



Build a Bayesian Network from FMECA in the Production of Automotive Parts: Diagnosis and Prediction

I. Ben Brahim, Sid-Ali Addouche, A. El Mhamedi, Y. Boujelbene

► To cite this version:

I. Ben Brahim, Sid-Ali Addouche, A. El Mhamedi, Y. Boujelbene. Build a Bayesian Network from FMECA in the Production of Automotive Parts: Diagnosis and Prediction. IFAC-PapersOnLine, 2019, 52 (13), pp.2572-2577. 10.1016/j.ifacol.2019.11.594 . hal-03034479

HAL Id: hal-03034479

<https://hal.science/hal-03034479>

Submitted on 2 Dec 2020

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Build a Bayesian Network from FMECA in the Production of Automotive Parts: Diagnosis and Prediction

I. BEN BRAHIM^{*,**} S.A. ADDOUCHE^{*}
A. EL MHAMEDⁱ Y. BOUJELBENE^{**}

^{*} QUARTZ Laboratory EA 7393, IUT of Montreuil - Paris8 University
- 140, Rue de la nouvelle France, 93100 Montreuil, France (e-mail:
{i.benbrahim, addouche, a.elmhamed}@iut.univ-paris8.fr)

^{**} URECA - Sfax University - Airport Road Km4, 3018 Sfax, Tunisia
(e-mail: younes.boujelbene@gmail.com)

Abstract: Failure Modes, Effects and Criticality Analysis (FMECA) is one of the well-known methods of quality management that is used for continuous improvement in product or process design. This method uses linguistic expressions and has good information about cause-effect chains. However, it lacks probabilistic information. Transforming it into a Bayesian Network (BN) makes it possible to be used in maintenance for both diagnosis and prediction. The purpose of this paper is to develop a method that uses as much information as possible from FMECA, including frequency and detection to precisely make the configuration of the BN. To build a BN's structure from FMECA, we elaborate a tool to do it systematically. Moreover, we develop an algorithm to set the parameters of a BN obtained. Elicitation methods based on expert knowledge are used when data is not sufficient. A case study of FMECA in the automotive industry is introduced to verify the applicability of the proposed method in an industrial environment.

© 2019, IFAC (International Federation of Automatic Control) Hosting by Elsevier Ltd. All rights reserved.

Keywords: FMECA, Bayesian Network, Decision Support System, Diagnosis, Prediction, Expert Knowledge.

1. INTRODUCTION

The Failure Modes and Effects Analysis (FMEA) was formally introduced in the late 1940s for military usage by the US Armed Forces. After that, it was used for aerospace development to avoid errors. FMEA provides improved quality and product reliability by identifying solutions and corrective actions to eliminate the failure mode or to damp the adverse effects. For this reason, manufacturing industries use it in various phases of the product life cycle Prajapati (2012). The popularity of FMEA approach has increased in the last decade and it is now also used in different fields. It is widely used in the early stages of system development in automotive, semiconductor processing, aerospace, nuclear and other industries.

FMEA is extended by a Criticality Analysis procedure (CA) which evaluates the failure modes criticality. The combination of FMEA and CA procedures entitled the Failure Mode, Effects and Criticality Analysis (FMECA), Wei (1991). We can identify several different types of FMECA: Product FMECA which is the analysis of the design of the product, Process FMECA which is the analysis of productions processes, and productions means FMECA which is the analysis of design production means.

However, FMECA has some limits in terms of applicability, cause and effects representation, risk analysis and problem-solving. Besides, it can't be used for diagnosis when we have a failure for example. The lack of probabilistic information makes this tool poor and limited in decision-making. To solve this problem, we worked on the translation from FMECA to another more effective decision support tool. For that, we chose Bayesian networks (BN) that are among the best tools. BN is a well-established graphical representation for encoding conditional probabilistic relationships among uncertain variables. Our objective is to use as much information as possible from an FMECA to build structure and parameters of a BN. Once complete, BN can be used to improve the health care of equipment, to diagnose or predict a failure in order to make the right decision.

The remainder of this paper is organized as follows: in section 2, we explained the concept of FMECA, its limits, and solutions. In section 3, we introduced the BN, its advantages, and applications. In section 4, we developed our method to build a structure and parameters of BN from FMECA. In Section 5, we applied our method to the case study of thermoforming of car floor in the automotive industry. Then, we used the BN obtained for the diagnosis and prediction to make a good decision. Finally, section 6 is devoted to conclusions and perspectives.

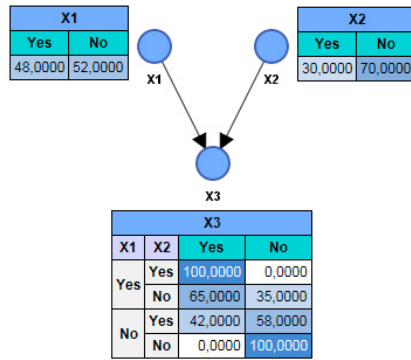


Fig. 2. Bayesian network with 3 nodes

this knowledge is uncertain, ambiguous, and/or incomplete (Nadkarni and Shenoy (2001)). Moreover, it is a well-established graphical representation for encoding conditional probabilistic relationships among uncertain variables using Bayes' theorem (Díez and Druzdzel (2007)). Thanks to a BN, it is possible to diagnose and predict failures of a system or equipment can be predicted in order to make the right decision.

The contribution of BN has continued to increase in the artificial intelligence community at first, then in all other scientific communities. This has led researchers and scientists to use these networks in various fields: health (diagnosis, gene localization), industry (maintenance, robot control), information technology and networks (intelligent agents), marketing (data mining, customer relationship management), banking and finance (scoring, financial analysis) and management (decision support, management of risk), etc.

4. FROM FMECA TO BUILD BN

FMECA is used primarily for the reliability of system operation or equipment to keep it always functional. While BNs are used to diagnosis a system when we are facing failure and also to predict it in order to avoid its appearance. Either it is better to transform an FMECA to a BN that will model the health care of our equipment and will be used both for diagnosis and prediction. For that, we have developed a method to transform FMECA to a BN. This method is based on two main steps. The first is to define the structure of our BN from the effects, causes and failure modes present in FMECA and to validate it with an expert. The second is to set our BN using elicitation methods and factors (F, D) present in FMECA (See Fig. 3).

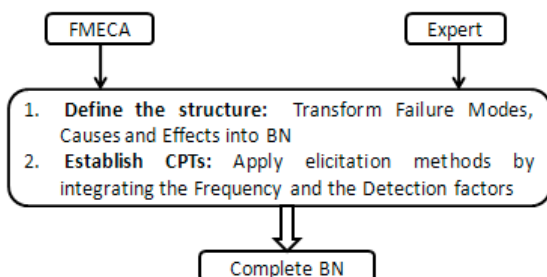


Fig. 3. Our steps to build a BN from FMECA

4.1 Qualitative Information to Build BN Structure

In the literature, some authors have already worked on obtaining the structure of the BN from FMECA (García and Gilabert (2011), Lee (2001), Lei (2007)). All these works converge towards the same structure: transforming the causes, failure modes and effects of FMECA to nodes and adding arrows pointing from the cause node to the failure mode node and from failure mode node to effect node (Fig. 4).

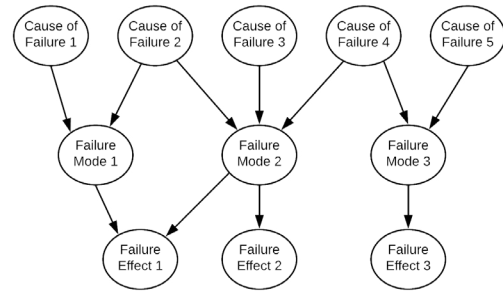


Fig. 4. BN including FMECA

Our contribution here consists in developing a tool that allows transforming an FMECA to a BN with the Java language. This tool receives an excel file of FMECA according to the structure of CNOMO standard (Fig. 1) and generates a BN in NET format which is compatible with BayesiaLab software (Fig. 5). It should be noted that BayesiaLab uses only files containing statistics and history for the automatic learning of a structure and parameters of a BN. It cannot read other forms of knowledge, precisely those of experts such as FMECA, Ishikawa, etc.

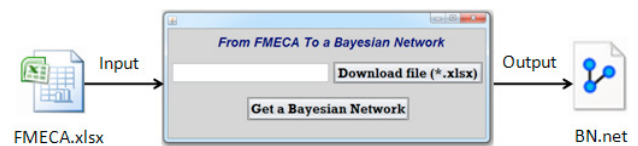


Fig. 5. Translation tool to get the BN structure

The BN obtained must be revised by merging the common nodes according to the cases cited in the works of García and Gilabert (2011). After that, we must validate the structure with the expert who will also set the possible states for each node.

4.2 Quantitative Information to Define BN Parameters

In order to set parameters for the BN obtained from FMECA, methods are diversified. The CPTs are filled from databases, or from domain expert elicitation (Noisy OR, Binary OR...), or using the combination of both, or in other works with maximum entropy concept (García and Gilabert (2011), Lee (2001)). Those methods did not use the information contained in the FMECA such as Gravity, Frequency and Detectability values.

Our aim in this part is to use as much information as possible from the FMECA to fill our CPTs. For that, we have integrated Frequency (F) and Detection (D) factors in our method. This method is a combination of three

types of elicitation methods. The first is the "Raw method" which is the ordinary method that requires an expert to fill CPTs without using facilitation or reduction methods Tang and McCabe (2007). The second is the "Weighted Sum Algorithm" (WSA) developed by Das (2004). This method reduces the number of information to elicit from an expert. The third method is our method "Cluster-WSA" which has been developed and compared with other elicitation methods in terms of the amount of information required by the expert knowledge in our preview paper Ben Brahim et al. (2018). This method comes as a remedy to the limit of the WSA method when the expert is unable to give compatible parental configuration for each state with other parents' states. This cluster approach allows us to introduce an intermediate node, to apply the WSA on a generated cluster and to use Raw method of elicitation for the remaining nodes. So, our algorithm 1 is developed below. This algorithm allows us to extract all CPTs and to insert them in BayesiaLab.

Algorithm 1 BN Parameter Setting

1- Fill in the marginal probability tables of Cause Nodes

Apply the **Raw Method** by asking the expert to give us all marginal probability tables of cause nodes

2- Fill in CPTs of Failure Mode Nodes

if Number of the parent nodes ≤ 2 **then**

Apply the **Raw Method**

else

if States of those nodes are compatible **then**

Apply the **WSA Method**

Use the **Frequency values** F_i given in FMECA as a probability of compatible parental configuration $P(x_c^m | \text{Comp}(X_{p_1} = x_{p_1}^{j_1})) = P(F_i)$

else

Apply the **Cluster-WSA Method**

Use the **Frequency values** F_i given in FMECA as a probability of compatible parental configuration

end if

end if

3- Fill in CPTs of Effect Nodes

if Number of the parent nodes ≤ 2 **then**

Apply the **Raw Method**

else

if States of those nodes are compatible **then**

Apply the **WSA Method**

Use the **Detection values** D_i given in FMECA to refine or adjust the final CPT whose the equation becomes:

$$P(x_c^m | x_{p_1}^{j_1} \dots x_{p_n}^{j_n}) = \frac{\sum_{i=1}^n w_i \cdot P(x_c^m | \{\text{Comp}(X_{p_1} = x_{p_1}^{j_1})\})}{\sum_{i=1}^n D_i} \quad (2)$$

else

Apply the **Cluster-WSA Method**

Use the **Detection values** D_i given in FMECA to refine or adjust the final CPT by applying the equation 2.

end if

end if

Where:

F_i : frequency value from the FMECA for the node i with $P(F_i) = F_i/10$.

D_i : detection value from the FMECA for the node i with a scale from 0 to 1 inversely proportional to the initial scale of detection. For example, the value 10 corresponds to 0 and the value 1 to 1 with the new scale.

x_c^m : the child node with l states, $m = 1, 2, \dots, l$.

$x_{p_n}^{j_n}$: the parent node with k_i states, $j_i = 1, 2, \dots, k_i$.

w_i : the relative weight for the parent node i .

$P(x_c^m | \text{Comp}(X_{p_1} = x_{p_1}^{j_1}))$: the probability distributions over X for compatible parental configurations.

This approach is applied to a case study which will be detailed in the next section.

5. CASE STUDY AND RESULTS

As a case of study, we chose the Process FMECA of thermoforming of car floor covering developed in the paper of Belu et al. (2013). This FMECA is used in the automotive industry to improve quality and product reliability by giving solutions and corrective actions to eliminate the failure mode or to damp the adverse effects.

We reformulated the initial FMECA according to CNOMO standard and we implemented it in our tool (Fig. 5). As a result, we obtained the following BN structure (Fig. 6) with BayesiaLab Tool:

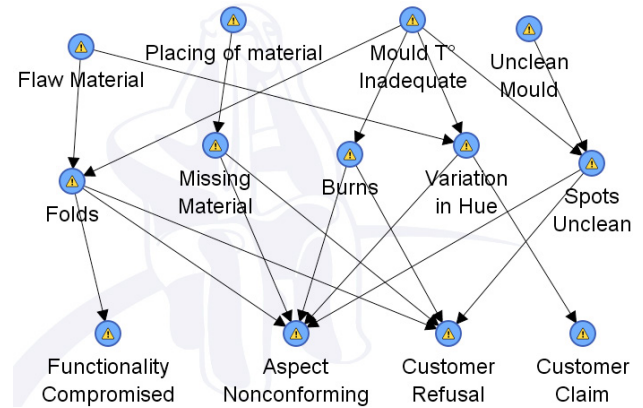


Fig. 6. BN structure of thermoforming of car floor covering

In this study, we assume that we have the expert who validates the BN and sets the possible states for each node. Here, for each node, there are two states: **Yes** to confirm the existence of the node's failure in question and **No** to deny its existence.

Now, we must apply our algorithm 1 to build all CPTs. By applying the first step of the algorithm, the expert gives us all marginal probability tables of cause nodes. Fig. 7 shows an example of a marginal probability table of *Mould Temperature Inadequate* node. In this case of study, all failure mode nodes have one or two parent nodes. So, the expert must elicit all CPTs using the Raw method according to the second step of the algorithm. The figure 7 shows an example of a CPT of *Folds* node.

Also, CPTs of effect nodes of *Functionality Compromised* and *Customer Claim* are giving by the expert with the Raw method. While effect nodes of *Aspect Nonconforming* and *Customer Refusal* have more than two parents nodes. According to the algorithm, we must apply a Cluster-WSA method which allowed to add intermediate nodes *Material Problem* and *Material Defect*. CPTs of those two nodes are completed with WSA method by integrating the Detection value D_i . As an example, the final CPT of *Material Defect* node is showing in figure 7.

Material Defect			
	Folds	Burns	Yes No
Mould T° Inadequate	Yes	Yes 95,5000 No 57,0000	4,5000 43,0000
	No	Yes 42,3330 No 38,3330	57,6670 61,6670
Folds			
Flaw Material	Mould T° Inadequate	Yes	No
Yes	Yes	85,0000	15,0000
	No	40,0000	60,0000
No	Yes	40,0000	60,0000
	No	0,0000	100,0000

Fig. 7. CPTs of some nodes of thermoforming BN

Finally, we obtained a complete BN (Fig. 8) which is ready to be used for diagnosis and prediction.

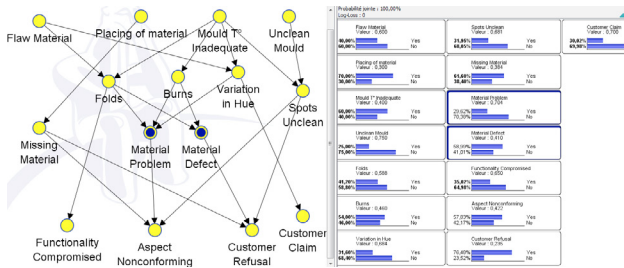


Fig. 8. Complete BN of thermoforming of car floor covering

When there is a failure in the equipment, we must look for its responsible causes. Indeed, the diagnosis makes it possible to explain the causes of failures by the back chaining in the BN. The graph is traversed in the direction from effects to causes. Therefore, the role of diagnosis is to detect, locate and identify failures in order to take appropriate actions for the proper conduct of the system. For example, assume that in our case we received a customer dissatisfaction by a refusal $P(\text{CustomerRefusal} = \text{Yes}) = 1$. We obtain the results shown in Fig. 9. Here, we want to know the main causes of this dissatisfaction. Therefore we must ask the BN from the effects to the causes. This allowed us to conclude that *Placing Material* with 78,92% *Missing Material* with 73,02%, *Material Defect* with 69,51%, *Mould Temperature Inadequate* 65,25% and *Burns* with 59,17% are the most probable causes for this dissatisfaction that it should be seen first.

Now, we suppose there's not a failure in the equipment, but we hope to know the probability of the consequences, since the causes of failures are known in advance. The BN can be used for this purpose. It's front chaining. The network is traversed from causes to effects. The role of prediction is therefore to prevent the risk of failure in the future

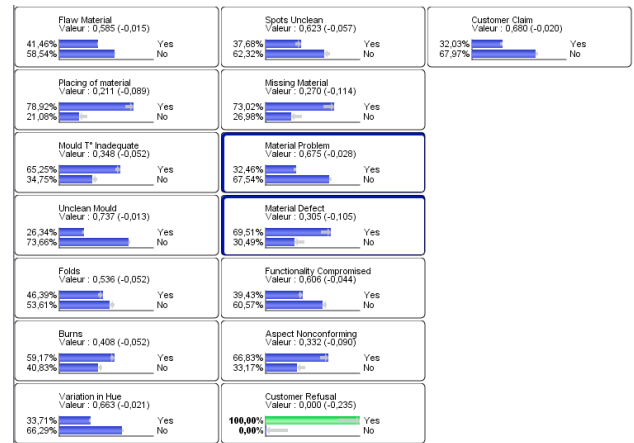


Fig. 9. Diagnosis dissatisfied client refusal

in order to take the necessary precautions to escape. For example, suppose that an inadequate mould temperature is detected in our BN $P(\text{Mould T Inadequate} = \text{Yes}) = 1$. In this case and according to Fig. 10, the probability of all effect nodes has increased. The most probable effect that can happen is *Customer Refusal* with 83,16%. Thereafter, the maintenance manager must find strategies to improve mould's temperature control given its severe effect in case of inadequate variation.

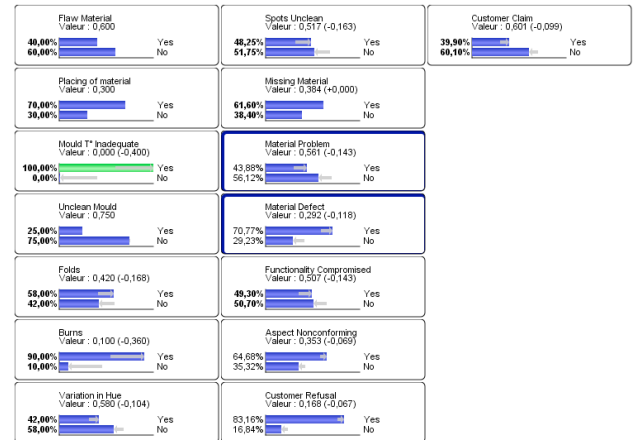


Fig. 10. Prediction inadequate mould temperature

6. CONCLUSION

Some industries use FMECA as the reliability of system operation tool that reduces the probability of critical failures by means of the analysis of potential failures and the development of improvement actions. But, when there is a failure in a system or in equipment, they must use other methods of decision making to analyze, diagnose the mains causes of this failure so as to repair it. In this paper, we elaborated an approach that allows us to build a BN from the existing FMECA. Indeed, this method is based on two main steps. The first step is to define the structure of our BN from the effects, causes and failure modes present in FMECA and to validate it with an expert. Our contribution here consists in developing a tool that allows transforming an FMECA to a BN with the Java language. This tool receives an FMECA according to CNOMO standard in the form of an excel file and

generates a BN in NET format which is compatible with BayesiaLab software. The second step is to fill our CPTs by using elicitation methods (Raw method, Weighted Sum Algorithm (WSA) method, Cluster-WSA method), Frequency and Detection values present in FMECA. For that, we developed an algorithm to be followed for this setting. This approach has been applied in the case study of thermoforming of car floor covering in the automotive industry. Once we got the final BN, we made two scenarios. In the first, we suppose that there is a failure and we want to identify its causes. Indeed, the diagnosis makes it possible to explain the causes of failures by the back chaining in the BN. In the second scenario, we suppose there's not a failure in the equipment, but we hope to know the probability of the consequences given the causes of failures is known in advance. So, we predict that by the front chaining in the BN. In conclusion, we were able to build a Bayesian decision support system with the least manual construction and the most automatic use of data revealed by FMECA. However, we haven't used the gravity value so far. This one will be used in our next research to build a performance indicator system. Also, we will try to code the second part of the configuration of our BN.

REFERENCES

- Belu, N., Khassawneh, N., and Al Ali, A.R. (2013). Implementation of failure mode, effects and criticality analysis in the production of automotive parts. *Calitatea*, 14(135), 67.
- Ben Brahim, I., Addouche, S.A., El Mhamedi, A., and Boujelbene, Y. (2018). Cluster-based wsa for decision support bayesian systems: Case of prognostic in maintenance management. In *Proceedings of the 15th International Conference on Informatics in Control, Automation and Robotics - Volume 1: ICINCO.*, 222–230. INSTICC, SciTePress. doi:10.5220/0006878502320240.
- Bowles, J.B. and Peláez, C.E. (1995). Fuzzy logic prioritization of failures in a system failure mode, effects and criticality analysis. *Reliability Engineering & System Safety*, 50(2), 203–213.
- Chang, D.S. and Paul Sun, K.L. (2009). Applying dea to enhance assessment capability of fmea. *International Journal of Quality & Reliability Management*, 26(6), 629–643.
- Commission, F. (2011). *Production means FMECA method, Standardization committee of the production facilities edition, E41.50.530.N.*
- Das, B. (2004). Generating conditional probabilities for bayesian networks: Easing the knowledge acquisition problem. *arXiv preprint cs/0411034*.
- De Aguiar, D.C., Salomon, V.A.P., and Mello, C.H.P. (2015). An iso 9001 based approach for the implementation of process fmea in the brazilian automotive industry. *International Journal of Quality & Reliability Management*, 32(6), 589–602.
- Defense, U.S.D. (1980). *Mil-Std-1629a: 1980: Procedures for Performing a Failure Mode, Effects and Criticality Analysis*. Department of Defense.
- Díez, F. and Druzdzel, M. (2007). Canonical probabilistic models for knowledge engineering. version 0.9.
- Ebrahimipour, V., Rezaie, K., and Shokravi, S. (2010). An ontology approach to support fmea studies. *Expert Systems with Applications*, 37(1), 671–677.
- García, A. and Gilabert, E. (2011). Mapping fmea into bayesian networks. *International Journal of Performance Engineering*, 7(6), 525–537.
- Kara-Zaitri, C., Keller, A.Z., Barody, I., and Fleming, P.V. (1991). An improved fmea methodology. In *Reliability and Maintainability Symposium, 1991. Proceedings., Annual*, 248–252. IEEE.
- Lee, B.H. (2001). Using bayes belief networks in industrial fmea modeling and analysis. In *Reliability and maintainability symposium, 2001. proceedings. annual*, 7–15. IEEE.
- Lei, Z. (2007). Bayesian diagnostic network based on fmea. *Dual Use Technologies & Products*, 8, 014.
- Lolli, F., Gamberini, R., Rimini, B., and Pulga, F. (2016). A revised fmea with application to a blow moulding process. *International Journal of Quality & Reliability Management*, 33(7), 900–919.
- Margaritis, D. (2003). Learning bayesian network model structure from data. Technical report, Carnegie-Mellon Univ Pittsburgh Pa School of Computer Science.
- Mendes, E., Pollino, C.A., and Mosley, N. (2009). Building an expert-based web effort estimation model using bayesian networks. In *EASE*, volume 9, 41–50.
- Nadkarni, S. and Shenoy, P.P. (2001). A bayesian network approach to making inferences in causal maps. *European Journal of Operational Research*, 128(3), 479–498.
- Pearl, J. (2014). *Probabilistic reasoning in intelligent systems: networks of plausible inference*. Elsevier.
- Prajapati, D. (2012). Implementation of failure mode and effect analysis: a literature review. *International Journal of Management, IT and Engineering*, 2(7), 264–292.
- Price, C.J. and Taylor, N.S. (2002). Automated multiple failure fmea. *Reliability Engineering & System Safety*, 76(1), 1–10.
- Regazzoni, D. and Russo, D. (2011). Triz tools to enhance risk management. *Procedia Engineering*, 9, 40–51.
- Spreafico, C., Russo, D., and Rizzi, C. (2017). A state-of-the-art review of fmea/fmecca including patents. *Computer Science Review*, 25, 19–28.
- Tang, Z. and McCabe, B. (2007). Developing complete conditional probability tables from fractional data for bayesian belief networks. *Journal of Computing in Civil Engineering*, 21(4), 265–276.
- Van Der Gaag, L.C., Renooij, S., Witteman, C.L., Aleman, B.M., and Taal, B.G. (1999). How to elicit many probabilities. In *Proceedings of the Fifteenth conference on Uncertainty in artificial intelligence*, 647–654. Morgan Kaufmann Publishers Inc.
- Wei, B.C. (1991). A unified approach to failure mode, effects and criticality analysis (fmecca). In *Reliability and Maintainability Symposium, 1991. Proceedings., Annual*, 260–271. IEEE.
- Xiao, N., Huang, H.Z., Li, Y., He, L., and Jin, T. (2011). Multiple failure modes analysis and weighted risk priority number evaluation in fmea. *Engineering Failure Analysis*, 18(4), 1162–1170.