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Integrating the human factor in FMECA-based risk evaluation through Bayesian networks

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1 Introduction and objectives

Risk management processes play a fundamental part in any business context and rely on accurate conduction of the risk assessment stage. Risks are commonly evaluated according to the preliminary definition of suitable parameters mainly aimed at highlighting their severity and the frequency of occurrence. However, it may be interesting to integrate the human factor as a parameter of evaluation, being human activity directly related with many risks of diverse nature. This contribution develops the traditional Failure Modes, Effects and Criticality Analysis (FMECA) [1] for quantitative risk analysis from a Bayesian Network (BN)-based perspective, which reveals to be useful to make more accurate predictions about parameters' values. The main purpose consists in providing a framework for analysing causal relationships for risk evaluation and deriving probabilistic inference among significant risk factors. These parameters are represented by linguistic variables and include the human factor as a key element of analysis.

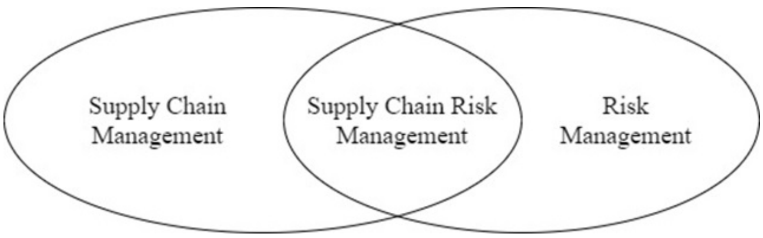

Figure 1: Supply chain risk management definition inspired in [13].

To substantiate this idea, we present and solve a real-world use case on a fundamental business topic, namely supply chain risk management (SCRM), which originates from the intersection between the processes of risk management and supply chain management [13], as exemplified in Figure 1. This choice is further motivated by the fact that FMECA has been recently extended to supply chain risk evaluation [14], currently being a lively topic of research.

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2 The proposed approach

Traditional approaches for risk evaluation and management performed by FMECA represent helpful tools to globally enhance systems and processes conditions [2]. However, such approaches require previous clarification of several assumptions/simplifications [3]. FMECA is a systematic procedure to identify and analyse all the failure modes potentially involving systems or their main components, through the definition of the related causes and effects. In particular, the method aims to prioritise the failure modes under analysis by calculating the index called Risk Priority Number (RPN) for each of them. The RPN is traditionally derived from the multiplication of three main factors, namely severity (S), occurrence (O) and detection (D), generally ranged within discrete intervals. Severity S measures the impact of a given failure mode with respect to the global performance; occurrence O estimates the frequency of a failure mode within a given time horizon; detection D expresses the probability of correct failure identification. The three risk factors are commonly assessed in a qualitative and subjective way, what may lead to imprecise results with the consequent adoption of ineffective decisions in terms of preventive and/or mitigation actions. This assumption represents one of the reasons why the traditional RPN has been widely criticized in the literature. The RPN formula appears far too simplistic [4,5], since it does not consider the different importance of the three aforementioned parameters [6,7], i.e. different weights in evaluating risks. Other studies underline as the non-continuous distribution of the values of the RPN makes imprecise the assessment of differences between two consecutive values assumed by the index [4,8]. Apart from other various drawbacks, one has to observe as FMECA does not consider the simultaneous occurrence of multiple failure scenarios.

A BN-based approach can provide a wider range of benefits in risk analysis, in terms of modelling complex systems, making accurate predictions about parameters' values, and computing with precision the occurrence probability of failure events [9]. A BN is a compact and modular distribution of random variables. A BN is an acyclic graph in which variables are placed at the nodes, and the arcs are loaded with probabilities [10, 11]. A BN is a twofold object: it has a qualitative aspect, i.e. the graph showing the mainly cause-effect relationships, and the quantitative distribution of probabilities [12]. In a BN, evidence information propagates and updates our belief (*a priori* probability) on non-observed variables to get new (*a posteriori*) knowledge. This is an objective of inference, including diagnosis, prediction, inter-causal relationships, etc. Conditional probabilities (and the structure itself) can be learnt from data. In this sense, BNs constitute optimal decision-making tools, which also enable simulation to observe outcomes derived from a range of actions. BNs rely on identifying relations of conditional independence; determining conditional probability tables and joint probability distributions, and performing inference: calculating *a posteriori* probabilities, $\mathbf{P}$, for variables of interest, $\mathbf{X}$, given observed values of some variables or evidence, $\mathbf{e}$, still considering hidden variables, $\mathbf{Y}$:

$$\mathbf{P}(\mathbf{X}|\mathbf{e}) = \alpha\mathbf{P}(\mathbf{X}, \mathbf{e}) = \alpha\sum_{\mathbf{y}}\mathbf{P}(\mathbf{X}, \mathbf{e}, \mathbf{y}).$$

Here α is a normalizing factor, and $\mathbf{P}(\mathbf{X}|\mathbf{e})$ expresses the (vector) probability of variables in vector $\mathbf{X}$, given the (vector) evidence $\mathbf{e}$.

We finally propose to consider new aspects with respect to those traditionally used for the RPN calculation. Specifically, the role played by human resources will be integrated within the risk function calculation, something that existing approaches scarcely take into account. Our objective is to integrate the human factor in FMECA-based risk assessment, taking advantage of BNs' ability for inference, which incorporates uncertainty, thus enabling to obtain valuable information for risk assessment to help decision-making processes in planning, operating, maintenance etc. in industry, and other fields.

Risks are herein quantitatively assessed on the basis of evaluations attributed to severity and occurrence probability, two of the three parameters considered by the traditional FMECA approach. Instead of considering the probability of detection as a third risk parameter, we introduce a new factor for risk evaluation as a novelty within the framework of traditional FMECA. This factor is linked to the concept of human error probability. By synthesising the degree of human experience, professional training, skills, and work-related stress when leading a given task, this factor considers the presence of human resources in charge of specific activities.

All the three considered risk parameters, namely severity (S), occurrence (O) and human factor (H), will be evaluated by means of a five-point scale. The higher/lower the evaluation of these parameters, the higher/lower the contribution to the risk function.

3 Real-world application

We consider a problem of SCRM involving the warehouse design and management for a real manufacturing company located in the south of Italy. The decision-making problem consists in optimising new procedures of warehouse operations as well as best practices to cope with the safety updates established by the COVID-19 protocol [15], and to pursue process automation and operational efficiency.

Ten major supply chain risks (SCRs) potentially impacting the warehouse reorganisation problem have been identified and various brainstorming sessions have been led to carry on the assessment process. To this end, a decision-making group made of twenty stakeholders was involved. Decision-makers were grouped into five main categories based on their roles: manager, responsible, worker (warehouse), worker (production), worker (external area). To exemplify the procedure of input data collection, Table 1 shows the evaluations provided by the responsible of the safety and security system, one of the experts belonging to the "responsible" category.

Table 1: SCRs and factors evaluations from the responsible of the safety and security system

ID	**SCR**	**S**	**O**	**H**	**Score**
SCR_1	Safety	5	3	2	3
SCR_2	Damages	2	2	2	2
SCR_3	Communication	4	3	1	2
SCR_4	Transportation	3	2	2	2
SCR_5	Commerce	2	3	2	2
SCR_6	Performance	4	2	1	2
SCR_7	Disruptions	5	2	1	2
SCR_8	Delivery	3	2	2	2
SCR_9	Environment	4	4	3	4
SCR_{10}	Strategy	3	3	2	3

Integer geometric mean values of the evaluations for the three risk parameter have been computed as a score (global risk value) associated to each SCR for the given decision-maker.

We aim to exploit the ability of BNs to model variables and their interconnected structure by identifying relations of conditional independence, and determining their conditional probability table as well as their joint probability distribution in order to eventually develop a Bayesian network integrating the human factor in FMECA-based risk assessment. Figure 2 and Figure 3, respectively, show the final network of relations, and the incorporation of evidence into the BN. Results have been obtained by iterating the BIC algorithm through the Hugin software for BN learning. One can note, both SCRs and decision-makers' roles are considered as variables in the network.

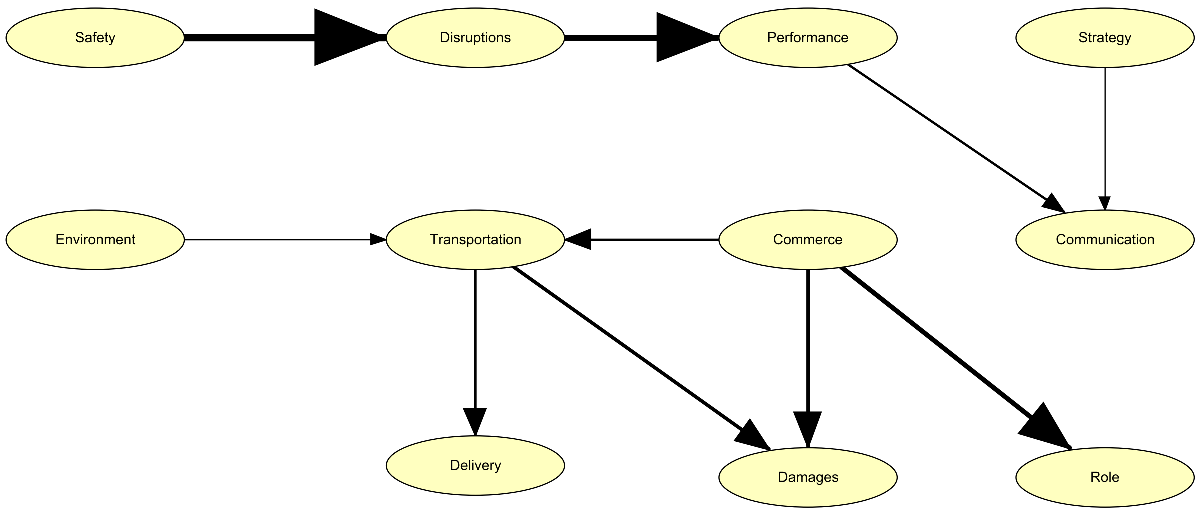

Figure 2: Network of relationships

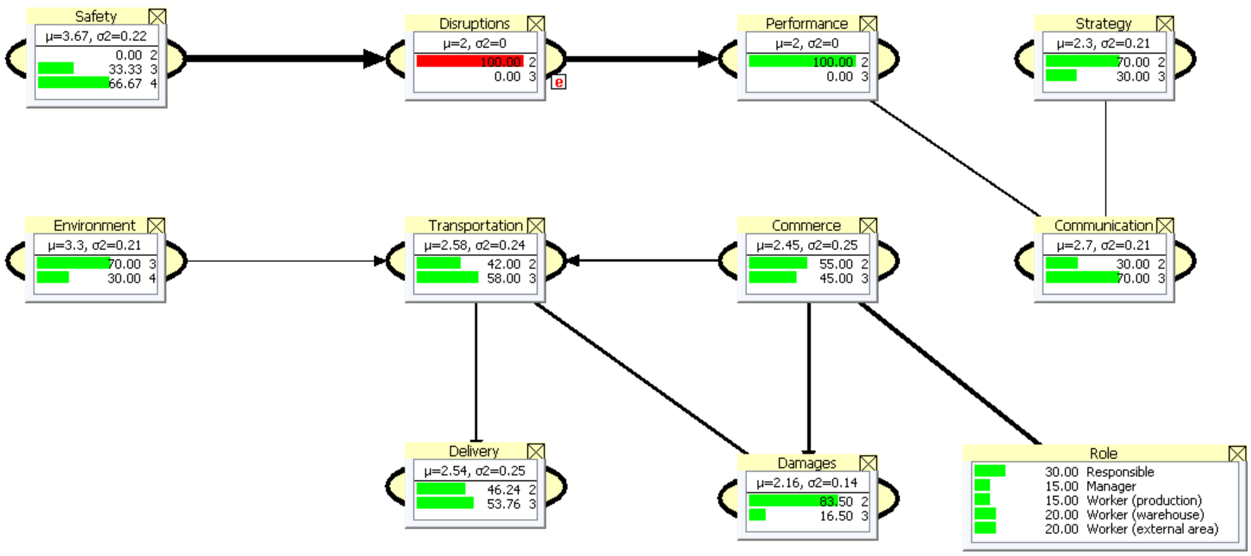

Figure 3: Entering evidence into the BN

4 Discussion of results

We can derive various considerations by observing results reported in the final network. First of all, we point out the existence of two main groups of SCRs in terms of dependence as well as the presence of stronger mutual relations, highlighted by the thickness of the arrows.

Immediate practical implications are described as follows. Safety and disruptions risks are highly related but inversely whereas significant relations between other risks (such as for instance between disruptions and performance or among transportation, commerce and damages) are directly proportional. This result is justified by the fact that, the occurrence of a disruption implies the temporary breakdown of operational activities, what minimises risks for human safety. Safety risks are instead higher in absence of disruptions, that is when loading and unloading operations are carried out in continuum.

Another important result refers to the relation of dependence between the variable ”role” and commercial risks. Differently from other types of risks, for which evaluation is more objective and independent on the role of the decision-maker who is expressing opinions, commercial risks are role-sensible; in other terms, differently perceived by managers, responsible human resources and workers. This consideration leads to the fact that decision-makers belonging to different categories will attribute significantly different evaluations to the parameters related to commercial risks and/or unpredictable price raises. Managers typically associate them with higher values; responsible subjects, medium values; and workers, lower values.

Lastly, we can observe as environment risks contemplating the high degree of uncertainty enterprises are experiencing during the COVID-19 era are mainly related with transportation difficulties, which are, in their turn, connected with such fundamental logistic aspects as commercial problems, packaging damages and inefficient delivery.

5 Conclusions and future work

This contribution is focused on the importance of leading an accurate risk assessment in order to proceed towards an effective risk management. The traditional FMECA analysis has been presented as the most common way for risk evaluation purposes on the basis of the RPN index for each identified risk. The possibility of integrating the human factor under a BN-based perspective has been discussed and a use case on SCRM has been solved by showing the presence of significant dependence among the considered variables.

Future developments of the present work of research regard the possibility of considering diverse scenarios of risk evaluation. For example, several decision-makers of different enterprises may be involved to generalise the process of supply chain risk evaluation for a given industrial sector of activity. Moreover, different weights may be attributed to the considered risk factors by integrating a multi-criteria decision-making approach. Also, networks resulting from different algorithms may be compared.

References

[1] I. E. Commission, Analysis Techniques for System Reliability: Procedure for Failure Mode and Effects Analysis (FMEA). International Electrotechnical Commission, 2006.

[2] Curkovic, S., Scannell, T., Wagner, B. Using FMEA for supply chain risk management *Modern management science & Engineering*, 1(2):251–265, 2013.

[3] Flage, R., Askeland, T. Assumptions in quantitative risk assessments: when explicit and when tacit? *Reliability Engineering & System Safety*, 106799, 2020.

[4] Liu, H.-C., Liu, L., Liu, N., Mao, L.-X. Risk evaluation in failure mode and effects analysis with extended VIKOR method under fuzzy environment *Expert Systems with Applications*, 39(17):12926–12934, 2012.

[5] Liu, Y., Fan, Z.-P., Yuan, Y., Li, H. A FTA-based method for risk decision-making in emergency response *Computers & Operations Research*, 42:49–57, 2014.

[6] Zhang, Z., Chu, X. Risk prioritization in failure mode and effects analysis under uncertainty *Expert Systems with Applications*, 38(1): 206–214, 2011.

[7] H.-C. Liu, FMEA using uncertainty theories and MCDM methods, in *FMEA using uncertainty theories and MCDM methods*, 13–27, Springer, 2016.

[8] Chang, D.-S., Sun, K.-L. P. Applying DEA to enhance assessment capability of FMEA *International Journal of Quality & Reliability Management*, 2009.

[9] Zoullouti, B., Amghar, M., Nawal, S. Using Bayesian networks for risk assessment in healthcare system, in *Bayesian Networks-Advances and Novel Applications*, IntechOpen, 2019.

[10] Neapolitan, R.E. Learning Bayesian networks. Prentice Hall, 2004.

[11] Korb, K.B., Nicholson, A.E. Bayesian artificial intelligence. Chapman & Hall/CRC, 2004.

[12] Weber, P., Medina-Oliva, G., Simon, C., Iung, B. Overview on Bayesian networks applications for dependability, risk analysis and maintenance areas *Engineering Applications of Artificial Intelligence, Special Section: Dependable System Modelling and Analysis*, 25:671–682, 2012.

[13] Blos, M.F., Quaddus, M., Wee, H., Watanabe, K. Supply chain risk management (SCRM): a case study on the automotive and electronic industries in Brazil *Supply Chain Management: An International Journal*, 2009.

[14] Mzougui, I., Carpitella, S., Certa, A., El Felsoufi, Z., Izquierdo, J. Assessing supply chain risks in the automotive industry through a modified MCDM-based FMECA *Processes*, 8(5), 579:1–22, 2020.

[15] INAIL. Documento tecnico sulla possibile rimodulazione delle misure di contenimento del contagio da SARS-CoV-2 nei luoghi di lavoro e strategie di prevenzione. `https://www.inail.it/cs/internet/comunicazione/pubblicazioni/catalogo-generale/pubbl-rimodulazione-contenimento-covid19-sicurezza-lavoro.html`, 2020.