Learning from Accidents: Analysis and Representation of Human Errors in Multi-attribute Events

Raphael Moura
PhD Student, Institute for Risk and Uncertainty, University of Liverpool, UK

Michael Beer
Professor, Institute for Risk and Uncertainty, University of Liverpool, UK

John Lewis
Lecturer, Institute for Risk and Uncertainty, University of Liverpool, UK

Edoardo Patelli
Lecturer, Institute for Risk and Uncertainty, University of Liverpool, UK

ABSTRACT: Regardless of the evolution of engineering systems and fabrication methods, recent major accidents exposed the risk behind modern human economic activities to an inquiring and perplexed society. These events brought out the fact that interactions between complex systems, cutting-edge technologies and human factors may trigger particular accident sequences that are very difficult to predict and mitigate through traditional risk assessment tools. Thus, the purpose of this study is to overcome barriers to dealing with complex data by translating multi-attribute events into a two-dimensional visualisation framework, providing means to communicate high-technology risks and to disclose surrounding factors and tendencies that could lead to the manifestation of human errors. This paper first discusses the human error and human factors role in industrial accidents. The second part applies Kohonen's self-organising maps neural network theory to an accident dataset developed by the authors, as an attempt to improve data exploration and classify information from past events. Graphical interfaces are then generated to produce further insight into the conditions leading to the human errors genesis and to facilitate risk communication among stakeholders.

1. INTRODUCTION

1.1. Perspectives on human errors

Human error is a term coined in numerous fields, such as engineering, management, design, economics, psychology, sociology and philosophy, for different purposes. From a general perspective, it can be commonly defined as a failure to perform a certain task that leads to an adverse consequence, whereas the understanding of the relationship between humans, tasks, technologies, organisations and the surrounding environment is usually called "Human Factors". The growth of this applied discipline as a way to improve human reliability at work and enhance systems' safety is closely associated with the development of human error studies and understanding. However, the interdisciplinary nature of this subject allows for some controversy regarding the use of the term "error" to define human underperformance. Hollnagel (1998) believes that the term human error is misleading, pointing out some differences among the views of engineers, psychologists and sociologists, and thus in terms of meaning. Basically, he claims that engineers tend to analyse humans as a component that can be successful or fail to complete a task, while psychologists generally try to understand the mental mechanisms that led to the erroneous action. Sociologists usually search for an explanation related to the socio-technical system, and errors can be attributed to a management problem, incorrect training or social pressure. Another compelling aspect of Hollnagel's argument is that the term error is currently used

to define the cause (when accidents are said to be due to human error), the event (when an action, e.g. the early activation of a switch, is said to be a human error) or the consequence (when the outcome of the action is said to be an error, e.g. the driver made the error of fuelling with diesel instead of petrol, inferring a car malfunction). So, how can we communicate risks intimately associated with human performance, without a common ground regarding its definition, understanding and handling?

Notwithstanding this, Reason (2013) has recently reaffirmed his former definition for the term, emphasising three basic characteristics to define error: plans, actions and consequences, surrounded by two situational factors: intention and absence of chance interference (e.g. an act of God). This view is particularly useful to tie up two loose ends: firstly, the need for a common understanding of human error, a deeply rooted term in both technical and general public reality, serving as a useful bridge between the two worlds; and secondly, a clear and convenient definition, focused on the characteristics of the analysed subject and on the genesis of error, to facilitate communication among authorities, the general public and wider stakeholder groups.

1.2. Echoes from recent high-technology, multi-attribute accidents

The significance of human factors to industrial domains was extensively highlighted by current studies. Graeber (1999) portrayed human error as a major contributor to more than 70% of commercial airplane hull-loss accidents. According to Dhillon (2007), the United Kingdom Protection and Indemnity (P&I) Club reported costs of US$541 million per year for the marine industry due to human error.

Likewise, the chairman of the independent investigation commission appointed to investigate the Fukushima nuclear disaster that occurred in March 2011, Mr. Kiyoshi Kurokawa, during the presentation of his final report, pointed out that the tsunami was not the sole cause of the accident, regarding cultural issues and human factors as vital contributing factors (Kurokawa et al, 2012): *"What must be admitted – very painfully – is that this was a disaster 'Made in Japan'. Its fundamental causes are to be found in the ingrained conventions of Japanese culture (…). Therefore, we conclude that the accident was clearly 'man-made'".*

Undoubtedly, this accident triggered a worldwide commotion, and the information released to the general public caused Japanese public opinion and the international community to perceive the nuclear industry as unsafe.

It is important to notice that the interaction between operators, technology and organisation is also a common issue during the information release from investigations of high-technology accidents. The final report of the *Bureau d'Enquêtes et d'Analyses pour la sécurité de l'aviation civile* (2011) on the AF-447 Rio-Paris flight accident described an apparently simple equipment defect (i.e. ice blockage of the Pitot probes) due to a design failure, resulting in an inconsistency of speed parameters. This deficiency triggered several human-related events (wrong system diagnosis and inappropriate control inputs, among others) which led to 228 fatalities and the loss of the Airbus A-330 in 1ˢᵗ June 2009. Besides, this emblematic investigation report has also stressed some features such as the de-structuring of the task-sharing during the response to the abnormal event, the lack of training in manual aeroplane handling in high altitudes, and the absence of a clear display of the airspeed inconsistencies in the cockpit, exposing an intricate combination of factors leading to the disaster.

The examples above highlight the complexity behind erroneous actions, mental models, technology, organisational issues, culture and the environment in high-technology industries, posing a significant challenge to how industry, governments and regulatory bodies will learn from these multi-attribute events and translate it into an approachable scheme to communicate risks appropriately. Moreover, high-impact accidents usually attract the utmost public and media attention, and the government capacity to maintain a reliable network to cope with asymmetries of information is naturally exceeded.

Therefore, this work aims to overcome barriers to dealing with complex data by means of applying an unsupervised learning neural network algorithm to an accident dataset developed by the authors, generating two-dimensional graphical representations of the multi-attribute events. The graphical interface will provide innovative means to communicate high-technology risks and to disclose surrounding factors and tendencies that could lead to the manifestation of human errors.

2. DATA SOURCE AND ANALYSIS METHOD

2.1. The Accidents Database - Multi-attribute Technological Accidents Dataset (MATA-D)

Complex industrial accidents are multi-attribute events, and many specific interactions are necessary to generate undesirable consequences. These attributes are usually exposed after laborious and sensitive investigations following serious events, the reports from which can be considered a very important source of accidents data. However, despite the considerable number of institutions responsible for investigating accidents and issuing recommendations to minimise the possibility of similar occurrences, the unavailability of a suitable dataset on human performance to consolidate data and promote profounder predictions is a significant bottleneck highlighted by Swain (1990) and the International Atomic Energy Agency (1990), among other academic and professional institutions. Attempts to reduce this bottleneck, such as the CORE-DATA database developed by Gibson and Megaw (1999), have not prospered so far, due to several complications, e.g. accessibility, taxonomy limitations and updating issues.

To overcome these issues and assuming that one of the primary methods to better understand multi-attribute events is to analyse data from past accidents, a Multi-attribute Technological Accidents Dataset (MATA-D) was developed by the authors, to highlight common features and reveal comparable conditions under which serious accidents may occur. Major accident reports from numerous industrial sectors were classified under a common framework based on Hollnagel's (1998) Cognitive Reliability and Error Analysis Method (CREAM) taxonomy, which allows up to 53 different attributes per event. Further data collection and usage restrictions, as well as an extensive description of CREAM are widely explored by Moura et al (2015). Currently, the MATA-D contains 216 industrial accidents.

2.2. Data clustering using Self-Organizing Maps

A well-stablished clustering method has been applied in this work in order to support the data exploration process and to disclose relevant associations within the MATA-D multi-attribute dataset. Self-Organizing or Kohonen's Map (SOM) is an unsupervised learning neural network algorithm created by Teuvo Kohonen, which provides simplified visualisation (usually two-dimensional) of multi-dimensional data, in a way that similar models are mutually attracted and associated with adjacent grid nodes in a topographic map.

Basically, the network is trained with the definition of the best matching unit (BMU) in the output space, defined as the one that minimises the Euclidean Distance $\|\vec{x} - \vec{m_i}\|$ between each input pattern x and output node m_i (Eq. (1)).

$$v(t) = \arg\min_{i \in \Omega} \|x(t) - m_i(t)\| \qquad (1)$$

A neighbourhood function h_{ci} will define the spatial influence of the BMU, attracting adjacent nodes to the BMU in the output space, and all the neighbours nodes will be successively updated following the Eq. (2). This sequence will be repeated (through iterations) until the map converges (Kohonen, 2001).

$$m(t + 1) = m_i(t) + \propto (t)h_{ci}[x(t) - m_i(t)] \quad (2)$$

The method is considered to be amongst the most relevant unsupervised learning algorithms (Araujo and Rego, 2013). It has been extensively used for data mining, clustering applications, to visualise large datasets and for dimensionality reduction (Cottrell et al, 2009, Hammer, Gisbrecht and Schulz, 2013, Kohonen, 2013).

The fact that SOM's learning process is designed not to be affected by external influence can be extremely helpful in this specific research, as it avoids potentially biased concepts and prevents excessively subjective interpretations during the analysis of circumstances which leads to the genesis and perpetuation of human errors.

3. THE MATA-D EXPLORATION USING SELF-ORGANISING MAPS

3.1. SOM Input Data

As an attempt to go beyond data statistical analysis and gain further insight into the relationship among contributing factors leading to accidents, the Self-Organising Maps was applied in this work, using the MATA-D as input data.

According to Kohonen (2013), the usage of a variant of the Eq. (2) updating rule is recommendable for practical applications, to eliminate convergence complications and generate steadier asymptotic m_i values. Consequently, he developed the batch-learning version of SOM (Batch-SOM) expressed in Eq. (3), which will be applied in the current dataset, to generate more robust results.

$$m_i^* = \frac{\sum_j n_j h_{ji} \overline{x_j}}{\sum_j n_j h_{ji}} \qquad (3)$$

Therefore, in the practical case, the learning factor $\propto$ was no longer necessary, with the codevectors being updated once, rather than in a recursive fashion. Each m_i^* is the centroid of the influence region defined by $\overline{x_j}$ (the mean value of x(t)), the neighbourhood function and the number of samples n_j.

Maps were generated from the 216 records with 49 attributes each, as four CREAM categories were not found in any event, i.e. Cognitive Style, Sound, Humidity and Other. The width of the kernel (the radius of the neighbourhood function) was 0.75, and the output space was trained with 84 batches.

3.2. SOM Results

The expert version of Viscovery® SOMine software was used to produce maps and enhance graphical visualisation. A quality measurement for different cluster numbers, which indicated the chosen grouping as a possibly good clustering (highest quality indicator factor), was used to favour the resulting arrangement shown in Figure 1.
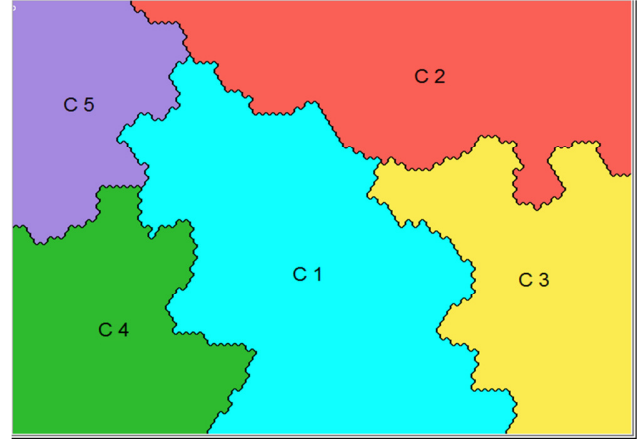

Figure 1: SOM Clustering Results

Table 1: Clusters main characteristics

Cluster	Events #	Factors #				
		Min	Max	Mean	Median	Mode
C1	50	04	19	08.6	08	08
C2	52	01	11	04.3	04	04
C3	53	01	05	02.7	03	02
C4	36	05	20	09.4	09	09
C5	25	06	24	11.3	10	10

Table 2: Factors incidence per cluster

Factor	C1	C2	C3	C4	C5
Wrong Time	**0.380**	0.058	*0.019*	0.028	0.320
Wrong Type	**0.260**	0.173	*0.019*	0.083	0.080
Wrong Object	0.020	0.038	*0.000*	**0.056**	*0.000*
Wrong Place	0.060	0.288	*0.000*	0.528	**0.840**
Observation missed	0.260	0.154	0.019	*0.000*	**0.440**
False Observation	*0.000*	*0.000*	*0.000*	0.028	**0.160**
Wrong Identification	0.020	*0.000*	*0.000*	0.056	**0.120**
Faulty diagnosis	0.160	0.038	*0.000*	0.111	**0.560**
Wrong reasoning	0.200	0.038	*0.000*	**0.278**	0.160
Decision error	0.120	0.154	*0.000*	0.028	**0.160**
Interpretation delay	0.080	0.038	*0.000*	0.056	**0.120**
Incorrect prediction	0.060	0.019	*0.000*	**0.111**	*0.000*
Inadequate plan	0.160	0.096	*0.019*	0.028	**0.240**
Priority error	**0.140**	0.115	*0.000*	0.028	0.040
Memory failure	*0.000*	**0.038**	*0.000*	*0.000*	*0.000*
Fear	0.020	0.019	0.019	*0.000*	**0.080**
Distraction	0.040	0.019	*0.000*	0.028	**0.400**
Fatigue	0.040	*0.000*	*0.000*	0.028	**0.160**
Perform. variability	*0.000*	*0.000*	*0.000*	*0.000*	**0.120**
Inattention	0.020	0.019	*0.000*	*0.000*	**0.120**
Physiological stress	*0.000*	0.019	*0.000*	**0.028**	*0.000*
Psychological stress	0.020	0.038	*0.000*	0.056	**0.080**
Functional impairmt.	**0.020**	*0.000*	*0.000*	*0.000*	*0.000*
Cognitive bias	0.100	0.038	*0.000*	0.083	**0.280**
Equipment failure	0.820	0.231	**0.925**	0.611	*0.080*
Software fault	*0.000*	*0.000*	*0.000*	0.056	**0.160**

Poor procedure	0.440	0.423	*0.038*	0.778	**0.840**
Access limitations	*0.000*	*0.000*	0.000	0.028	**0.080**
Ambiguous info	0.060	*0.000*	*0.000*	0.028	**0.080**
Incomplete info	0.200	0.058	*0.000*	0.167	**0.440**
Access problems	0.020	*0.000*	*0.000*	**0.056**	0.040
Mislabelling	*0.000*	0.019	0.019	**0.028**	*0.000*
Communic. Failure	**0.260**	0.038	*0.019*	0.056	0.240
Missing information	0.200	0.135	*0.057*	**0.583**	0.080
Maintenance failure	0.420	*0.058*	0.283	**0.833**	0.280
Poor quality control	0.820	*0.173*	0.472	**0.972**	0.720
Managemt. problem	0.180	*0.019*	*0.019*	**0.194**	0.160
Design failure	**0.860**	*0.423*	0.472	0.833	0.760
Poor task allocation	0.620	0.577	*0.132*	**0.972**	0.920
Social pressure	*0.000*	0.058	0.000	**0.222**	0.160
Insufficient skills	**0.720**	0.212	*0.057*	0.361	**0.720**
Insuffic. knowledge	0.600	0.154	*0.057*	**0.639**	0.400
Temperature	0.020	*0.000*	0.019	*0.000*	**0.040**
Illumination	*0.000*	*0.000*	0.000	**0.056**	*0.000*
Adv. ambient cond.	0.040	**0.173**	0.075	0.056	*0.000*
Excessive demand	0.020	0.077	*0.000*	0.056	**0.200**
workplace layout	0.020	0.038	*0.000*	0.028	**0.080**
Poor team support	0.040	0.019	*0.000*	0.056	**0.120**
Irreg. working hours	0.020	0.000	0.000	0.056	**0.240**

Table 1 summarises the main characteristics of the generated clusters, while Table 2 presents factors frequency results (minimums in italic, maximums in bold) per cluster.

4. DISCUSSION AND CONCLUSIONS

4.1. Clustering Interpretation

The first cluster comprises 50 accidents, 23.28% of the dataset. Design Failure (86%) highest incidence is grouped with two specific execution factors, Wrong Time and Wrong Type, which attained their maximum clustering values (38% and 26%, respectively), indicating that in-built design deficiencies seem to have prompted basic execution errors (timing, duration, force, distance/magnitude, speed or direction).

A specific cognitive function related to planning, namely Priority Error, showed strong similarity with the Wrong Type execution factor, while Communication Failure (26%) was linked to the Wrong Time factor. Also, the significance of the organisational factor Insufficient Skills can be highlighted, which reached its maximum figures (72%). An example of graphical analysis of the isolated factors' SOM is shown through the comparison between Figures 2 and 3, where the relationships above mentioned can be

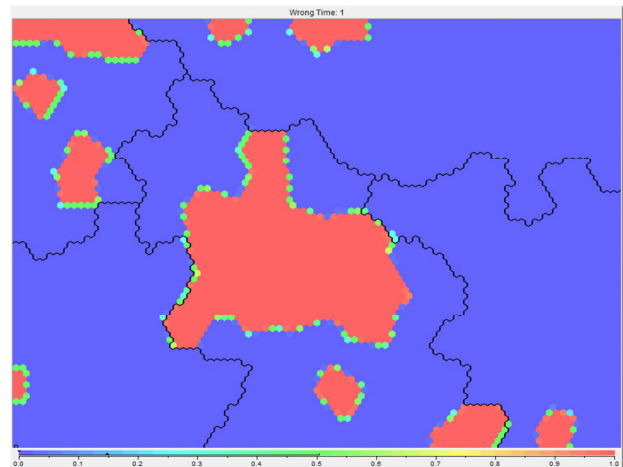depicted, providing further support to risk communication.
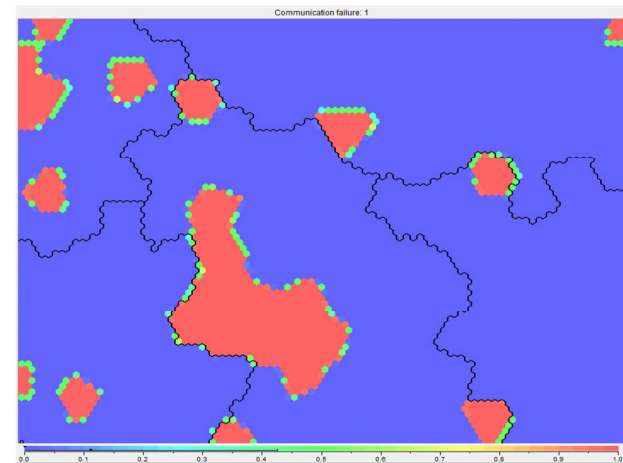

Figure 2: Wrong Time SOM

Figure 3: Communication Failure SOM

Therefore, design failures appear to directly affect planning cognitive functions, leading to very basic erroneous actions due to some human performance failure or equipment mishandling (lack of skills). This scenario is aggravated by communication gaps, when the message does not reach the intended receiver. Several "timing" erroneous actions (Wrong Time factor) were combined with communication deficiencies to decisively contribute to serious events. The Piper Alpha accident is one of the most acknowledged examples of this identified interaction, in which pumps were started before the conclusion of maintenance works due to poor communication between shifts (Cullen, 1990), clearly concurring

with the findings depicted in the Figures 2 and 3 above.

The Adverse Ambient Conditions factor attained its maximum level in Cluster 2 (17.3%), and the analysis leads to an association with Design Failure and Equipment Failure. For this group, design seems to have failed to cope with foreseeable adverse ambient conditions, resulting in some kind of equipment failure.

Accidents within cluster 3 are strongly characterised by the Equipment Failure technology factor, with 92.5% of frequency. However, the grouping shows 53 accidents encompassing one to five factors, with low mean, median and mode values. It means that the majority of accidents have limited identified factors leading to the undesirable outcome. Fundamentally, the main finding which can be extracted from the analysis is that Inadequate Quality Control and Design Failure are more associated with Equipment Failure (and to be regarded as its cause) than a Maintenance Failure. Although further assumptions regarding this group might be unsupported, due to the low amount of straight recognisable relationships among features, it is possible to suggest that some strong evidence found during an accident investigation (such as an equipment failure) may influence the event's examination process as a whole (being considered the main or direct cause) and override the search for further underlying causes.

Cluster 4 is largely dominated by the Inadequate Quality Control (97.2%), Inadequate Task Allocation (97.2%) and Maintenance Failure (83.3%), being also apparent a high frequency of the Design Failure factor, with 83.3% of incidence. Insufficient Knowledge (63.9%) and Missing Information (58.3%) reached their maximums, and Permanent Interface technological problems (Access Problems and Mislabelling) related to design are noticeable too.

Specific cognitive functions related to interpretation (Wrong Reasoning and Incorrect Prediction) are strongly associated to the Insufficient Knowledge factor, emphasising a lack of understanding of the current situation or being not certain about the action that should be performed. The Missing Information factor high incidence means that information provided by organisations within the group is generally lacking, incorrect or misunderstood. Hence, communication issues seem to have poisoned these organisations, being largely reflected by the Inadequate Task Allocation, Inadequate Quality Control and Maintenance Failure maximum figures, and disclosing an asynchrony between organisation of work, task planning, managerial rule and the information available.
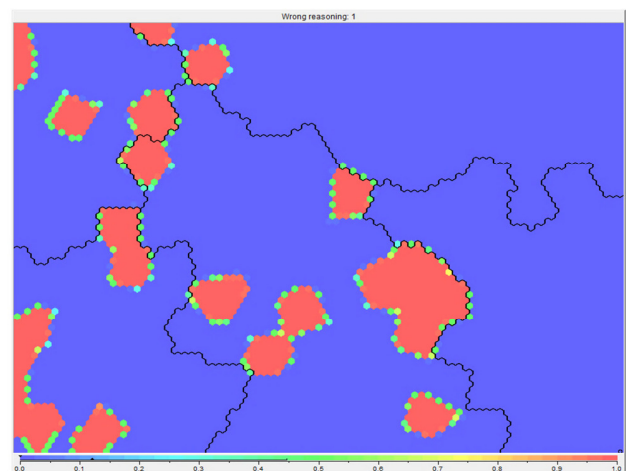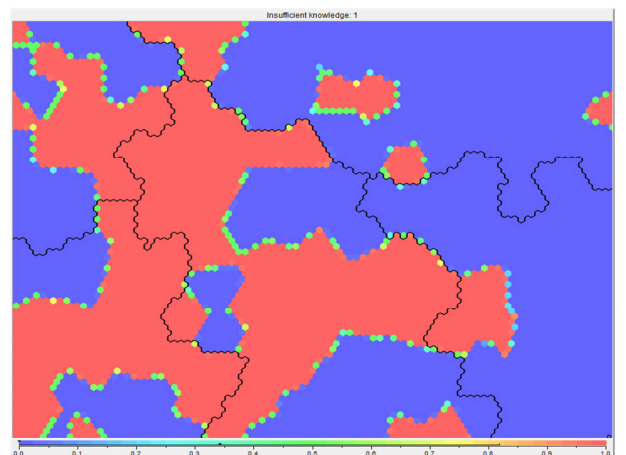

Figure 4: Wrong Reasoning SOM

Figure 5: Insufficient Knowledge SOM

Figure 4 topographic similarities with Figure 5 highlight the relationship between Wrong Reasoning and Insufficient Knowledge, and the 2001 American Airlines Flight 587 accident, which resulted in 265 fatalities, illustrates this strong connection. According to the investigation report (NTSB, 2004), pilots were not aware of

the existing structural protection level when full or abrupt flight control inputs are made at airspeeds below the manoeuvring speed (Insufficient Knowledge) and the first officer associated wake turbulence encounters with the need for aggressive roll upset recovery techniques (Wrong Reasoning, i.e. deduction error).

Cluster 5 shows a very robust presence of the Wrong Place erroneous action factor, with 84% of frequency. This sequence factor is combined with all three categories of cognitive functions: (i) Observation (Observation Missed, False Observation and Wrong Identification); (ii) Interpretation (Faulty Diagnosis, Decision Error and Delayed Interpretation) and (iii) Planning (Inadequate Plan), in addition to the highest incidence of Temporary and Permanent Person Related Functions.

Consequently, this cluster is indisputably the most significant in terms of human-related features and it is intensely associated with Technology issues, especially Inadequate Procedure (84%) and Incomplete Information (44%) as well as Working Conditions organisational factors, which were all significant for this group.

These features indicate that deficient technology information (from interface – warnings, alarms and indications – and from procedures – ambiguous, incomplete, incorrect or mismatched with reality) required for the safe operation of systems boosted difficulties to identify signals, events or measurements which should have prompted a suitable action. As a result, the wrong system diagnosis led to a wrong action sequence issue (omission, jump forward, jump backwards and extraneous actions).

4.2. Final Remarks

The possibility of reducing a 216-event dataset with 49 attributes each to a two-dimensional map is a noteworthy feature taken from the SOM algorithm, which permitted the translation of extremely intricate data into a friendly interface to communicate high-technology risks to stakeholders, support findings and assist the decision-making process. Furthermore, the usage

of a techno-social framework such as the Cognitive Reliability and Error Analysis Method to organise and create the MATA-D dataset, followed by a mathematical method to explore data and disclose surrounding factors and tendencies, provided a very useful common ground for cross-disciplinary understanding of risks and allowed the visualisation and interpretation of case studies from the real world.

Clustering and nodal analysis indicated that design must anticipate the skills and knowledge level that should be required from operators, possibly providing some training recommendations to minimise interpretation and mental planning issues leading to execution errors. Skills are usually linked to practical experience, thus setting up on-the-job trainings with senior instructors seems to be a reasonable alternative. Relevant technology information (from interface and procedures) must be identified and assessed in terms of adequacy, focusing on how some missing information could induce erroneous human actions or inhibit correct actions during operations, directing at arrangements prone to be affected by sequence issues. The establishment of a specific method to maintain communication channels, to improve the message format and to timely deliver the required information is vital for the organisation of work, task planning and managerial rule. Also, the quality of accident investigations involving equipment failures is an issue that deserves additional attention by managers. A strong indication (e.g. an equipment failure) might induce a biased conception from investigators towards a final conclusion, without further reflection concerning deeper underlying causes and contributing factors. Those conclusions from the dataset are naturally visualised and communicated with the use of a graphical interface, considering that the algorithm has perfectly conserved the input factors in the output space, allowing further interpretation of isolated factors.

4.3. Future Developments

The clustering analysis based on Self-organising Maps algorithm confirmed the link between

human-related features and other dataset relevant factors which figured frequently, such as inadequate quality control, equipment failure, inadequate task allocation and training, indicating a pathway for further investigation. Future research could also focus on the usage of graphical methods to communicate risks to specific stakeholder groups, such as the workforce – as a tool to improve awareness and allow them to recognise potentially hazardous patterns – or the general public, to depict past accident data in an approachable way and reduce information asynchronies.

Furthermore, other datasets such as the ASRS (Aviation Safety Reporting System) could be solely used or integrated with the MATA-D to produce further insight.

5. ACKNOWLEDGEMENTS

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