences). Humans as agents in such systems are influenced dynamically by the changing system’s environment. Since human error is an attribute of humans (the most dynamic element in any socio-technical system) which is continuously altered according to the system’s state, the most appropriate methodology to model the dynamic nature of such systems without manifesting it, is system dynamics.

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