THE USE OF BAYESIAN NETWORK MODELLING FOR RISK ASSESSMENT IN MANUFACTURING INDUSTRY

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ABSTRACT

The increasing complexity of product design, coupled with stringent regulations and a fluctuating market, underscores the critical importance of conducting risk assessments for ensuring operational success. Depending on the type of activity and its priority, risks can vary significantly in interpretation and evaluation methods. Generally, risk assessment involves measuring the likelihood (frequency) and consequences (impact) of an event. Historical data or expert opinions, whether qualitative or quantitative, are commonly utilized to estimate both frequency and impact. Furthermore, qualitative data often needs to be translated into numerical values to facilitate its integration into the assessment model. Enterprise risk assessment typically encompasses strategic, operational, legal, and reputational risks, which are often challenging to quantify. Consequently, expert-derived data, often gathered through scorecard approaches, tends to be the primary source for risk analysis in many cases. Bayesian Networks offer a valuable tool for amalgamating diverse information, especially for analyzing the joint distribution of risks using expert-collected data. This paper aims to present a potential approach for constructing Bayesian Networks, focusing specifically on scenarios where only prior probabilities of node states and marginal correlations between nodes are available, and where variables have binary states. This study introduces a novel approach to assess risks in production lines, focusing on operational risks that impact line performance. Bayesian Belief Networks (BBN) are employed to model the causal relationships between operational risks. To evaluate the repercussions of these risks, a simulation model of the production line is constructed using the System Dynamics (SD) methodology. By integrating BBN and SD, a comprehensive methodology is developed, capable of capturing the dynamic causal interplay within complex systems, the uncertainties inherent in risk events, and the enduring effects of operational risks on production line efficiency.

Keywords: Risk Assessment; Bayesian Belief Networks; System Dynamics.

INTRODUCTION

The manufacturing sector faces escalating risks due to the heightened complexity of products, stringent regulations, and the ever-evolving market landscape. In response to intensifying competition, companies are increasingly willing to embrace additional risks to thrive. In this environment, failure to promptly address challenges such as raw material shortages, downtimes, or equipment deterioration can result in substantial financial losses. Consequently, conducting a comprehensive company-wide risk assessment becomes imperative, offering a holistic understanding of the risks and avenues for mitigation. ISO 31000 advocates for risk-based decision-making, mandating the development of a 'Risk Profile' to guide organizational strategy.A company-wide risk assessment encompasses both internal and external operations. While internal operations represent a narrower scope, their assessment holds significant value, affording companies a competitive advantage by bolstering financial resilience, product quality, and customer satisfaction. To evaluate production line risks effectively, a dynamic methodology is essential, capable of capturing the evolving nature of risk events and their interrelationships. This entails assessing the impact of risk events on the production line over time.A Bayesian Network (BN) emerges as a potent tool for this purpose, characterized by a directed acyclic graph where each node denotes a random variable with discrete or continuous states. The connections between variables, depicted by arcs, are elucidated through conditional probabilities derived from Bayes' theorem. By leveraging BNs, companies can gain insights into the intricate dynamics of risk events and their implications for production line performance.

LITERATURE REVIEW

The efficient and effective maintenance of industrial systems is crucial for preserving and extending a company's physical assets. Maintenance encompasses actions aimed at retaining or restoring items to a functional state, making it a vital aspect of modern industries. By enhancing productivity, reducing downtime costs, and preventing equipment failures, maintenance contributes significantly to overall operational efficiency. To achieve these objectives, companies must implement cost-effective maintenance strategies.Delay-time analysis emerges as a valuable maintenance modeling technique, particularly in manufacturing environments. By inputting specific parameters, such as failure rate (λ), delay-time analysis can determine optimal inspection intervals from both downtime and cost perspectives. However, the determination of the failure rate parameter typically relies on simplistic methods, such as the number of failures over time based on historical data averages.This thesis aims to enhance the accuracy and understanding of failure rates by exploring and identifying the factors influencing failures. Bayesian network modeling is employed for this purpose, enabling a precise consideration of various influences on failures. By utilizing Bayesian network modeling, this research seeks to improve maintenance strategies by providing a more nuanced understanding of failure mechanisms.

Imperfect Preventive Maintenance Policy for Complex Systems Based on Bayesian Networks ;E. MokhtarRadouane LaggouneA. Chateauneuf. Maintenance planning poses a significant challenge due to the need for realistic modeling of maintenance policies. This paper specifically addresses the optimization of maintenance for complex repairable systems using Bayesian networks. A novel policy is introduced, focusing on periodic imperfect preventive maintenance coupled with minimal repair at failure. This approach accommodates various types of preventive maintenance with differing efficiency levels. Bayesian networks serve as a powerful tool for modeling complex systems, enabling the assessment of model parameters.The methodology proposed in this paper facilitates the evaluation of Weibull parameters and maintenance efficiency through Bayesian inference. To demonstrate the effectiveness of the approach, a real-world application is conducted on a turbo-pump within the oil industry. By leveraging Bayesian networks and Bayesian inference, this research contributes to the development of optimal maintenance plans for intricate industrial systems, thereby enhancing reliability and efficiency in maintenance operations.

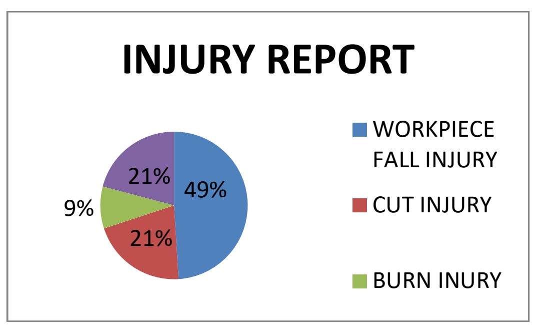
Incorporating Bayesian Networks in Markov Decision Processes R. FaddoulW. RaphaelA. SoubraA. Chateauneuf. This paper introduces an enhancement to partially observable Markov decision processes (POMDPs) to incorporate the potential availability of future free information at the planning outset. This information is assumed to follow a Bayesian network structure. The proposed method offers reduced computational complexity compared to traditional approaches for dynamic Bayesian networks. Additionally, it enables leveraging prior probability distributions of relevant random variables, even those without direct causal relationships with the system state. Moreover, the approach allows for the rational consideration of the impacts of accidental or rare events that might occur throughout the planning horizon.To demonstrate the methodology, the paper presents a case study involving the optimization of inspection, maintenance, and rehabilitation strategies for road pavement over a 14-year planning period. Through this example, the effectiveness of the proposed approach is illustrated, showcasing its applicability in real-world decision-making scenarios involving complex systems.

Steps of Risk Assessment

- Identify the hazards.
- Identify the people who might be harmed and how.
- Evaluate the risk and decide precaution.
- Record the significant findings and implement them.
- Review and update as necessary.

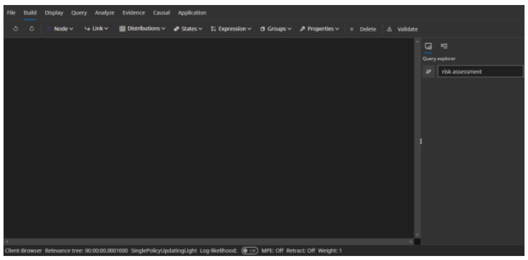
Objectives/Purpose of Risk Assessment

- To prevent accidents and ill health
- Breaches of statute law
- Direct and indirect cost.



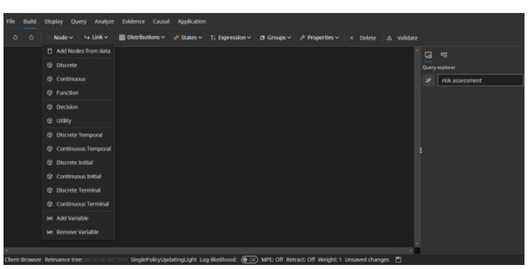
BAYESIAN NETWORK

Bayesian networks, belonging to the Probabilistic Graphical Model family, serve as effective tools for constructing models derived from either data or expert input. Their versatility enables their application across various tasks such as diagnostics, reasoning, causal modeling, decision-making under uncertainty, anomaly detection, automated insight generation, and prediction.



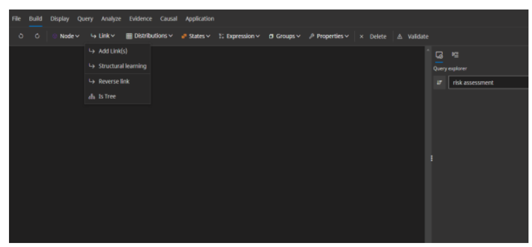
Nodes

In most Bayesian networks, individual nodes represent variables, such as height, age, or country, with each variable being either discrete (e.g., Country = {US, UK, etc.}) or continuous (e.g., age). In Bayes Server, nodes can encompass multiple variables, termed multi-variable nodes. These nodes, along with their interconnections, constitute the structural specification of the Bayesian network. Bayes Server accommodates both discrete and continuous variables, as well as function nodes, facilitating comprehensive modeling capabilities.

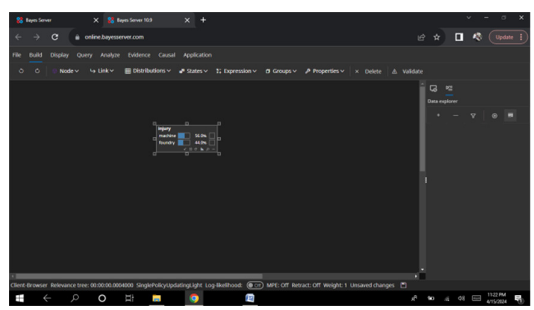


Links

Connections between nodes in a Bayesian network signify direct influence from one node to another. However, the absence of a link between two nodes doesn't imply complete independence; they may still be interconnected through other nodes within the network. The dependency or independence between nodes can be contingent upon the evidence set on other nodes within the network. Thus, nodes may exhibit dependency or independence based on the contextual information provided by the network's structure and the evidence presented.



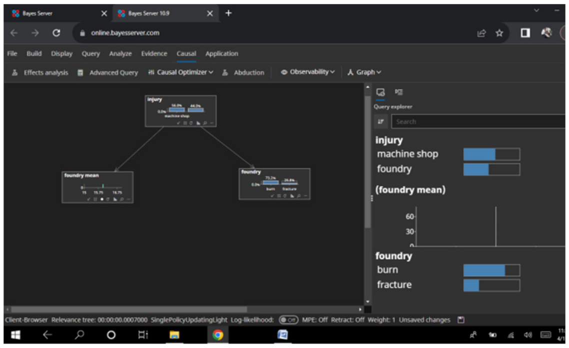
RESULTS



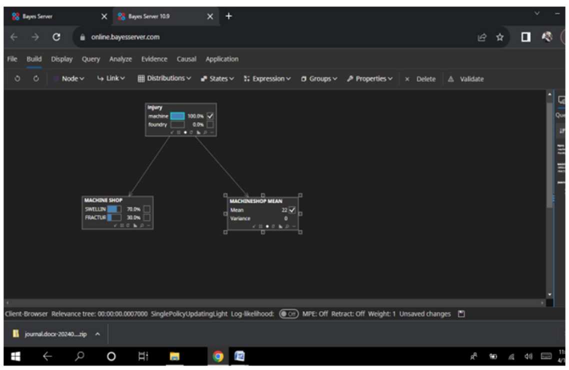
INJURY REPORT

MACHINE SHOP-56%

FOUNDRY-44%



MACHINE SHOP INJURY PROBABILITY



CONCLUSION

A Bayesian Network (BN) model has been proposed to evaluate the risk of injury in a foundry or machine shop setting, considering the influence of various trauma-inducing factors identified in the literature. This model enables the calculation of quantitative measures that demonstrate how different factors contribute to the overall risk of injury. By synchronizing the estimated risk of injury with existing injury data, the model provides insights into the impact of different factors on injury occurrence.

The BN model offers a valuable tool for injury prevention and risk management by enabling analysis and precautionary measures to reduce injury risks. However, to enhance the quantitative assessment of injury risk, additional data on trauma rates within the industry and parameter learning for the model are essential.

Probability theory, particularly Bayesian reasoning, has proven highly effective in risk analysis by providing a framework to address uncertainties inherent in real-world scenarios. By embracing the concept of probability, Bayesian methods offer advantages over traditional approaches, particularly in their ability to handle diverse and conflicting information while maintaining a universal framework for analysis. This pluralistic approach to probability allows for a more comprehensive understanding of risk factors and enables informed decision-making in injury prevention strategies.

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