LEARNING ABOUT RISK: MACHINE LEARNING FOR RISK ASSESSMENT

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1. INTRODUCTION

In the safety-critical sector of the petroleum and chemical business, new information is constantly changing how we perceive risk. Although this business aims for improved system performance, the loss of dangerous substances could put many people in danger. Although frequently used, Kaplan and Garrick's (1981) definition of RISK (R), which takes into account what SCENARIO (s) could go wrong, the PROBABILITY(p) that it would happen, and the severity of the CONSEQUENCE (c); defined by a mathematical equation

$$\mathbf{R = f(s,p,c)}$$

, falls short of being able to encompass all of risk's nuances. Methods like establishing precise operational guidelines, receiving advanced training, and engaging in mindful interaction between actors and operating environment constituents have all been recommended to ensure high dependability in organisational performance in risk environments. Highly sensitive computational management programmes of machines that offer more consistently dependable management of technical operations in fluctuating risk settings are now the centre of attention for organisational control. The research suggests a method for overcoming the difficulties in risk assessment based on the use of machine learning techniques, which is covered in more detail in the following sections.

2. METHODOLOGY AND CONTEXT

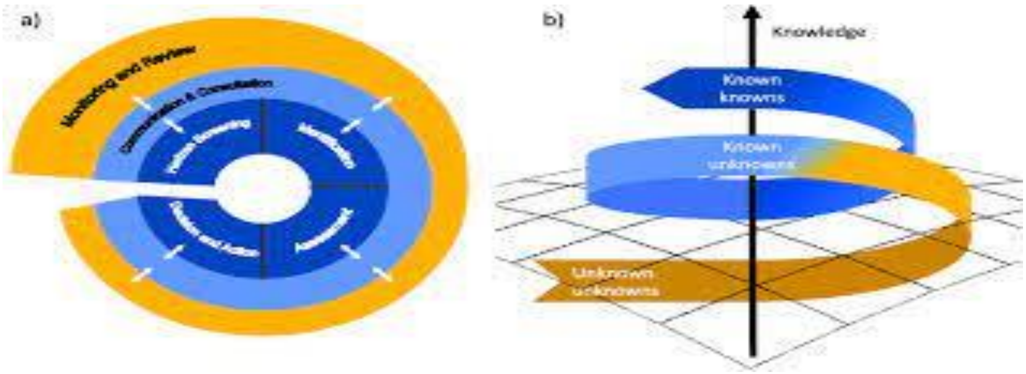
2.1 RISK KNOWLEDGE : Risk knowledge is the study issue covered in this article, and it advocates adding a new dimension to the concept of risk, i.e., Knowledge. **Aven and Krohn(2014)** suggested a new mathematical equation that has a component of **Knowledge(k)** in it.

$$\mathbf{R = f\ (s,\ p,\ c,\ k)}$$

The paper makes the case that communicating the degree of expertise utilised for risk assessment is a fundamental aspect of calculating the value of risk. The need of effectively recognising and analysing hazards to guarantee successful risk management is the basis for the relevance of this study issue.

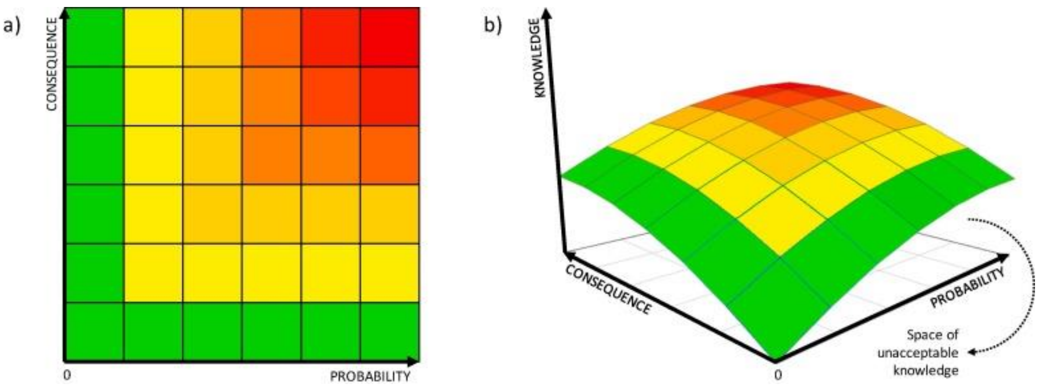
Paltrinieri et al.'s **Dynamic Risk Management Framework (DRMF)** is used (2014). DRMF focuses on the ongoing systematic organisation of knowledge on fresh risk evidence. To prevent self-sustaining processes and vicious cycles, it has an open form. Through ongoing monitoring, it exposes the process to fresh information, early warnings, and unwelcome occurrences.

Fig : (a) Dynamic Risk Management Framework (DRMF - clockwise) (b) DRMF revolving around the knowledge dimension.



The body of research on this subject is now rather substantial, with several studies suggesting various methods and frameworks for identifying and managing risks. However, there is still opportunity for more investigation into the best ways to integrate a dynamic approach to risk management and quantify the knowledge component in risk assessment.
By suggesting a new definition of risk that incorporates the **knowledge** component and highlighting the significance of a dynamic approach to risk management, this article adds to the body of previous work.

Fig : (a) 2-D risk matrix and (b) 3-D risk matrix.



The essay also makes the case that risk analysis may take changing conditions into account and enhance system knowledge through calibration and adjustment based on fresh facts. In conclusion, this paper offers insightful information on how decision-makers may efficiently evaluate and manage risks in complicated and dynamic system.

State of the art and overall challenges : Numerous strategies address the requirement for ongoing risk assessment updates and may be divided into two major categories:
(i) Empirical : It strategies are often created by seeing a lot of pertinent data.
(ii) Theoretical : Scarce data would force the use of theory-based procedures, which would entail making certain unavoidable assumptions.

2.2 SMALL THINGS: How presumably little occurrences can have a role in catastrophic mishaps. The author believes that recognising and attending to these tiny things might assist avert accidents and reduce their likelihood. In the corporate world, a number of methods, including reasoning trees and safety barriers, are used to evaluate and minimise risk. Paté-Cornell, 2012, and Haugen and Vinnem, 2015 caution against misusing the Black Swan concept and emphasize the need to take safety measures and issue regulations against predictable situations. The essay further emphasises the value of ongoing education and safety measure development while cautioning against the abuse of the Black Swan idea.

2.3 Machine learning: The article explains how machine learning, in particular deep learning, has the ability to close gaps in risk assessments for businesses where safety is crucial. The author mentions Diekmann (1992) forecast that future risk analysis would depend on developments in artificial intelligence and observes that industrial risk analysis has not kept up with this forecast. Deep learning is marketed as a method for teaching computers to evaluate risk by digesting vast volumes of data from everyday operations and historical occurrences. The author admits the arbitrary nature of risk definition and makes the point that each event's degree of risk must be determined under professional supervision.

According to the study, deep learning offers the possibility of bridging some methodological gaps in risk analysis and enabling real-time risk assessment of monitored systems. Overall, the study offers a positive assessment of deep learning's potential for risk analysis.

2.3.1 Deep Neural Network (DNN) : It is defined in the literature as a feed-forward neural network with several layers of functional transformations. It computes the hidden units and produces the output, which in this case is a risk index, using a non-linear activation function. In order to anticipate the output based on fresh inputs, the model might be trained in a supervised manner. Utilizing a DNN over a linear model has the key benefit of being able to capture non-linear interactions between inputs and outputs. However, the performance and accuracy of the DNN model are not discussed in the text, making it impossible to assess how successful it is.

2.3.2 Model Application : The use of a DNN model and a multiple linear regression model to forecast the risk increase given indicator patterns is described in the text. For 50 separate categories over a 30-year period, the indicator values were simulated, and the models' inputs were their time-dependent derivatives. To train and evaluate the models, two datasets were produced. The DNN model structure was based on **Cheng et al. (2016)**, and it was implemented using the TensorFlow framework. A multiple linear regression model was also used to assess how well the DNN model performed. However, the performance or accuracy of the models are not discussed in the text, making it impossible to assess their efficacy.

3. **Result:** The article employed DNN and MLR models to forecast the rise in risk brought on by the frequency of wellhead damage in the oil and gas sector. For the first 40 years quarters, the risk value was discovered to be essentially constant, but the incidence of well damage was found to change. The DNN model exhibited greater accuracy but poorer recall since it had

more false negatives and fewer false positives than the MLR model. The DNN model demonstrated great levels of precision, accuracy, and recall for low tolerance values when the results were also tested using a set of tolerance values for the risk derivative. The MLR model performed better in terms of recall, but due to a persistent false positive error, it could not achieve 100% accuracy and precision for high tolerance values.

4. Strength and Weakness:

Strength	Weakness
The paper tackles a serious issue in the petroleum and chemical industry's safety-critical sector and offers a thorough analysis of current risk assessment techniques while highlighting their shortcomings.	The recommended risk assessment procedures in the article are not backed up by any actual data.
The study makes a significant addition to the discipline by advocating for a dynamic approach to risk management and offering a new definition of risk that incorporates the knowledge component.	The use of machine learning algorithms in risk assessments may have ethical implications, however they are not discussed in this study.
Understanding the suggested techniques is made easier by the use of the Dynamic Risk Management Framework and the 2-D and 3-D risk matrices to explain the topics discussed in the article.	A more thorough debate on the value of paying attention to minute details in risk management is lacking at the moment.
Report emphasises the need of taking risk management seriously and offers an illustration of how this might be done in the offshore oil and gas business.	To guarantee that readers without a technical experience can grasp the recommended techniques, the article would benefit from more thorough explanations of some of the technical jargon and ideas utilized, including the Deep Neural Network (DNN).
The study also examines how deep learning, a type of machine learning, may be used to enhance risk assessments and provides a thorough explanation of the Deep Neural Network(DNN).	The article's scope is restricted to the petroleum and chemical industry's safety-critical sector, and it's possible that the suggested approaches won't work in other fields or sectors.