International Congress on Environmental Modelling and Software

9th International Congress on Environmental Modelling and Software - Ft. Collins, Colorado, USA - June 2018

Jun 26th, 9:00 AM - 10:20 AM

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iEMSs International Congress on Environmental Modelling and Software

9th International Congress on Environmental Modelling and Software
Fort Collins, Colorado, USA, Mazdak Arabi, Olaf David, Jack Carlson, Daniel P. Ames (Eds.)
https://scholarsarchive.byu.edu/iemssconference/2018/

Exploratory Participatory Modelling with FCM to Overcome Uncertainty: Improving Safety Culture in Oil and Gas Operations

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Abstract: This work combines qualitative text analysis, participatory modeling with Fuzzy Cognitive Maps (FCM) with Exploratory Modelling and Analysis (EMA). FCM is suitable for modeling in data-poor environments when the system under study is not well described in quantitative terms. A case in point is safety culture, which describes the values, routines, and work processes that allow an organization to prevent disasters by avoiding and quickly bouncing back from mistakes. The concept is particularly relevant in oil and gas industry, where initially small errors have potentially devastating environmental, social, and economic impacts. In this setting relevant quantitative data on safety culture is virtually non-existent: when nothing happens, nothing is reported, and when an accident happens and is reported, the report provides no direct information about the culture. Accordingly, our project creates a system model of safety culture based on published (mainly qualitative) research and expert inputs. EMA, on the other hand, is used to address uncertainty about the model structure, such as a lack of knowledge on how to quantify causal links. Rather than synthesizing knowledge into one model, EMA constructs an ensemble of plausible models and explore their impacts. Our work integrates the two approaches and demonstrates the results with data on oil and gas safety. In this paper, we discuss the general approach and present data on the first step: creating an FCM model of safety culture based on qualitative analysis. We present the use of thematic analysis and t-coefficient.

***Keywords**:* Exploratory Modelling Analysis; Participatory Modelling; Fuzzy Cognitive Maps; Safety Culture; Oil and Gas Operations.

1 INTRODUCTION

Accidents in offshore oil and gas operations can have devastating consequences, including loss of lives, poor health outcomes, damaged ecosystems, reduced economic opportunities, disruption of local communities, and hits to government budgets. A case in point is the Deepwater Horizon accident that reduced BP's bottom line and taxable income by more than 61 billion US dollars[1]. Such damages should provide a strong incentive for companies to prevent accidents. Yet, accident rates in offshore oil and gas remain stubbornly high (NASEM, 2016; BSEE, 2017) for multiple reasons (NASEM, 2016; NEB, 2014): Systems are complex, increasingly virtual, and often span across multiple companies and landscapes, which makes on the ground observations difficult and creates uncertainty about system states. For technical and economic reasons, production pressure is continuous, leading to long work hours and fatigue. Many companies rely on temporary/contracted workforce for operations and disasters response who do not share the same training, experiences, and sometimes also language. Industry culture historically values toughness (i.e., Roughnecks) and "can do" attitude over deliberation and analysis. Also, relevant data is scarce: The investigation of accidents provides some insights into how a similar accident can be prevented in the future but does not provide an understanding of the

[1] https://www.usatoday.com/story/money/2016/07/14/bp-deepwater-horizon-costs/87087056/

many instances of non-accidents (i.e., safety), where errors did not occur or were corrected in time (NASEM, 2016).
Borrowing from the toolset of participatory environmental modelling, we combine Fuzzy Cognitive Mapping (e.g. (Gray, et al., 2015; Henly-Shepard, et al., 2015)) and Exploratory Modelling and Analysis (Kwakkel & Pruyt, 2013; Kwakkel, et al., 2010) to investigate how safety in oil and gas operations can be improved. In this paper, we discuss the background of the work and the general research approach and present data on the first research step, the development of a literature-derived FCM model of safety culture.

2 BACKGROUND

2.1 Safety Culture

Safety culture is defined as; "the product of individual and group values, attitudes, perceptions, competencies to, and the style and proficiency of, an organization's safety management" (ACSNI, 1993, p. 23). It is a multi-faceted phenomenon that builds on organizational values, leadership commitment, and continuous improvement of safety-related practices (Singer & Vogus, 2013; Weick & Sutcliffe, 2015). As such, it is never a stable endpoint but requires ongoing management to ensure that positive changes are sustained, despite a tendency of systems to migrate towards states of higher risk (Leveson, 2011). Within various approaches to conceptualize safety culture, a distinct stream of research looks at so-called high reliability organizations (HROs), which refer to complex and potentially hazardous organizations such as nuclear power plants, air traffic control operations (Vogus, et al., 2010), and naval aircraft carriers (Weick & Sutcliffe, 2015). In those organizations, the operations take place in environments described to be socially and politically challenging (Weick, et al., 1999), technologically sophisticated (Vogus & Sutcliffe, 2007), interdependent and timely pressured (Vogus & Sutcliffe, 2007), uncertain and hazardous (Weick, 1987). Nevertheless, they perform at a constant and high level of safety (Weick & Sutcliffe, 2015), almost error-free. As such, they are HROs. Research on their practices define five principles as the hallmark of HROs (Weick & Sutcliffe, 2015); (1) preoccupation with failure, (2) reluctance to simplify, (3) sensitivity to operations, (4) commitment to resilience, and (5) deference to expertise. Table 1 below briefly defines each of these five principles (Sutcliffe, 2011).

Table 1 Definitions of HROs' Five Principles

Principle	Definition
Preoccupation with Failure	A chronic precaution that motivates a proactive and preventative examination of potential weaknesses and treats any failure or near-miss as an indicator of potentially large-scale issues.
Reluctance to Simplify	The tendency to question assumptions, think critically and create a more complete and nuanced picture of operations.
Sensitivity to Operations	Collaboration and constant sharing of information that enables members of the organization to develop a system view on the operations so that they can make adjustments to preclude errors from accumulating, particularly human and organizational.
Commitment to Resilience	Developing and enhancing competencies that enable the organization to quickly notice, contain, and learn from errors that have already happened, and quickly bounce back to normal operations.
Deference to Expertise	Whenever needed, decision-making power migrates to people with specialized expertise.

The culture in HRO encourages employees to seek information actively and to take action (i.e., think, say, urge, tell, negotiate, report, etc.), while responsibilities are shared, failures are inquired, and new ideas are welcomed and rewarded (Westrum, 1993; 2004). Furthermore, HROs' processes provide a cognitive infrastructure that make adaptive learning and reliable performance possible (Weick, et al., 1999). Widespread adoption of HRO principles in offshore oil and gas operations could thus improve everyday safety performance and prevent severe accidents that lead to spills and other environmental impacts. However, achieving such a culture in oil and gas organizations, which are complex technical and social systems with variation in human and technical elements, is challenging. The translation of

HRO principles into the organizational context of oil and gas industry requires that that managers take a system view. In particular, they need to leverage the inherent dynamics of the system (see “leverage points” discussed by Meadows (2008)) to create “virtuous” cycles of continuous improvement, while also taking indirect, far-reaching, and potentially undesirable effects of their actions into account.

2.2 Fuzzy Cognitive Mapping

Fuzzy Cognitive Map (FCM) modeling (Kosko, 1988; Jetter & Kok, 2014) is a system thinking technique that builds quantitative models from causal cognitive maps, which are captured from academic experts, as well as key actors of the organization (e.g., managers, operators, emergency responders). Causal cognitive maps represent the elements (“concepts”) of a system. They can be qualitative and difficult to quantify. Causal links between concepts are represented as arrows with positive or negative signs. For example, a positive arrow pointing from concept A (e.g., the organization’s attitude to show “deference to expertise”) to concept B (e.g., the organizational practice of “empowerment of low-level decision makers”) means that the attitude of “deference to expertise” causes “empowerment” to increase. Despite the qualitative nature of these concepts and connections, FCM modeling allows quantitative simulations. Quantitative simulations is possible because FCM combines neural network theory and fuzzy set theory. Because of their ability to simulate system behavior, FCM models can answer the question if a large increase in one concept leads to an equally large increase in a connected concept or if other system elements buffer or counteract this effect. Moreover, the insights from different people can be captured in individual FCM models and subsequently combined to get a “full picture.”
For example, Figure 1 illustrates the idea of capturing individual models as FCM. It shows, purely as an illustrative demonstration, what a supervisor in an oil and gas operations might think about issues related to safety culture. In his/her personal worldview safe operations increase productivity and occur because no errors are made, and errors that do occur are addressed immediately, also by lower level employees. Expert operators, with years of knowledge and – consequently – high standing in the organization have an ambivalent role: on the one hand, they make few mistakes and have system knowledge that permits them to fix mistakes immediately.

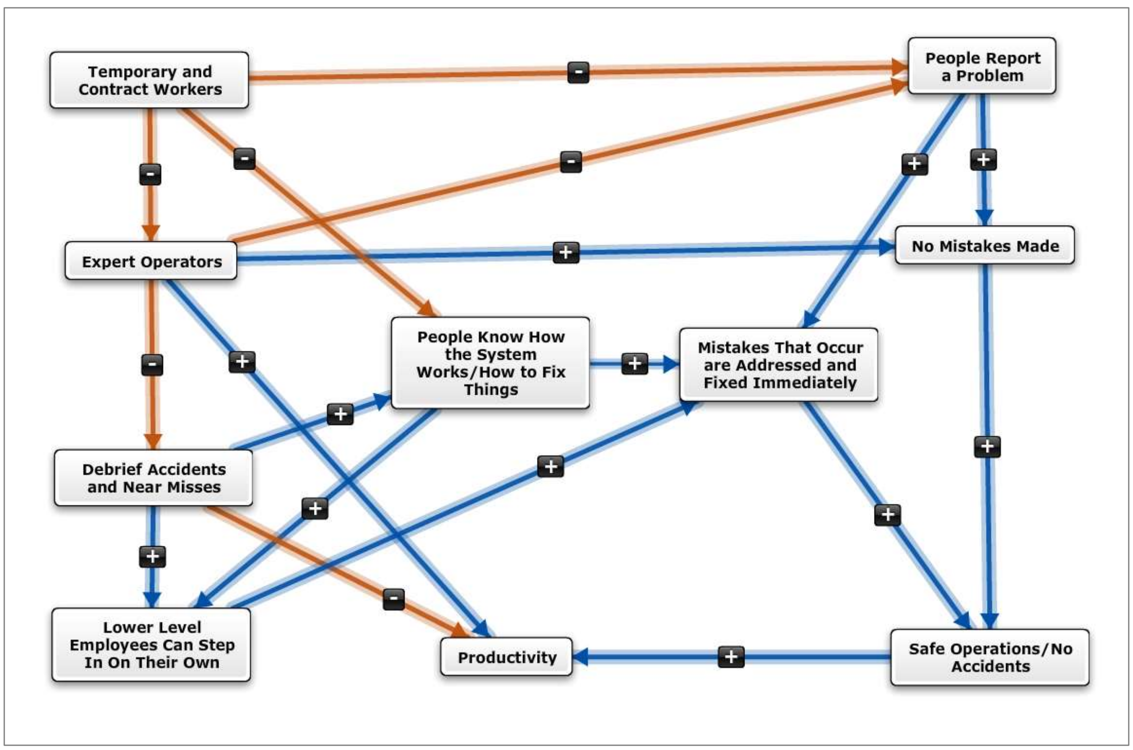

Figure 1 Mental Model of Safe Operations

On the other hand, they tend to take action without reporting and without wanting to waste time on analyzing “near misses,” which limits the ability of other workers to see and respond to problems. (The width of the arrows between concepts indicates the strength of the connection). The model can be used to test – among others - what would happen if the number of expert operators increases or decreases and how an increase of contract workers would impact safety outcome. Figure 2 shows a simulation run for a scenario in which temporary and contract workers increase at a higher rate than expert operators. The model predicts that safe operations and productivity would go down.

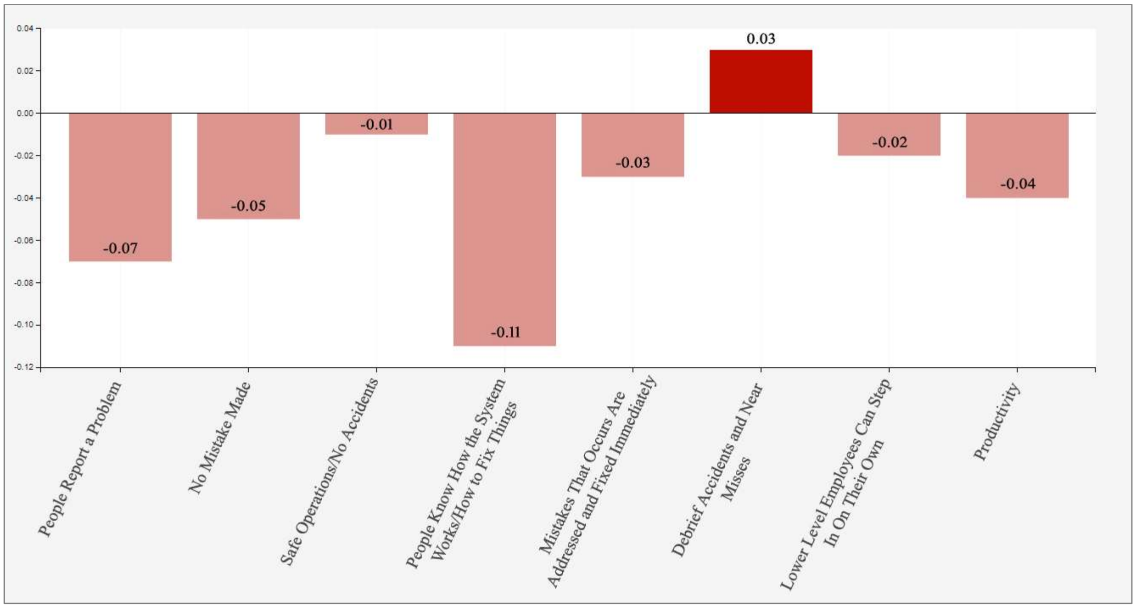

Figure 2 Simulation results, showing model predictions for scenario 1: a small increase in expert operators, a large increase in temporary workers

In an alternative scenario, the number of expert operators is slightly reduced because “old timers” retire, while temporary and contract workers increase. In this case, the model predicts a smaller deterioration of safe operations and a higher loss in productivity.

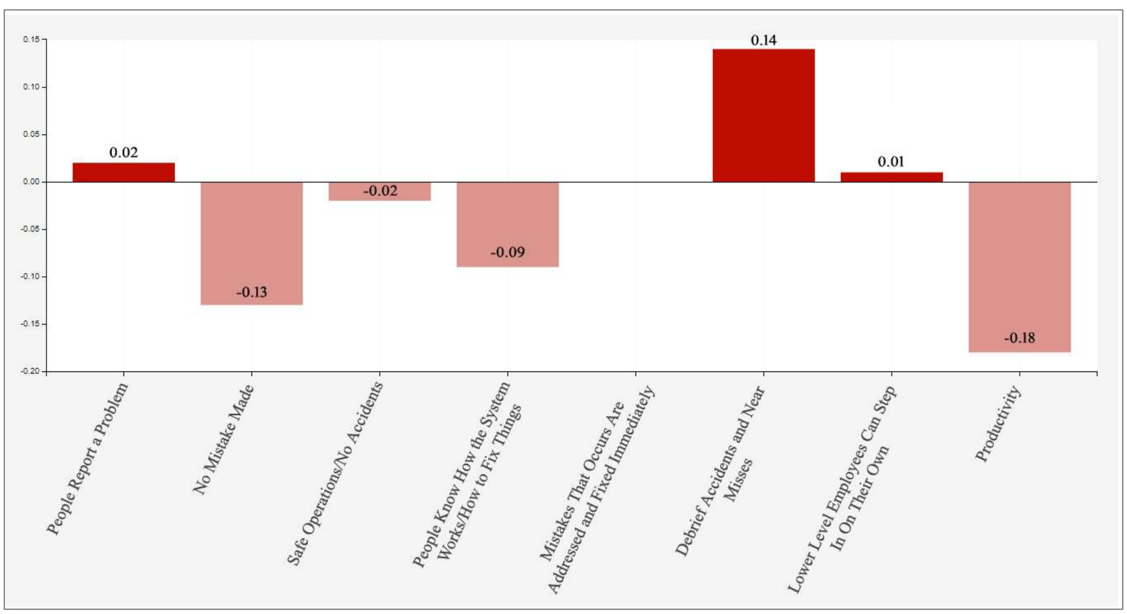

Figure 3 Simulation results, showing model predictions for scenario 2: a small reduction in expert operators, a large increase in temporary workers

The examples above were modeled and calculated with a free software tool, Mentalmodeler (mentalmodeler.org), which was developed by one of the authors, Gray. Approaches for eliciting FCM models from experts and laypeople and integrating their insights into a single model that pools knowledge are well documented in the literature (e.g. (Jetter & Kok, 2014; Gray, et al., 2015)). Moreover, FCM modeling is increasingly used in participatory modeling.

2.2 Exploratory Modelling and Analysis

Exploratory modeling (Kwakkel & Pruyt, 2013; Bankes, 1993) is an approach to system modeling that can be applied to various modeling techniques, including FCM methodology. In traditional (so-called consolidative or predictive) modeling, modelers attempt to build a single model whose structure correctly represents "how the system works". This model predicts outcomes for any given input. In the case of FCM scenario techniques, the inputs are uncertain, and range of input combinations are tested with the same model, leading to a range of outcomes (Alizadeh, 2018). In complex systems, however, not only the inputs but also the structure of the system and consequently the model may be partially unknown. For example, in Figure 1, a modeling team may agree that there is a positive relationship between the concepts of "expert operators" and "no mistakes made" and create their FCM model accordingly, but some experts and stakeholder may perceive the link to be very strong while others consider it to be weak. In exploratory modeling, the simulation would be run for various weights in the interval from "weak" to "very strong," thus effectively not only simulating outcomes in one FCM model but in multiple FCM models.

3 METHOD

We use published research on HRO to develop a baseline FCM model that represents the state-of-the-art of HRO theory. We then review the model and the system behavior it encodes together with oil and gas industry practitioners (safety engineers, operations managers, safety analysts, etc.), thus employing participatory modeling and analysis. This step will uncover uncertainties about the model structure because experts may disagree with the model derived from the literature (which builds on research in other industries) and may disagree among themselves because they rely on limited observations and individual experience but lack objective data. EMA will be used to address these uncertainties by developing a range of models. Managers in oil and gas industry will be able to use the insights gained from the models to plan so-called robust interventions: approaches that lead to safety culture improvements in many of the possible futures. The following section describes the first steps of this work: Building and testing a literature-derived baseline model.

3.1 Building a baseline model

As discussed before, our work is located in a data-poor environment because safety culture factors are difficult to measure and not usually tracked in industry. Instead, we rely on published research on HROs practices and use qualitative research methods to analyze the literature: For a different FCM study, Alizadeh & Jetter (2017) used content analysis to capture causal relationships from secondary sources of data. In this research, we use the thematic analysis (TA) (Braun & Clarke, 2006; Guest, et al., 2014) and thematic network analysis (Attride-Stirling, 2001). TA is considered a suitable approach for conducting qualitative research in applied settings, such as health or policy research or education, early childhood development, and safety. It is a highly structured process, typically enabled by qualitative research software, such as Atlas.ti or NVivo, that tends to ensure the reliability and validity of qualitative research by enforcing a clear and traceable procedure. It results in a so-called thematic network, a structure of themes and relationships among them, not unlike a cognitive map. In thematic analysis, texts are first coded (or "tagged") to dissect the text into meaningful segments. For example, a passage of text that talks about how employees do not think that their safety matters to the organization if managers fail to adhere to safety regulations, may be broken up into codes relating to "employee perceptions about the employer" and "managers following procedure". In a second step, themes are identified in the codes. Themes represent more abstract ideas that emerge from several codes and are distinct from other themes. For example, a theme could be "managers serving as examples". The themes are further organized into groups to identify basic themes, which will become thematic networks. The passage initially coded in our example may thus contribute to multiple basic themes. Basic themes are grouped and for each group, organizing themes are identified. For example, researchers may choose to group several themes relating to management behavior together. Each organizing theme is further explored to identify propositions, assertions, assumptions and its basic claim (the main "takeaway" from the text). Such a theme could be "manager behavior needs to consistently prioritize safety". This basic claim becomes a so-called global theme, which is illustrated as a non-hierarchical network that shows the connections between the global theme (the main claim), the organizing themes that contribute to the global theme, and the basic themes that feed into the organizing themes. In our study, the connections are causal but other types or connections are possible.

Based on TA, our study identifies five global themes and thus results in five network models. Each model represents one of the HROs five principles and consists of concepts (i.e. basic and organizing themes) that are causally connected. We converted these casual maps into a single FCM and visualized and analyzed it in Mental modeler: It consists of 51 concepts with total 138 casual connections. The model density is 0.054, the connection per concept is 2.7, the number of drivers is 10, and the complexity score is 0.1. To calculate edge weights (i.e. the strength of a connection arrow), a thematic proximity method (Armborst, 2017) was used, resulting in a so-called thematic coefficient (t-coefficient) for each map. The t-coefficient indicates how much content two descriptive units (themes) share with each other regarding words frequencies. This coefficient is calculated using the following equation;

$$t = \frac{1}{2}\left(\frac{n12}{n1} + \frac{n12}{n2}\right)$$

Where, n1 is the total number of words classified with theme 1, n2 is the total number of words classified with theme 2, and n12 is the number of intersecting words between the casually connected two themes. Using ATLAS.ti retrieval tools to generate a table of words frequencies, we calculated t-coefficient for the all the connections in this model. We thus interpret t-coefficient as an indicator of the strength of a causal link.

3.2 Testing the baseline model

Strategies for testing, calibrating, and validating FCM models are underreported in the literature. Jetter and Kok (2014) recommend adopting tests from the systems dynamics literature, such as expected behavior, extreme condition, and sensitivity analysis. We follow the same strategies, yet face the additional challenge that we are, to our knowledge, the first to quantify edges in an FCM with the t-coefficient. We, therefore, ran a variety of model tests: First, we tested input vectors with varying activation levels for single concepts at a time and observed the impact on the five principles of HRO because they are well described in the literature and it is relatively easy to determine what system behavior to expect. In one instance, the model behavior relating to a particular theme was unexpected. We traced back every decision that was made during the thematic analysis process, all the way to the original text. This was done by two researchers who, as is common in qualitative research, had to agree before a change was made. Since the change was warranted by the data and agreed upon, we re-calculated the t-coefficient for the concepts in question and modified the FCM accordingly. After this change, the model behaved as expected. We furthermore randomly varied up to five concepts in the input vector at a time (based on the notion that managers focus their intervention on a limited number of activities) to explore the range of possible outcomes for all five HRO principles. Again, results are within what is to be expected. However, both of our testing strategies show that the choice of lambda[2] is important and involves trade-offs for both, the sigmoid and the hyperbolic tangent function. If we want results to map into the more easily interpretable range of [0,1] or [-1,1] the slope of the functions become steep, resulting in more tipping point, which may be difficult for industry experts to understand. Our next research step, the review of the model with practitioners, will likely give us insights into how to resolve this conflict.

4 RESULTS TO DATE AND CONCLUSIONS

Our work to date shows that (1) it is possible to use thematic analysis and t-coefficient to analyze secondary data to create an FCM model with quantified edges, and (2) that this model, in principle, reflects expected system behavior. This opens the possibility for participatory modeling projects that provide decision-support on solid theoretical footings: rather than relying on participants, however well informed they may be, to fully capture the system, we can use published research, even in data-poor environments. Our next research step is to investigate differences between the literature-derived model and expert insights, as well as disagreement among the experts. This will give us additional insights into the usefulness of the t-coefficient by testing model behavior against the expectations of a broader group of people. It will also allow us to identify uncertainties that can be approached with EMA. Over time, we expect this to result in a system model of HRO, tailored to the realities of offshore oil and gas, that will help improve safety and prevent environmental disasters.

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[2] Lambda is a parameter used to determine the appropriate shape of the squashing function. It is a constant number, by which modelers specify function slope or the degree of fuzzification.

Despite its relatively early stage, our work makes several contributions: it provides the first comprehensive thematic analysis and the first quantitative system model of HRO, which is relevant to many settings, not only oil and gas industry. Furthermore, we have innovated the use of thematic analysis for FCM modeling, as well as the use of the only recently published t-coefficient.

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