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ELECTRE TRI-based approach to the failure modes classification on the basis of risk parameters: An alternative to the risk priority number

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ABSTRACT

Failure Mode and Effects Analysis (FMEA) is an engineering technique aimed at the detection of potential failures, their causes and consequences on the system/process under investigation. When used for the failure modes prioritization, FMEA is also referred to as Failure Mode, Effects and Criticality Analysis (FMECA). In traditional FMECA, risk priorities of failure modes are determined through the Risk Priority Number (RPN), which is a function of the three risk parameters Occurrence (O), Severity (S), and Detection (D). In the present paper, an alternative approach to the RPN is proposed for the criticality assessment of process/system failure modes. Particularly, the Multi-Criteria Decision Making (MCDM) method ELECTRE TRI is employed to assign failure modes to predefined and ordered risk classes, from the highest to the lowest risky one. Contrarily to the traditional RPN, the method allows the Decision Maker (DM) at taking into account the relative importance of risk parameters as well as his/her uncertainty in assigning each failure mode to a specific risk class. The ELECTRE TRI-based approach is implemented on the applicative case proposed by Kurt and Özilgen (2013) with reference to Turkish dairy manufacturing industries. A sensitivity analysis is finally performed in order to test the influence of the input parameters on the classification results.

1. Introduction

The International Standard IEC 60812 (2006) defines the Failure Mode and Effects Analysis (FMEA) as a systematic procedure for the analysis of a system/process to identify the potential failure modes, their causes and effects on the system/process performance. FMEA is a predictive methodology commonly performed by a multi-disciplinary team of experts with the aim of supporting the Decision Maker (DM) in the identification, prioritization, and elimination of potential failures from the system, design or process (Omdahl, 1988). In particular, when addressed to the prioritization of failure modes, FMEA is referred to as Failure Mode, Effects and Criticality Analysis (FMECA). FMEA/FMECA starts with the definition of the system/process boundaries and carries on with the hierarchical decomposition of the system/process into its basic components (Fig. 1).

Then, potential failure modes of each basic element are identified as well as their causes and consequences on the other components in the same subsystem and on the subsystem as such (local effects), and on the overall system (global effects).

For prioritization aims, a metric called Risk Priority Number (RPN) is commonly used in practice. It is computed as the multiplication of values taken by the Occurrence (O), Severity (S) and Detection (D) parameters related to each failure mode. In particular, S stands for the level of damage on the system/process and on its surroundings due to the failure mode occurrence, whereas O and D represent the frequency of occurrence and the detection value of the failure mode respectively (Scipioni, Saccarola, Centazzo, & Arena, 2002). As suggested by the IEC 60812 (2006), parameters O, S and D are generally measured on a 10-point scale (Tables 1–3) wherein greater O and S numbers stand for increasing values of the frequency of occurrence and of the severity respectively, whereas D is ranked in a reverse order, namely the higher the detection value, the lower the detection probability of the failure mode. Therefore, the way O, S and D numbers are measured assure that higher RPN scores refer to more critical failure modes on which paying further attention for the overall system improvement. Actually, once identified, critical potential failure modes are commonly quantitatively analyzed by Fault Tree and Event Tree Analyses (FTA and ETA) to estimate their exact probability/frequency of occurrence as well as that of their consequences. On

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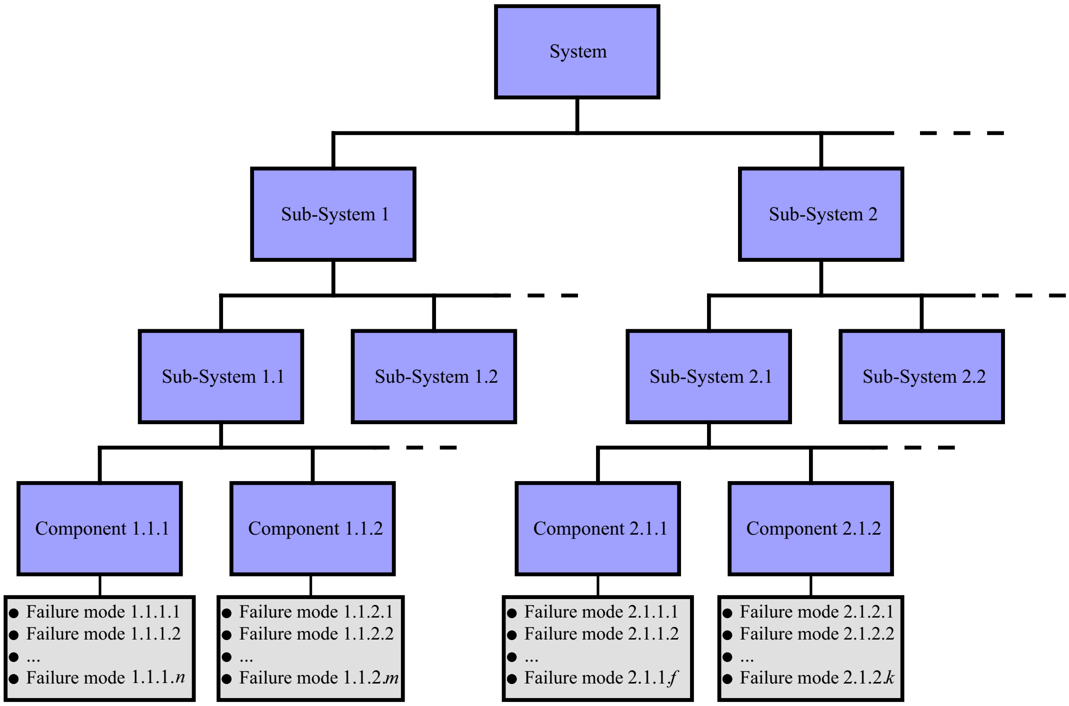

Fig. 1. Hierarchical decomposition of the system under investigation.

Table 1
Failure mode severity.

Severity (S)	Criteria	Ranking
None	No discernible effect	1
Very minor	Negligible effect on component/system performance	2
Minor	Slight effect on component/system performance. Non-vital faults will be noticed most of the time	3
Very low	Minor effect on component/system performance	4
Low	Reduced performance with gradual performance degradation	5
Moderate	Component/system operable and safe but performance degraded	6
High	Component/system performance severely affected	7
Very high	Component/system inoperable but safe	8
Hazardous with warning	Component/system failure resulting in hazardous effects highly probable	9
Hazardous without warning	Component/system failure resulting in hazardous effects almost certain	10

Table 2
Failure mode occurrence related to frequency.

Occurrence (O)	Frequency	Ranking
Remote: Failure is unlikely	$\leq$0.010 per thousand items	1
	0.1 per thousand items	2
Low: Relatively few failures	0.5 per thousand items	3
	1 per thousand items	4
Moderate: Occasional failures	2 per thousand items	5
	5 per thousand items	6
High: Repeated failures	10 per thousand items	7
	20 per thousand items	8
Very high: Failure is almost inevitable	50 per thousand items	9
	$\geqslant$ 100 in thousand items	10

the basis of the obtained results, (prevention or mitigation) measures to be undertaken to reduce risks under acceptable thresholds are finally decided.

So far, FMECA has been extensively applied in a wide range of industrial areas (Arvanitoyannis & Savelides, 2007; Arvanitoyannis & Varzakas, 2007; Cicek & Celik, 2013). Nevertheless, the use of the classical RPN for the criticality analysis of the system/process failure modes has been criticized to have many drawbacks (Liu et al., 2011; Montgomery, Pugh, Leedham, & Twitchett, 1996; Seyed-Hosseini, Safaei, & Asgharpour, 2006; Signor, 2002; Wang, Chin, Poon, & Yang, 2009; Yang, Bonsall, & Wang, 2008), some of which are listed below.

Table 3
Likelihood of detection of failure modes.

Detection (D)	Criteria: Likelihood of detection	Ranking
Almost certain	Control system will almost certainly detect a potential cause and subsequent failure mode	1
Very high	Very high chance the control system will detect a potential cause and subsequent failure mode	2
High	High chance the control system will detect a potential cause and subsequent failure mode	3
Moderately high	Moderately high chance the control system will detect a potential cause and subsequent failure mode	4
Moderate	Moderate chance the control system will detect a potential cause and subsequent failure mode	5
Low	Low chance the control system will detect a potential cause and subsequent failure mode	6
Very low	Very low chance the control system will detect a potential cause and subsequent failure mode	7
Remote	Remote chance the control system will detect a potential cause and subsequent failure mode	8
Very remote	Very remote chance the control system will detect a potential cause and subsequent failure mode	9
Absolutely uncertain	Control system will not and/or cannot detect a potential cause and subsequent failure mode	10

– The formula for calculating the RPN is at least questionable and debatable. There is no strong reason why O, S and D should be multiplied to produce the RPN.
– Factors O, S and D are assumed to be equally important.
– Diverse judgments on O, S and D may lead to the same RPN even if the risk implications are totally different. For instance, let have two failure modes which O, S and D values are 2, 6, 2 and 4, 2, 3 respectively. The resulting RPN is 24 in both cases. However, the two failure modes have different severities so that they may variously contribute to the risk.
– The RPN just takes into account safety aspects so that other important factors, such as the economical one, are ignored.
– The three risk factors are often difficult to be precisely evaluated.
– The RPN is not a continuous function. The latter causes some problem in interpreting the meaning of the differences between two consecutive RPNs. For instance, is the difference between 1 and 2 the same as or less than the difference between 900 and 1000?

With these recognitions, the present paper proposes an alternative approach to the traditional RPN with the aim of classifying the system/process failure modes into predefined and ordered risk classes (i.e. very low, low, medium, high and very high). To this purpose, the Multi-Criteria Decision Making (MCDM) method ELECTRE TRI (Yu, 1992) is suggested. Specifically, ELECTRE TRI belongs to the family of ELECTRE methods initially introduced by Roy in 1968 (Roy, 1968). They use the outranking relation concept to deal with different types of decisional problems as choice (ELECTRE I, IS), ranking (ELECTRE II, III, IV) (Lupo, 2015) and classification (or sorting) (ELECTRE TRI) of alternatives. Among these problem statements (i.e. choice, ranking or sorting), Mousseau, Slowinski, and Zielniewicz (2000) affirm that "a major distinction concerns *relative vs absolute judgment* of alternatives". Choice or ranking problems refer to relative judgments, namely alternatives are compared one to each other against all evaluation criteria. Then, the presence (or absence) of an alternative in the set of the best alternatives (i.e. choice problems) or the position of an alternative in the preference order (i.e. ranking problems) results from the comparison of such an alternative to the others. Instead, sorting problems refer to absolute judgments, namely each alternative is considered independently from the others in order to determine its intrinsic value by means of comparisons to norms or references (Mousseau et al., 2000). Therefore, the assignment of an alternative to a specific category results from the intrinsic evaluation of the alternative itself on all criteria with respect to profiles that define categories, namely the assignment of an alternative to a particular category does not influence the category to which another alternative should be assigned (Mousseau et al., 2000). Sorting problems are conceptually different from clustering. Actually, the former consider classes that are defined *a priori* by the DM, whereas the latter result from a partition of the set of alternatives into categories unknown *a priori*.

Therefore, the present paper deals with a multi-criteria sorting problem where alternatives to be classified by the ELECTRE TRI method are the system/process failure modes previously identified by means of the classical FMEA. To the best of the authors' knowledge, anyone else MCDM method has not been yet proposed in the literature to directly classify failure modes on the basis of their contribution to the risk. As emphasized in (Chang, Tay, & Lim, 2015; Tay, Jong, & Lim, 2015), failure modes classification in FMECA applications is very important because it presents failure modes as a structure that is easy to understand and visualize, it allows the DM to quickly access or analyze FMEA with a large number of failure modes, and it leads to more efficient processes for making decisions and taking actions. The traditional RPN approach does not directly return the failure modes classification into risk categories but a ranking where the higher the RPN values, the more critical the failure modes. Therefore, on the basis of the obtained RPN-based ranking, the problem of choosing failure modes on which paying further attention for next quantitative analyses still holds, and strictly depends on the DM expertise as well as on the amount of human and financial resources available. In other words, the DM is asked to decide up to which value of the RPN failure modes have to be considered so much critical to be further analyzed and/or appropriate (prevention or mitigation) measures need to be taken with priority in order to reduce the risk to acceptable values. The proposed ELECTRE TRI-based approach overcomes such a limitation of the traditional RPN method through a well defined classification of failure modes on the basis of the related risk. As aforementioned, the ordered risk classes are defined *a priori* by the DM on the basis of his/her specific need to satisfactorily differentiate failure modes, namely classes' definition does not depend on failure modes' judgments on risk criteria but on the analyzed context and on the DM expertise and perception. In addition, differently from the classical RPN approach, the use of the ELECTRE TRI sorting method permits the intransitivity of preferences (Tversky, 1969) and also allows the DM at taking into account the relative importance of criteria as well as his/her unavoidably uncertainty in precisely assigning each failure mode to a risk category rather than another one. ELECTRE TRI actually is an outranking technique that provides a way to deal with the uncertainty of the DM during the evaluation process by means of the introduction of specific thresholds. The latter makes ELECTRE TRI a suitable method to better approximate the attitude of the DM, which is usually characterized by a gradual transition from the indifference to the preference state. Furthermore, the methodology is easily implementable, requires short computational time to get the final classification results and allows the DM at easily verifying the efficacy of taken actions. However, one must bear in mind that the DM' expertise and perception of the industrial context under investigation still remain fundamental for the definition of risk categories as well as of the other input parameters required by the method.

The remainder of the paper is organized as follows. The literature review is reported in Section 2 whereas an overview on the ELECTRE TRI method is supplied in Section 3. Section 4 synthesizes the proposed ELECTRE TRI-based approach to the failure modes classification into risk categories and its application to a real case. Conclusions are finally drawn in Section 5.

2. Literature review

So far, the main part of literature contributions addressed to the failure modes prioritization is based on the use of the classical RPN. Nevertheless, such a method has been widely criticized to have many shortcomings so that various alternative risk priority models have been proposed to enhance the performance of FMECA (Liu, Liu, & Liu, 2013). An Analytic Hierarchy Process (AHP)-based approach (Saaty, 1994) for the failure modes analysis is proposed by Braglia (2000). Alternatives to be compared are the potential causes of failure whereas decisional criteria are the classical risk factors O, S and D, and the expected cost due to failures as a further criterion. A combined FMEA and AHP-based method is also proposed by Chen and Wu (2013) to construct a supplier evaluation system and to discuss potential failure factors and their effects on the system in a risky supply chain environment. Bevilacqua, Braglia, and Gabbrielli (2000) propose a modified FMECA where the RPN consists of the weighted sum of six parameters (safety, machine importance for the process, maintenance costs, failure frequency, downtime length, and operating conditions). A sensitivity analysis based on the Monte Carlo simulation to verify the robustness of the final results is also performed. Alternative linguistic scales on the basis of which evaluating risk parameters are proposed by Puente, Pino, Priore, and Fuente (2001) and Sankar and Prabhu (2001).

Aiming at dealing with the uncertainty and imprecision often affecting experts' judgments on risk parameters (Certa, Enea, Galante, & La Fata, 2013; Certa, Enea, & Lupo, 2013; Curcurù, Galante, & La Fata, 2012, 2013; Francese, Galante, La Fata, & Passannanti, 2015; Liu, You, & You, 2014), the fuzzy logic technique has been extensively proposed (Bowles & Peláez, 1995; Cayrac, Dubois, & Prade, 1996; Lupo, 2016; Xu, Tang, Xie, Ho, & Zhu, 2002) even if developing and testing an extensive set of fuzzy rules is a complex and time-consuming activity. In this respect, Tay and Lim (2010) investigate on the possibility of using fuzzy rule interpolation and reduction techniques to design new fuzzy RPN models. A two-stage Fuzzy Inference System (FIS)-based approach is proposed in (Jee, Tay, & Lim, 2015) to prioritize failures. Particularly, a Genetic Algorithm (GA) is firstly suggested to search for a small set of fuzzy rules to be collected from FMEA users, and then a monotonicity-preserving similarity reasoning scheme is used to deduce the remaining fuzzy rules. Also Kerk, Tay, and Lim (2015) and Pang, Tay, and Lim (2016) deal with the importance of the monotonicity property of FIS-based models in FMECA applications. A combined application of fuzzy logic and AHP techniques is suggested by Braglia and Bevilacqua (2000) in order to support the maintenance staff into the identification of failure modes criticality. Braglia, Frosolini, and Montanari (2003a) propose a fuzzy criticality assessment model easy to implement and design. A risk function which permits if-then fuzzy rules to be generated in an automatic way is presented and the proposed methodology tested with relation to a real process plant. A further fuzzy RPN-based approach is presented in (Zhang & Chu, 2011). In particular, a fuzzy Weighted Least Squares Model (WLSM) is used to aggregate the DMs' opinions and the relative importance of O, S and D factors are also considered. A partial order method based on fuzzy preference relations is employed for the final ranking of failure modes. In (Zammori & Gabbrielli, 2011), the FMEA is combined together with the Analytic Network Process (ANP) technique (Saaty & Ozdemir, 2005) to take into account the possible interactions among the principal causes of failure. Braglia, Frosolini, and Montanari (2003b) present a fuzzy-Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)-based technique to overcome the intrinsic difficulty encountered in assessing parameters O, S and D by means of crisp values. Differently from the fuzzy logic applications commonly proposed in the literature, authors integrate fuzzy logic into the multi-criteria decision model without needing the definition of a rules matrix, and a particular classification method is then adopted to rank the final fuzzy criticality values. A further fuzzy-TOPSIS-based approach is suggested by Carpitella, Certa, Galante, Izquierdo, and La Fata (2016) to rank failure modes of a street cleaning vehicle on the basis of three evaluation criteria, two related to the severity (i.e. time of operation and modality of the maintenance action execution) and a further criterion related to the occurrence. A combined fuzzy-TOPSIS and fuzzy-AHP approach is proposed in (Kutlu & Ekmekçioğlu, 2012). In particular, the fuzzy-AHP method is applied to weight the risk factors that are later used into the fuzzy-TOPSIS approach to get the final closeness coefficients on the basis of which prioritizing the failure modes. In Certa, Hopps, Inghilleri, and La Fata (2017), a novel Dempster-Shafer Theory-based FMECA methodology (Dempster, 1967; Shafer, 1976) is proposed. In particular, crisp or interval-valued opinions on O, S and D are elicited from a team of equally credible and reliable experts, and a multiple-value characterization of RPNs is obtained. A particular methodology based on Belief and Plausibility distributions is then suggested for the prioritization of failure modes.

Since its conception, ELECTRE TRI has been applied on a wide range of decisional classification problems as location (Sànchez-Lozano, Antunes, García-Cascales, & Dias, 2014; Sànchez-Lozano, García-Cascales, & Lamata, 2014), skills evaluation (de Moura & Sobral, 2016; de Oliveira Nepomuceno & Costa, 2015), service quality evaluation (Jerônimo & Medeiros, 2014) and so on. To the contrary, its use on decisional classification problems related to risk issues is quite recent. Merad, Verdel, Roy, and Kouniali (2004) apply ELECTRE TRI to categorize a certain number of zones within the Lorraine iron-mining basin into four predefined classes of risk. As allowed by the method, both qualitative and quantitative criteria are taken into consideration. In (Brito, de Almeida, & Mota, 2010), authors integrate the utility theory together with the ELECTRE TRI method for assessing risk in natural gas pipelines, and for classifying their sections into risk categories by taking into consideration the human, environmental and financial impacts of natural gas leakage accidents. A further application of ELECTRE TRI is proposed in (Silva, Alçada-Almeida, & Dias, 2014) in order to determine the most suitable sites for locating biogas plants in a specific region of Portugal. ELECTRE TRI is used to evaluate the land-use suitability of alternatives on the basis of 13 environmental, economical and social/safety criteria.

3. Overview on the ELECTRE TRI method

Among the ELECTRE methods, ELECTRE TRI addresses to the assignment of alternatives to predefined and ordered classes on the basis of their evaluations against quantitative and/or qualitative criteria differently weighted. According to Figueira, Mousseau, and Roy (2005), classes have to be defined *a priori*. Then, the assignment of an alternative a to a specific class results from the comparison of a with the reference profiles defining the limits of the classes (Mousseau et al., 2000).

Let $(C_1, C_2, \ldots, C_n)$ be the classes ordered from the worst to the best one, whereas let j $(j = 1, 2, \ldots, J)$ be the jth evaluation criterion

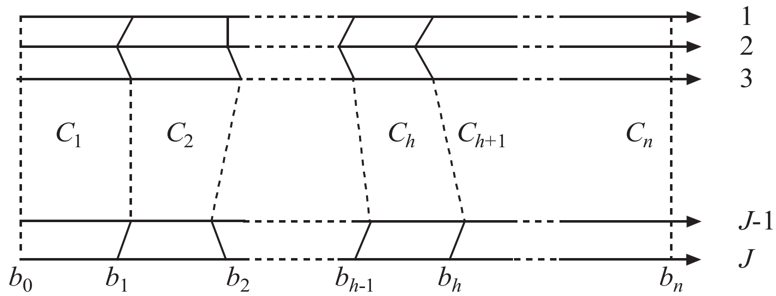

Fig. 2. Ordered classes and reference profiles under each criterion j.

among the whole set of criteria. Each class C_h ($h = 1, 2, \ldots, n$) is characterized by the lower profile $b_{h\text{-}1}$ and the upper profile b_h (Kadziński & Słowiński, 2015) (Fig. 2). Reference profiles are commonly directly provided by experts (Damart, Dias, & Mousseau, 2007) or indirectly determined by means of various elicitation techniques (Mousseau & Ngo-The, 2002; Mousseau & Słowiński, 1998).

ELECTRE TRI assigns alternatives to classes by two consecutive steps:

- development of an outranking relation S that characterizes the comparison between the alternative and the limits of classes;
- exploitation of the relation S in order to assign each alternative to a specific class. Two assignment procedures are suggested in such a step, namely the pessimistic and optimistic ones.

3.1. Phase 1 of the ELECTRE TRI method: development of the outranking relation

As stressed by Lourenço and Costa (2004), the ELECTRE TRI method is grounded upon the outranking relation concept (Figueira, Greco, Roy, & Slowinski, 2010) that is fundamental in all the ELECTRE methods. In detail, ELECTRE TRI develops an outranking relation S between each alternative a and profile b_h (i.e. "$a\ S\ b_h$"), whose meaning is "*a is at least as good as* b_h". Then, such an assertion needs to be validated on the basis of the concordance/discordance principle. It consists in the existence verification of a concordance among criteria in favor of the assertion that an alternative is at least as good as the profile, and that a strong discordance among the score values that may reject the previous assertion does not exist (Mousseau, Slowinski, & Zielniewicz, 1999). ELECTRE TRI makes use of the credibility index $\sigma(a, b_h) \in [0, 1]$ ($\sigma(b_h, a)$ respectively) to validate the outranking relation "$a\ S\ b_h$" ("$b_h\ S\ a$" respectively). Therefore, $\forall j \mid j = 1, 2, \ldots, J$ and $\forall h \mid h = 1, 2, \ldots, n - 1$, the computation of the credibility index requires the definition of the following input parameters.

- Criteria weights w_j.
- Alternative evaluation $g_j(a)$ on each criterion j, $\forall a \mid a = 1, 2, \ldots A$.
- Indifference threshold q_j that represents the greatest performance difference for which the indifference holds on criterion j between the alternative a and the profile b_h.
- Preference threshold p_j that represents the smallest performance difference for which the strict preference occurs on criterion j between the alternative a and the profile b_h.
- Veto threshold v_j that represents the difference that completely nullifies (raises a "veto" against) the outranking relation.

As already introduced with relation to the reference profiles, the other preference parameters required by the method, i.e. criteria weights and threshold values are determined by a preference elicitation process that proceeds through an interaction between experts and DMs in which experts express information about their preferences within a specific aggregation procedure (Figueira et al., 2005). Direct or indirect elicitation techniques may be used (Certa, Enea, Galante, & La Fata, 2009; Figueira & Roy, 2002; Mousseau, 1995).

Without any loss of generality, let now suppose that evaluation criteria have to be minimized, namely $g_j(a)$ has a decreasing direction of preference. Then, the following steps need to be implemented $\forall j \mid j = 1, 2, \ldots, J$, $\forall h \mid h = 1, 2, \ldots, n - 1$ and $\forall a \mid a = 1, 2, \ldots A$ (Roy, 1991, 1996; Certa, Enea, & Lupo, 2013) to build the outranking relation between the alternative a and the profile b_h.

(a) Computation of the partial concordance index $c_j(a, b_h)$. It expresses to which extend the criterion j supports the assertion "$a\ S\ b_h$".

$$c_j(a,b_h) = \begin{cases} 1 & \text{if } [g_j(a) - g_j(b_h)] \leqslant q_j \\ \frac{[g_j(b_h) - g_j(a) + p_j]}{[p_j - q_j]} & \text{if } q_j < [g_j(a) - g_j(b_h)] \leqslant p_j \\ 0 & \text{if } [g_j(a) - g_j(b_h)] > p_j \end{cases} \tag{1}$$

(b) Computation of the global concordance index $c(a, b_h)$. It expresses to which extend evaluations of a and b_h on all criteria are concordant with the assertion "$a\ S\ b_h$".

$$c(a,b_h) = \frac{\sum_{j=1}^{J} w_j \cdot c_j(a,b_h)}{\sum_{j=1}^{J} w_j} \tag{2}$$

(c) Computation of the discordance index $d_j(a, b_h)$. It expresses to which extend the criterion j opposes to the assertion "$a\ S\ b_h$".

$$d_j(a,b_h) = \begin{cases} 1 & \text{if } [g_j(a) - g_j(b_h)] \geqslant v_j \\ \frac{[g_j(a) - g_j(b_h) - p_j]}{[v_j - p_j]} & \text{if } p_j \leqslant [g_j(a) - g_j(b_h)] < v_j \\ 0 & \text{if } c_j(a,b_h) \neq 0 \end{cases} \tag{3}$$

(d) Computation of the credibility index $\sigma(a, b_h)$ of the outranking relation:

$$\sigma(a,b_h) = c(a,b_h) \cdot \prod_{j \in J^*} \frac{1 - d_j(a,b_h)}{1 - c(a,b_h)} \tag{4}$$

where J^* is the sub-set of criteria for which $d_j(a,b_h) \geqslant c(a,b_h)$.

However, when the DM does not deem opportune to define the veto threshold, the credibility index coincides with the global concordance index.

Once all $\sigma(a, b_h)$ are computed, they are compared to the so called cutting level λ to define the preference situation between a and b_h. Specifically, the cutting level λ is the smallest value of the credibility index compatible with the assertion "$a\ S\ b_h$". It has to range between 0.5 and 1 (Roy & Bouyssou, 1993) as well as it has to be greater than [1 − (highest weight/total weight)] (Merad et al., 2004). Therefore, indicating by $\succ$ the preference relation, I the indifference relation and R the incomparability relation, the following binary relations between a and b_h may occur (Fig. 3):

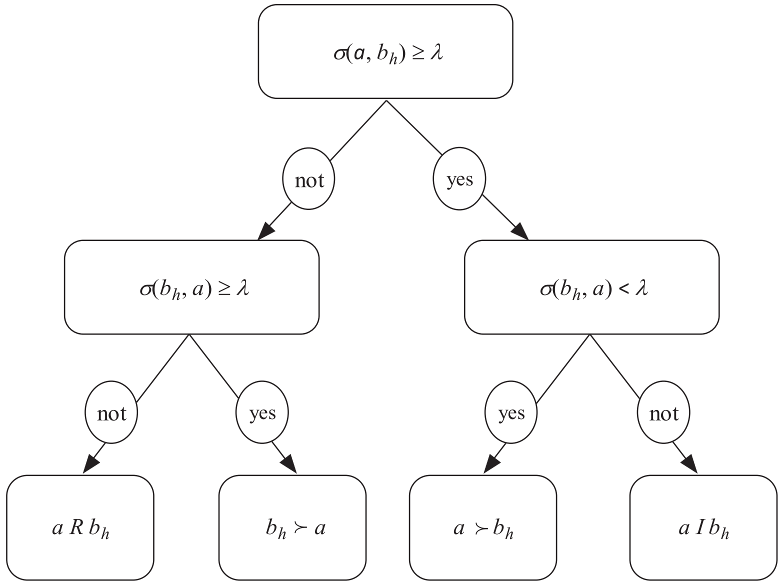

Fig. 3. Definition of the binary relations $\succ$, I and R.

- $a\ I\ b_h \Leftrightarrow a\ S\ b_h$ and $b_h\ S\ a$
- $a \succ b_h \Leftrightarrow a\ S\ b_h$ and not $b_h\ S\ a$
- $b_h \succ a \Leftrightarrow$ not $a\ S\ b_h$ and $b_h\ S\ a$
- $a\ R\ b_h \Leftrightarrow$ not $a\ S\ b_h$ and not $b_h\ S\ a$.

For increasing values of the cutting level λ, it becomes less and less easy for an alternative to outrank a profile and conversely (Takougang, Aimé, Pirlo, Yonkeu, & Some, 2015). Correlatively, an increasing number of incomparability relations can be observed (see left branch of Fig. 3).

3.2. Phase 2 of the ELECTRE TRI method: exploitation of outranking relations for the alternative assignments

The second phase of the ELECTRE TRI method concerns the alternatives' assignment to classes on the basis of the outranking relations arising from the previous phase. ELECTRE TRI proposes two assignment procedures, namely the pessimistic and optimistic ones.

The optimistic rule assigns the generic alternative a to the lowest class C_h for which the upper profile b_h is preferred to a, i.e. $b_h \succ a$. The optimistic procedure can be stated as follows:

- compare a successively to b_r, $r = 1, 2, \ldots, n-1$;
- the limit b_h is the first encountered profile such that $b_h \succ a$;
- assign a to the class C_h.

The pessimistic rule assigns the alternative a to the highest class C_h such that a outranks b_h, i.e. $a\ S\ b_h$. The pessimistic procedure can be stated as follows:

- compare a successively to b_r, $r = n-1, 2, \ldots, 1$;
- the limit b_h is the first encountered profile such that $a\ S\ b_h$;
- assign a to the class C_{h+1}.

A divergence exists between the two assignment procedures only when an alternative is incomparable to one or several profiles. Actually, the pessimistic rule assures the maximum caution and, in the presence of incomparability relations, it tends toward assigning the alternative to a lower class (i.e. higher risk) than the optimistic rule. This is the reason why the pessimistic rule is preferred to the optimistic one when a more conservative result is required.

4. Failure modes classification by the ELECTRE TRI method: Applicative case

In the present work, alternatives to be classified on the basis of risk criteria (Roy, 2002) are the failure modes potentially occurring within the manufacturing processes of dairy industries. In particular, the ELECTRE TRI-based approach for failure modes classification is applied to the real case proposed by Kurt and Özilgen (2013). Authors approached the criticality assessment of manufacturing processes of six widely consumed dairy products in Turkey by means of the traditional RPN method. The major significance of that study is that comprehensive real data collected from 75 food safety audits carried out in 30 dairy factories between 2006 and 2011 were used to implement the FMECA analysis. Sixty-seven potential failure modes in the processes were identified and the potential risks for each failure mode were analyzed. Then, RPNs were calculated to identify the risk level of each potential failure mode and food safety improvement actions for different stages (pretreatment, filling, closing, incubation, transportation for sharp cooling, etc.) of manufacturing processes were suggested.

In order to implement the proposed ELECTRE TRI-based approach, the input evaluations on risk parameters O, S and D supplied by Kurt and Özilgen (2013) are here used and reported into the Appendix A. As suggested by the IEC 60812 (2006), O, S and D are all measured on a ten-point scale. For the aim of the present

Table 4
Reference profiles and thresholds.

	Criteria		
	O	S	D
b_1	8	8	8
b_2	6	6	6
b_3	4	4	4
b_4	2	2	2
q_j	1	1	1
p_j	2	2	2

Table 5
Pessimistic and optimistic assignment results for fixed criteria weights ($w_O = 0.\overline{3}$, $w_S = 0.\overline{3}$, $w_D = 0.\overline{3}$) and increasing cutting level λ.

Cutting level λ	Failure mode	Pessimistic rule	Optimistic rule
0.7; 0.8; 0.9	33	Class 1	Class 3
	34	Class 1	Class 1
	42	Class 1	Class 2
	17–21; 24; 25; 35–41; 45–47; 49–51; 55	Class 2	Class 2
	23; 26; 27; 32; 52; 53; 56–61; 65	Class 2	Class 3
	66	Class 2	Class 4
	1–11; 22; 28–31; 43; 44; 48; 54; 62–64	Class 3	Class 3
	12; 15; 67	Class 3	Class 4
	13; 14;16	Class 4	Class 4

Table 6
Pessimistic and optimistic assignment results for fixed criteria weights ($w_O = 0.5$, $w_S = 0.25$, $w_D = 0.25$) and increasing cutting level λ.

Cutting level λ	Failure mode	Pessimistic rule	Optimistic rule
0.5	34; 39	Class 2	Class 2
	1; 17; 22; 24; 35–38; 41; 43–45; 47; 48; 50; 58; 60; 63; 64; 67	Class 3	Class 3
	2–10; 12–14; 18–21; 23; 25; 26; 28–32; 40; 42; 46; 49; 51–55; 57; 61; 62; 66	Class 4	Class 4
	11; 15; 16; 27; 33; 56; 59; 65	Class 5	Class 5
0.55; 0.65; 0.7	18–21; 34; 35; 37; 39; 41; 47	Class 2	Class 2
	23; 27; 56	Class 2	Class 3
	1–3; 5–7; 10; 17; 22; 24–26; 29–31; 36; 38; 40; 42–46; 48–54; 57–60; 63; 64; 67	Class 3	Class 3
	4; 8; 9; 11–14; 28; 32; 33; 55; 61; 62; 65; 66	Class 4	Class 4
	15; 16	Class 5	Class 5
0.8; 0.9	33	Class 1	Class 3
	34	Class 1	Class 1
	42	Class 1	Class 2
	17–21; 24; 25; 35–41; 45–47; 49–51; 55	Class 2	Class 2
	23; 26; 27; 32; 52; 53; 56–61; 65	Class 2	Class 3
	66	Class 2	Class 4
	1–11; 22; 28–31; 43; 44; 48; 54; 62–64;	Class 3	Class 3
	12; 15; 67	Class 3	Class 4
	13; 14; 16	Class 4	Class 4

paper, such risk parameters represent the evaluation criteria on the basis of which performing the failure modes classification. All evaluation criteria are characterized by a decreasing preference *versus*.

Five ordered risk categories are defined, namely very low (Class 5), low (Class 4), medium (Class 3), high (Class 2) and very high (Class 1). For each criterion, the upper reference profiles (b_h) of classes are synthesized in Table 4 together with the indifference (q_j) and the preference (p_j) thresholds. No veto is introduced in the present study. As a consequence of such an assumption, all discordance indices are zero and the concordance ones are equal to the credibility indices. Preference parameters are here supposed to be directly defined by the DM.

The evaluation criteria are initially assumed to be equally important, namely the weight of each criterion (w_O, w_S, w_D) is set equal to 1/3. As concerns the cutting level λ, it has to range between 0.5 and 1 as well as it has to be greater than [1 − (highest weight/total weight)], i.e. above 0.67 in the present case. Both the pessimistic and optimistic procedures are used for the assignment of the 67 failure modes. Considering the huge number of alternatives to be classified, the ELECTRE TRI-based methodology is implemented by means of a Visual Basic Macro developed *ad hoc*. Then, aiming at investigating on the influence of the parameters' weights and of the cutting level λ on the classification results, a sensitivity analysis is performed. The obtained results are reported in Tables 5–8.

On the basis of results reported in Tables 5–8, one can observe that some empty classes may occur for specific combinations of criteria weights and cutting level λ. For instance, in Table 5 both the pessimistic and optimistic rules lead to the assignment of all

Table 7
Pessimistic and optimistic assignment results for fixed criteria weights ($w_O = 0.25$, $w_S = 0.5$, $w_D = 0.25$) and increasing cutting level λ.

Cutting level λ	Failure mode	Pessimistic rule	Optimistic rule
0.5	18–21; 23; 27; 34; 35; 39; 56;	Class 2	Class 2
	17; 22; 24–26; 29–31; 36–38; 40–54; 57–60; 63; 64; 67	Class 3	Class 3
	1–14; 28; 32; 33; 55; 61; 62; 65, 66	Class 4	Class 4
	15; 16	Class 5	Class 5
0.55; 0.65; 0.7	34	Class 1	Class 1
	33; 42	Class 1	Class 2
	17–21; 23–27; 32; 35; 36; 38–40; 45; 46; 49–51; 53; 55–61; 66	Class 2	Class 2
	65	Class 2	Class 3
	1; 8; 9; 11; 12; 15; 22; 28–31; 37; 41; 43; 44; 47; 48; 52; 54; 62–64; 67	Class 3	Class 3
	2–7; 10; 13; 14	Class 4	Class 4
	16	Class 5	Class 5
0.8; 0.9	33	Class 1	Class 3
	34	Class 1	Class 1
	42	Class 1	Class 2
	17–21; 24; 25; 35–41; 45–47; 49–51; 55	Class 2	Class 2
	23; 26; 27; 32; 52; 53; 56–61; 65	Class 2	Class 3
	66	Class 2	Class 4
	1–11; 22; 28–31; 43; 44; 48; 54; 62–64	Class 3	Class 3
	12; 15; 67	Class 3	Class 4
	13; 14; 16	Class 4	Class 4

Table 8
Pessimistic and optimistic assignment results for fixed criteria weights ($w_O = 0.25$, $w_S = 0.25$, $w_D = 0.5$) and increasing cutting level λ.

Cutting level λ	Failure mode	Pessimistic rule	Optimistic rule
0.5	18–21; 23; 27; 34; 35; 56	Class 2	Class 2
	1; 17; 22; 24–26; 29–31; 36–38; 40; 42–46; 48; 49; 51–54; 57; 59	Class 3	Class 3
	2–8; 11; 28; 32; 33; 39; 41; 47; 50; 55; 61; 62; 65	Class 4	Class 4
	9; 10; 12–16; 58; 60; 63; 64; 66; 67	Class 5	Class 5
0.55; 0.65; 0.7	18–21; 23; 27; 34; 35; 39; 52; 56	Class 2	Class 2
	1;4; 17; 22; 24–26; 29–31; 36–38; 40–51; 53; 54; 57–60; 63; 64	Class 3	Class 3
	67	Class 3	Class 4
	2; 3; 5–14; 16; 28; 32; 33; 55; 61; 62; 65; 66	Class 4	Class 4
	15	Class 5	Class 5
0.8; 0.9	33	Class 1	Class 3
	34	Class 1	Class 1
	42	Class 1	Class 2
	17–21; 24; 25; 35–41; 45–47; 49–51; 55	Class 2	Class 2
	23; 26; 27; 32; 52; 53; 56–61; 65	Class 2	Class 3
	66	Class 2	Class 4
	1–11; 22; 28–31; 43; 44; 48; 54; 62–64	Class 3	Class 3
	12; 15; 67	Class 3	Class 4
	13; 14; 16	Class 4	Class 4

Table 9
Final failure modes classification.

Failure mode	Class assignment
33; 34; 42	Class 1
17–21; 23–27; 32; 35–41; 45–47; 49–53; 55–61; 65; 66	Class 2
1–12; 15; 22; 28–31; 43; 44; 48; 54; 62–64; 67	Class 3
13; 14;16	Class 4

failure modes between Classes 1 and 4, namely the Class 5 is empty. In this regard, one must bear in mind that reference profiles are not identified on the basis of failure modes' evaluations, but on the basis of the DM expertise in assessing the risk arising from certain O, S, and D values.

For fixed risk parameters' weights, an increasing value of the cutting level λ leads to the assignment of failure modes to worse categories. *Vice versa*, for fixed values of λ, a variation on parameters' weights implies a different failure modes assignment only for small values of the cutting level. Bearing in mind that the cutting level λ represents the lowest degree of credibility for which one can assert that a failure mode outranks a profile, the DM should refer to high values of λ for the failure modes classification. Such a choice makes robust the classification results as regards the parameters' weights on which the DM may be affected by some uncertainty. Actually, the obtained results show how the failure modes classification is stable under different criteria weights and cutting levels over 0.8. From Tables 5–8, one can also observe that some failure modes are differently classified by the two assignment procedures as a consequence of the presence of incomparability relations. Considering that the failure modes classification is the goal of the here proposed methodology, the pessimistic assignment is preferred to the optimistic one so that more conservative results are obtained. Summing up, on the basis of the aforementioned considerations about the choice of the cutting level λ and of the pessimistic/optimistic rule, the following Table 9 synthesizes the suggested failure modes classification. In particular, it is obtained for cutting levels λ greater than or equal to 0.8, for whatever combination of weights among those considered, and using the pessimistic assignment rule.

5. Conclusions

In traditional FMECA, failure modes are commonly prioritized by the Risk Priority Number (RPN) which is computed as the product of the three risk parameters Occurrence (O), Severity (S), and Detection (D). Differently from the RPN method, the present paper suggests the ELECTRE TRI Multi-Criteria Decision Making (MCDM) technique to classify the system/process failure modes into predefined and ordered risk categories (i.e. very low, low, medium, high and very high). Therefore, alternatives to be classified are the potential failure modes previously identified by means of the classical FMEA, whereas evaluation criteria on the basis of which the classification process is carried out are the risk parameters O, S and D. Once failure modes are assessed against each criterion on a ten-point scale, the ELECTRE TRI methodology carries on with a two-stage assignment process. Firstly, outranking relations between each alternative and reference profile are developed, and then the outranking relations are exploited in order to decide the risk category which failure modes have to be assigned to. As a consequence of the assignment process, failure modes are classified on the basis of the related risk so that the most critical ones (those belonging to the first class) are identified.

To the authors' knowledge, ELECTRE TRI has not yet been applied in the literature for the criticality assessment of process/system potential failures. Differently from the classical RPN, the use of ELECTRE TRI allows the Decision Maker (DM) at taking into account the relative importance of criteria as well as his/her uncertainty in precisely assigning each failure mode to a risk category rather than another one. Actually, ELECTRE TRI is an outranking technique that provides a way to deal with the uncertainty of the DM during the evaluation process by means of the introduction of specific thresholds. The latter makes the method able to better approximate the attitude of the DM, which is usually characterized by a gradual transition from the indifference to the preference state. In addition, contrarily to the traditional RPN approach which returns the failure modes ranking, the ELECTRE TRI-based methodology gives back the failure modes classification into risk categories so that it is possible to directly visualize and identify failure modes on which corrective actions need to be taken with the priority required by the class they belong to. Further strengths of the proposed methodology are listed below:

- it is easily implementable, and it requires a short computational time to get the classification results;
- assignment results are dynamic, namely the method allows the DM at easily verifying if the assignment class of a potential failure mode changes or not as a consequence of the implementation of a corrective action;
- it is possible to highlight the reason/s why a failure mode is assigned to a high risk class by means of the identification of criterion/criteria that more significantly determine such an assignment.

In real-life FMECA applications, ELECTRE TRI can hence represent a useful decision aiding tool for the DM because of its ability to directly return the failure modes classification into risk categories. Although designed with relation to FMECA, the here proposed ELECTRE TRI-based methodology could be extended to other application areas where the DM deals with the risk such as the project risk management. However, one must bear in mind that the DM expertise and perception of the industrial context under investigation still remain fundamental for the definition of the reference profiles as well as of the other input parameters (i.e. criteria weights, threshold values, and alternative evaluations) required by the method.

Future developments may concern the extension of the approach to a multi-DM context.

Appendix A

N° Activity	Common failures and cause	**O**	**S**	**D**
1	Physical contaminants or small pieces from the packaging materials and/or lids	6	5	6
2	Rusty metal particles from the air ventilation channels	7	5	4
3	Physical impurities from impure salt and/or milk powder	6	5	4
4	Contamination due to improper practices during the process	5	4	6

(*continued on next page*)

Appendix A (*continued*)

N° Activity	Common failures and cause	**O**	**S**	**D**
5	Foreign materials from the environment	6	5	4
6	Teflon coating particles from the blanching equipment	6	4	5
7	Foreign materials from the transferring equipments (boxes, cars, etc.)	6	5	4
8	Metal, glass or plastic particles from the ingredient containers (i.e. containers of the cream, culture)	4	6	4
9	Impurities due to inadequate clarification	5	6	3
10	Inadequate filtration caused by torn or damaged filtration equipment	6	4	3
11	Metal pieces from the worn mixing pedals	3	6	4
12	Physical contaminants in raw milk due to improper handling and agricultural practices (glass, metal, insect parts, etc.)	5	6	2
13	Plastic particles from the damaged equipment (plastic measuring caps, plastic drainer, etc.)	5	4	3
14	Physical contamination from torn or damaged filtration equipment	4	4	3
15	Glass particles from the lamps of the filling machine	2	6	3
16	Foreign particles, such as sponge parts and fibers from the cleaning materials used for measuring cups	3	3	4
17	Veterinary drug residues in milk due to improper veterinary practices	7	8	7
18	High level of aflatoxin in milk due to improper agricultural practices and from contaminated feed that are used on the field	5	8	9
19	Migration of chemicals from the packaging materials	5	8	8
20	Heavy metal residues from the packaging material	5	8	8
21	Heavy metal residues from the seal	5	8	8
22	Contamination from the hand sanitizers that is placed close to the packaging lines	6	7	7
23	Heavy metal residues from water (arsenic, antimony, boron, cadmium, chrome, copper, lead, mercury, etc.)	4	8	9
24	Excessive use of preservatives (both direct addition and spraying after production)	6	8	6
25	Chemicals residues in raw milk due to adulteration of raw milk (alkaline addition)	5	8	7
26	Contamination from chemical substances in water (bromate, cyanide, acrylamide, benzene, etc.)	4	8	7
27	Pesticide residues in milk from contaminated feed and/or water (dioxins, organophosphates, etc.)	3	8	8
28	Detergent and/or disinfectant residue due to inadequate rinsing of measuring equipment and utensils after cleaning (manual cleaning)	5	7	5
29	Detergent and/or disinfectant residue from the equipment and utensils due to inadequate rinsing and improper storage of chemicals (CIP cleaning)	4	7	6
30	Nitrite, Nitrate contamination from water	4	7	6
31	Lubricant residues in foods from the pedals	4	7	6
32	Mycotoxins from the contaminated cheeses that are added during the process	5	8	4
33	Chemical contaminants due to the use of containers empty food containers to store chemicals and mislabeling of containers	3	10	5
34	High number of pathogen (*E. coli* O157:H7, *Salmonella* spp., *Mycobacterium tuberculosis*, *Shigella dysenteria*, etc.) in milk caused by improper handling	8	10	9
35	Pathogenic microorganisms from water	6	9	8
36	Microbiological contamination due to inappropriate practices	7	8	7
37	Microbial growth due to temperature abuse during transportation	8	7	6
38	Contamination due to air coming from the ventilation channels	7	8	6
39	Contamination due to improper sealing of the covers	8	8	5
40	Pathogen contamination from the contaminated culture and other ingredients	5	9	7
41	High number of spoilage microorganisms in milk due to improper handling before and during receiving	9	7	5
42	Microbial growth caused by inadequate processing time and/or temperature	5	10	6
43	Contamination from the packaging materials and/or lids	6	7	7
44	Contamination from the environment	6	7	7
45	Microbiological contamination caused by inadequate cleaning or improper storage of equipment and utensils, i.e., measuring cups, blades (manual cleaning)	6	8	6
46	Microbiological contamination from contaminated chemicals that are used during processing, i.e., salt and milk powder	5	8	7
47	Microbial growth due to temperature abuse during storage	8	7	5
48	Microbial growth due to improper storage temperature	6	7	6
49	Microbiological contamination caused by inadequate cleaning of equipment, utensils or connectors (CIP)	5	8	6
50	Microbial growth caused by improper process time and/or temperature	6	8	5
51	Microbiological contamination due to improper storage conditions	5	8	6
52	Parasite in water	4	7	8
53	Microbial contamination due to mishandling	4	8	7
54	Pathogens from contaminated chemical additives	5	7	6
55	Isolation of *Staphylococcus* Spp. and *Strepptococcus* spp., in milk which might be the indication of animals with mastitis disease	5	8	5

Appendix A (*continued*)

N° Activity	Common failures and cause	O	S	D
56	Parasites (*Protozoa* - *Cryptosporidium* spp., etc.) in milk from unhealthy animal sources	3	8	8
57	Microbiological contamination from in-plant delivery carts	4	8	6
58	Microbiological contamination (*E. coli* 0157: H7, *Shigella* spp., *Salmonella* spp.) form pests, such as flies	7	9	3
59	Microbiological contamination from the cream containers	3	8	7
60	Mold growth due to inadequate moisture removal	7	8	3
61	Microbiological contamination due to inadequate cleaning of equipment (manual cleaning)	5	8	4
62	Microbiological contamination from improperly sealed mixing pedals	4	7	4
63	Microbial growth due to increased time lap between processes	6	6	3
64	Microbial growth due to environmental temperature fluctuation during the process	6	6	3
65	Microbiological contamination caused by inadequate cleaning	3	8	4
66	Growth of pathogens due to inappropriate incubation temperature	5	9	2
67	Microbiological contamination from inappropriate cleaning materials (i.e., sponge)	6	7	2

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