

Safety Decision-Making for Laboratory Processes in Academia

Anastasia Jung, Thierry Meyer*

Ecole Polytechnique Fédérale de Lausanne, Institute of Chemical Sciences and Engineering, Group of Chemical and Physical Safety, Station 6, 1015 Lausanne, Switzerland.
thierry.meyer@epfl.ch

There is a need for a tool that facilitates safety decision-making in the academic environment. As this environment is very different from that of industry or other public sectors, there is no information available on the factors that influence the decision-making process when it concerns laboratory safety issues. Since most processes are new and change frequently, there is no standard list of safety measures to be applied. Thus, most processes require an initial risk assessment. This work aims to determine the factors that can be evaluated during the risk assessment by the safety expert, which will influence the decision-making process. However, this information is too specific for non-expert decision-makers. A decision aiding tool that provides decision-makers with a list of the most optimal safety solutions is an effective way to quickly solve laboratory processes safety problems. The results show that subjective optimization methods do not help to overcome the existing contradictions between different decision-makers in the academic environment. Reference methods provide higher reliability because they are more objective and based on existing information. Comparing the Pareto Optimal approach with the two-reference method, the latter demonstrates higher reliability.

1. Introduction

Safety in academia was overlooked until 1991 (Commission Health and Safety, 1991) and can be considered as not extensively researched. Universities and research laboratories are often perceived by society as being safer than the industrial environment, which is not the case (Banholzer et al., 2013). Safety management in the academic environment is challenging because of its low attractiveness to the various stakeholders, both in terms of money and time. The high impact of human factors in the daily operation of the laboratory is a challenge for safety management. The frequent turnover of staff, the overload of the risk portfolio in the same physical space, the lack of formalization of rules, the flat organizational structure, and the difficulty of budgeting are just some factors that make safety management a weak point in academia. While process automatization, standardization of procedures, and planning are effective tools to reduce the negative impact of human factors on safety in industry, this approach does not work in academic laboratories. The absolute need to maintain a highly creative atmosphere with a high degree of freedom of work for members of academic laboratories shifts the role of the employee from stakeholder to decision-maker. The whole safety decision-making process has different mechanisms in industry and in academia. The hierarchical and organizational diversity of the academic world makes the safety decision-making process similar to a negotiation that requires optimal and objective solutions. The standard decision-making process consists of five main steps: 1) Identification of the problem, 2) Identification of decision criteria, 3) Development of potential alternatives, 4) Analysis of alternatives, 5) Selection among alternatives. While the first and third steps are the easiest and cause almost no conflict, the second and fourth steps determine whether the proposed decision will solve the existing problem. To make decisions quickly, the human brain applies different shortcuts (Payne et al., 1993). "These shortcuts, approximations, or rules of thumb for searching through a space of possible solutions" (Hoffrage & Reimer, 2004) in cognitive psychology are usually referred to as heuristics. Although heuristics can be very useful, especially when decisions have to be made quickly, such shortcuts can lead to various cognitive biases, affecting the outcomes of decision making. Heuristics can be helpful for simple, everyday intuitive decisions (Gigerenzer & Gaissmaier, 2011). It simplifies life, whereas with increasing complexity of systems failures

(Charles, 1994; Perrow, 1984) which are also caused by shortcuts of the mind, become inevitable. To reduce the impact of the decision maker's heuristics and subjectivity, the scientific community has focused over the last two decades on the creation and development of various decision support system (DSS), which help decision-makers determine the most optimal solutions (Joussleme, A. et al., 2012; Raskob, 2008; Zhao & Liu, 2018). Decision support tools are also essential as they are the only way to reduce decision-making time (Torretta et al., 2017).

Different DSS has been developed for various industries to make strategic decisions during typical performance and crisis management. They have also been developed for personal decision-making in healthcare (Cowie & Burstein, 2018). While there is a wealth of literature on safety decision-making in industry, such tools are still not available for academia.

The identification of key stakeholders, their needs, and their impact on the process is essential for developing decision criteria. As process safety decision-making involves multiple stakeholders, their objectives and therefore their preferences for the proposed solutions may often conflict.

A literature review, participant observations, interviews, and case studies were used (O'Hara et al., 2014). In the outcome, three main factors were identified: a) the contribution to risk directly associated with a hazard/activity, b) the financial factor and c) the factor related to the reliability of the proposed solution.

A reference-based approach (A. Wierzbicki, 2008) is proposed for ranking according to these factors evaluated during the risk assessment. The use of this system can be extended beyond the academy environment, providing SMEs and start-up laboratories with an effective safety management tool.

2. Methods

2.1 Qualitative methods

For triangulation purposes, the qualitative exploration of factors influencing decision-making process was divided into two rounds. The first round of qualitative factor exploration combined participant observations of various risk assessments and discussions with university safety experts. Several factors were developed:

- Risk-related factors, which can be combined into a single risk index (Pluess et al., 2016).
- Financial factors
- Soft factors characterizing the effectiveness of the proposed safety solutions

During the second round, semi-structured interviews (Keeney, 1996) were conducted with three categories of decision-makers: 1) University central OHS (Occupational Health and Safety), 2) University infrastructure service, and 3) Head of the laboratory/PI (principal investigator). As decision-makers are also subject to bias, the opportunity to generate objectives from multiple sources can diminish the bias' effect. The third decision-makers were not safety experts. Therefore, the generation of objectives was essential for them.

Moreover, it is the only decision-maker for whom the safety of the process and, in general, any decision taken as part of the risk assessment will not fall in the category of core objectives but will play the role of means objective, thus less essential and sometimes even meaningless from the first glance. In the first step of the objective generation process, to facilitate it, we will use the second type of approach proposed by Bond (Bond et al., 2010) proposing decision-makers to generate their master-list based on the two categories of strategic objectives: a) Safety and b) Research. Representatives of all decision-makers were interviewed separately.

Consequently, the structure for the alternative safety assessment is shown in Figure 1. The mathematical formulation of the obtained risk index is described in the following paper (Kalugina & Meyer, 2021b), and will not be discussed in this article.

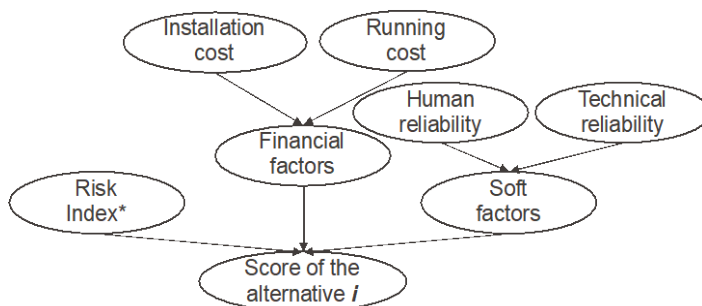


Figure 1: Structure and composition factors for ranking safer alternatives.

Two factors defining the efficiency of the risk reduction by the measure from the perspective of its interaction with the human-measure or measure-environment interactions and calculation method are exemplified in previous work (Kalugina & Meyer, 2021a).

2.2 Ranking

It is challenging to make a decision when several decision-makers with different preferences are involved in the process. In most situations, the decision-maker needs a decision support tool to select a rational and optimal alternative. This is even more important in the case of multiple decision-makers, as it will affect all parties involved. Even if absolute objectivity is probably unreachable, some methods allow a ranking that is « as objective as possible » (A. P. Wierzbicki, 2010). The reference point approach defined or established from the available information allows an approximation of the decision-maker's preferences (Ogryczak, 2006) and helps to achieve the required intersubjectivity. The application and limitations of two reference-based approaches were tested. In the first step, lower and upper points q_i^{lo} and q_i^{up} for the above mentioned factors in the *Figure 1* are determined, not necessarily absolute minimum and maximum, but out of available data inside the alternatives pool. Afterward, a partial achievement function is built:

$$\sigma_i(q_i, a_i, r_i) = \begin{cases} \frac{\alpha(q_i - q_i^{lo})}{r_i - q_i^{lo}}, & \text{if } q_i^{lo} \leq q_i < r_i \\ \alpha + \frac{(\beta - \alpha)(q_i - r_i)}{a_i - r_i}, & \text{if } r_i \leq q_i < a_i \\ \beta + \frac{(10 - \beta)(q_i - a_i)}{q_i^{up} - a_i}, & \text{if } a_i \leq q_i < q_i^{up} \end{cases} \quad (1)$$

Where $0 < \alpha < \beta < 10$ denote the values of partial achievement function for $q_i = r_i$ and $q_i = a_i$ correspondingly, while $\alpha = 3$ and $\beta = 7$ as in (A. Wierzbicki, 2008), where r_i – reservation and a_i – aspiration levels.

At the next step overall achievement function for all the criteria is calculated:

$$\sigma(q, a, r) = \min_{i \in I} \sigma_i(q_i, a_i, r_i) + \varepsilon/n \sum_{i \in I} \sigma_i(q_i, a_i, r_i) \quad (2)$$

Where n – number of alternatives, $q = (q_1, q_2, \dots, q_n)$ vector of criteria values $a = (a_1, a_2, \dots, a_n)$ and $r = (r_1, r_2, \dots, r_n)$ vectors of aspiration and reservation levels, based on the available alternatives:

$$q_i^{av} = \sum_{j \in J} \frac{q_{ij}}{n}; r_i = 0.5(q_i^{lo} + q_i^{av}); a_i = 0.5(q_i^{up} + q_i^{av}) \quad (3)$$

Using this method, a cost comparison is also possible, not discriminating against higher cost options. Another benefit of this method is debiasing the decision-making process through proposing objective alternatives, thus protecting the output from the Decoy (asymmetric dominance) effect, wishful thinking, and framing (Felfernig, 2014). In case when the decision-maker has primarily available constraints, either reference levels can be modified or an intersubjective definition of essential factors for every criterion can be made (A. Wierzbicki et al., 2007), thus modifying aspiration and reservation levels based not only on the information about available alternatives.

This method was compared with the traditionally used Pareto optimal approach. At the first step, metric d is introduced, so the distance between the points $x \in X$ to ideal solution x^* is quantified:

$d : R^d \times R^d \rightarrow R$, where $\min_{x \in X} d(f(x), f(x^*))$ need to be solved.

The l_∞ distance between two vectors, $x, y \in R^d$ is defined as $\|x - y\|_\infty = \max_{l \in [d]} |x_l - y_l|$, and the weighted l_∞ distance is given by $\|x - y\|_{\lambda_\infty} = \max_{l \in [d]} \lambda_l |x_l - y_l|$, where λ is a vector of weights (Bowman, 1976). In the discrete case when number of decision options are limited use of weighted distance creates a risk of missing important Pareto points, as they might be contained in the interior and not on the boundary of the convex cover of the set. This risk is avoided using reference point approach (A. Wierzbicki, 2008).

The third method used for comparison is the Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (FTOPSIS) (Krohling & Pacheco, 2015). FTOPSIS is often used in decision making as quick optimization of the results and their ranking representation based on the similarity of the alternative to the ideal solution:

$$C_i = d_i^- / (d_i^- + d_i^+), i = 1, 2, \dots, m \quad (4)$$

Where $d_{ij}^+ = \sum_{j=1}^n d(\tilde{v}_{ij} - \tilde{v}_j^+)$ with $\tilde{v}_{ij}^+ = (9,9,9)$ and $\tilde{v}_{ij}^- = (1,1,1)$ distances from the positive ideal solution A^+ . Distance from the negative solution A^- is calculated in the same way. Normalized decision matrix allows the use of different scales, combining parameters of a different kind in the decision-making process (Shi & Yang, 2009):

$$\tilde{D} = \begin{matrix} & C_1 & \dots & C_n \\ \begin{matrix} A_1 \\ \vdots \\ A_m \end{matrix} & \begin{pmatrix} \tilde{x}_{11} & \dots & \tilde{x}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \dots & \tilde{x}_{mn} \end{pmatrix} \end{matrix} \quad (5)$$

Where $\tilde{x}_{11} = (l\tilde{x}_{11}, m\tilde{x}_{11}, u\tilde{x}_{11})$, while weights are obtained during the Fuzzy Analytical Hierarchy Process (FAHP) process (Masmoudi & Dhiaf, 2018) :

$$\tilde{V} = [\tilde{V}_{ij}]_{m \times n}, i=1,2,..,m ; j=1,2,..,n \quad \text{and} \quad \tilde{V}_{ij} = \tilde{r}_{ij} \otimes \tilde{W}_j = (l\tilde{r}_{ij}, m\tilde{r}_{ij}, u\tilde{r}_{ij}) \otimes (l\tilde{W}_j, m\tilde{W}_j, u\tilde{W}_j) \quad (6)$$

Although some authors claim that the combination of FAHP and FTOPSIS is sufficient to overcome the drawbacks of traditional TOPSIS and AHP, such as uncertainty and ambiguity of information (Abd et al., 2017), this method still relies heavily on the subjective preference of the decision-maker. This subjectivity can be a serious problem and affect the reliability of the results (Madi et al., 2016) when some of the decision-makers do not have sufficient expertise on the issue.

3. Results & Discussion

To test the validity of the proposed decision aiding model, the results of the case risk assessment were compared with the Pareto optimal approach (Ehrgott, 2005). The results are compared to an actual selection made by one of the decision-makers. The initial factors used for the ranking are the Risk Index, the Delta Risk Index, Human Reliability, Technical Reliability, Implementation, and Running Cost. In the case of Pareto optimal approach for Tchebycheff scalarization, relative weights of the factors were obtained using the Rank Ordering Criteria method (Roszkowska, 2013). This leads to the following weights for the above factors (in the order they appear in the text): $\lambda = (0.41, 0.24, 0.16, 0.10, 0.06, 0.03)$.

The financial factors were defined as being the least important and therefore having the lowest weight. Minimization was applied to the following factors: Risk Index, Implementation, and Running cost. The relative weights of the above factors that were used for FTOPSIS are: 0.348, 0.224, 0.175, 0.104, 0.081 and 0.067. Delta Risk, Human and Technical Reliability have almost the same weight as those obtained by the ROC method. In the case of the two-reference method, no relative weights were used. However, several factors were treated as having negative value: the Risk Index, Implementation, and Running Cost. For all methods, Risk Index, Implementation, and Running cost, were considered negative from the decision-makers perspective, as the expectations for these values were as low as possible. While expectations for Delta Risk Index, Human and Technical Reliability were striving to the available for these factors' maximum. The desired solution would be to have a risk level as low possible with minimal financial investments.

We will take an actual example of the use of deuterium in a Tokamak-style fusion reactor to illustrate the results obtained with the different approaches. Deuterium is a highly flammable gas and several safety measures must be taken when working with it. The safety experts proposed the following safety measures after the risk assessment:

- A. Use warning signs in gas storage areas
- B. Eliminate all ignition sources
- C. Ensure gas equipment is in good operating order
- D. Equip the lab with gas-specific detectors
- E. Keep deuterium away from heat sources
- F. Store large gas cylinders in explosion-proof cabinet
- G. Use certified explosion-proof equipment
- H. Use flashback arrestors

Comparing the results of the three different methods (see Table 1) with the decision-maker choice, it can be seen that the two-reference method is the closest to the reasonable choice. All methods have their advantages and limitations. In the case of Pareto, the optimal weights used are taken from the literature. Thus, the decision-maker is only "allowed" to prioritize objectives. This, on the one hand, reduces the possible ambiguity in the case of multiple preferences by several decision-makers. On the other hand, it might not be an accurate representation of real priorities. However, the problem of agreement between decision-makers with different priorities remains. The FTOPSIS method is too much based on the subjective preferences of the decision-makers, and the results of FAHP will not be better than the simple average.

Table 1. Comparison of three methods with decision-maker's preferences.

| Safety Measure | Pareto Optimal | FTOPSIS | Two-reference method | Decision-maker |
|----------------|----------------|---------|----------------------|----------------|
| A | 1 | 3 | 2 | 2 |
| B | 5 | 4 | 5 | 4 |
| C | 3 | 2 | 1 | 1 |
| D | 6 | 1 | 7 | 6 |
| E | 4 | 7 | 4 | 5 |
| F | 8 | 8 | 7 | 8 |
| G | 7 | 6 | 6 | 3 |
| H | 2 | 5 | 3 | 7 |

The use of the two-reference level allows the decision-maker to be inconsistent with his preferences and thus to learn during the interaction with the decision-making system. The use of two references still allows a certain level of specificity to be maintained, and therefore necessarily when at least some of the constraints are known. In the case of safety decision-making in academic environment, it is necessary to maintain some flexibility when prioritizing factors. Firstly, as budget and planning are limited and safety projects appear as a daily problem, it is sometimes complicated to set financial constraints. Secondly, the different nature of the laboratory's activities influences the level of acceptance of various factors, such as Risk Index, Human and Technical Reliability. In addition, the presence of expert and non-expert decision-makers requires that both preferences be considered without undervaluing the latter.

4. Conclusion

This work reveals various factors which are important when making decisions to improve the process safety in each particular laboratory of a university. Three groups of factors were found to be essential for the decision-maker. As these factors have different natures, a decision-support tool is helpful to avoid unnecessary heuristics. It is also valuable because a non-expert decision-maker is involved in this process, for whom the issue of safety is not a top priority. We demonstrated the use of different optimizations methods that are widely applicable in decision-making. All tested methods assume rationality in decision-making, as we consider that safer alternatives will be selected only on the basis of the factors included in the decision support tool. The comparison of the three methods from a theoretical and practical perspectives suggests that the use of the two-reference method in the case of safety decision-making in academia can lead to more effective and useful decision-aiding than the other methods. It provides an objective ranking of the alternatives based on the available data and the minimum expectations of decision-makers. However, it also creates a solid basis for further discussion among them in case of new information or significant disagreements.

References

- Banholzer, W. F., Calabrese, G. S., & Confalone, P. (2013). The Importance of Teaching Safety. *Chemical & Engineering News*, 91(18). <https://cen.acs.org/articles/91/i18/Importance-Teaching-Safety.html>
- Bond, S. D., Carlson, K. A., & Keeney, R. L. (2010). Improving the generation of decision objectives. *Decision Analysis*, 7, 238–255. <https://doi.org/10.1287/deca.1100.0172>
- Bowman, V. J. (1976). *On the Relationship of the Tchebycheff Norm and the Efficient Frontier of Multiple-Criteria Objectives*. 76–86. https://doi.org/10.1007/978-3-642-87563-2_5
- Charles, P. (1994). The Limits of Safety: the Enhancement of a Theory of Accidents. *Journal of Contingencies and Crisis Management*, 2(4), 212–220.
- Commission Health and Safety. (1991). *Occupational health services in higher education*.
- Cowie, J., & Burstein, F. (2018). A decision support tool for supporting individuals living with long-term conditions make informed choices: LTC-Choices tool for continuous healthcare. *Journal of Decision Systems*, 27, 123–131. <https://doi.org/10.1080/12460125.2018.1460157>
- Ehrgott, M. (2005). Multicriteria Optimization. In *Multicriteria Optimization*. Springer Berlin Heidelberg. <https://doi.org/10.1007/3-540-27659-9>
- Felfernig, A. (2014). Biases in decision making. *CEUR Workshop Proceedings*, 1278, 32–37. <https://doi.org/10.19137/perspectivas-2019-v9n1a06>
- Gigerenzer, G., & Gaissmaier, W. (2011). Heuristic decision making. *Annual Review of Psychology*, 62, 451–482. <https://doi.org/10.1146/annurev-psych-120709-145346>
- Hoffrage, U., & Reimer, T. (2004). Models of Bounded Rationality: The Approach of Fast and Frugal Heuristics. *Management Revu*, 15(4), 437–459. <https://doi.org/10.5771/0935-9915-2004-4-437>

- Jousselme, A., Maupin, P., Debaque, B., & Prévost, D. (2012). A decision support tool for a Ground Air Traffic Control application. *15th International Conference on Information Fusion*, 60–67.
- Kalugina, A., & Meyer, T. (2021a). *Safety Decision-Making in Academia Safety Decision-Making in Academia* (Issue July 2020). Springer International Publishing. <https://doi.org/10.1007/978-3-030-50946-0>
- Kalugina, A., & Meyer, T. (2021b). *Semi-quantitative Model for Risk Assessment in University Laboratories* (Issue February). Springer International Publishing. https://doi.org/10.1007/978-3-030-68017-6_48
- Keeney, R. L. (1996). Value-focused thinking: Identifying decision opportunities and creating alternatives. *European Journal of Operational Research*. [https://doi.org/10.1016/0377-2217\(96\)00004-5](https://doi.org/10.1016/0377-2217(96)00004-5)
- Krohling, R. A., & Pacheco, A. G. C. (2015). A-TOPSIS - An approach based on TOPSIS for ranking evolutionary algorithms. *Procedia Computer Science*, 55(I tqm), 308–317. <https://doi.org/10.1016/j.procs.2015.07.054>
- Madi, E. N., Garibaldi, J. M., & Wagner, C. (2016). An exploration of issues and limitations in current methods of topsis and fuzzy TOPSIS. *2016 IEEE International Conference on Fuzzy Systems, FUZZ-IEEE 2016, July 2017*, 2098–2105. <https://doi.org/10.1109/FUZZ-IEEE.2016.7737950>
- Masmoudi, S., & Dhiaf, M. M. (2018). Criticality assessment risk; contribution of fuzzy logic. *Yugoslav Journal of Operations Research*, 28(1), 93–105. <https://doi.org/10.2298/YJOR161113005M>
- O'Hara, R., Johnson, M., Hirst, E., Weyman, A., Shaw, D., Mortimer, P., Newman, C., Storey, M., Turner, J., Mason, S., Quinn, T., Shewan, J., & Siriwardena, A. N. (2014). A qualitative study of decision-making and safety in ambulance service transitions. *Health Services and Delivery Research*, 2(56), 1–138. <https://doi.org/10.3310/hsdr02560>
- Ogryczak, W. (2006). On multicriteria optimization with fair aggregation of individual achievements. ... *CSM'06: 20th Workshop on Methodologies and Tools ...*, 1–11. http://www.iiasa.ac.at/~marek/ftppub/Pubs/csm06/pres/ogryczak_pap.pdf
- Payne, J. W., Bettman, J. R., & Johnson, E. J. (1993). *The Adaptive Decision Maker*. Cambridge University Press. <https://doi.org/10.1017/CBO9781139173933>
- Perrow, C. (1984). *Normal Accidents: Living with High-risk Technologies*. Basic Books.
- Pluess, D. N., Meyer, T., Masin, J., Mikulasek, P., & Ferjencik, M. (2016). Joint applicability test of software for laboratory assessment and risk analysis. *Journal of Loss Prevention in the Process Industries*, 40, 234–240. <https://doi.org/10.1016/j.jlp.2015.12.026>
- Raskob, W. (2008). Application of a Decision Support System in Nuclear and Radiological Emergency: Opportunities and Challenges. *Prevention, Detection and Response to Nuclear and Radiological Threats*, 207–221.
- Roszkowska, E. (2013). Rank Ordering Criteria Weighting Methods – a Comparative Overview. *Optimum. Studia Ekonomiczne*, 5(65), 14–33. <https://doi.org/10.15290/ose.2013.05.65.02>
- Shi, L., & Yang, S. (2009). The evaluation of software trustworthiness with FAHP and FTOPSIS methods. *Proceedings - 2009 International Conference on Computational Intelligence and Software Engineering, CiSE 2009*. <https://doi.org/10.1109/CISE.2009.5365827>
- Torretta, V., Rada, E. C., Schiavon, M., & Viotti, P. (2017). Decision support systems for assessing risks involved in transporting hazardous materials: A review. *Safety Science*, 92, 1–9. <https://doi.org/10.1016/j.ssci.2016.09.008>
- Wierzbicki, A. (2008). The problem of objective ranking: foundations, approaches and applications. *Journal of Telecommunications and Information Technology*, nr 3, 15–23.
- Wierzbicki, A., Granat, J., Makowski, M., Hordijk, L., & Director, I. (2007). Discrete decision problems with large number of criteria. *Interim Reports, IR-07-025, International Institute for Applied Systems Analysis (IIASA), December*. http://www.iiasa.ac.at/~marek/mca_doc/pdf/ir0725.pdf
- Wierzbicki, A. P. (2010). The need for and possible methods of objective ranking. In *International Series in Operations Research and Management Science* (Vol. 142, Issue September 2010). https://doi.org/10.1007/978-1-4419-5904-1_2
- Zhao, M., & Liu, X. (2018). Development of decision support tool for optimizing urban emergency rescue facility locations to improve humanitarian logistics management. *Safety Science*, 102(July 2017), 110–117. <https://doi.org/10.1016/j.ssci.2017.10.007>