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FlowSort-GDSS - A novel group multi-criteria decision support system for sorting problems with application to FMEA

Francesco Lolli [a], Alessio Ishizaka[1b], Rita Gamberini[a], Bianca Rimini[a], Michael Messori[a]

[a] Department of Sciences and Methods for Engineering, University of Modena and Reggio Emilia, Via Amendola 2 – Padiglione Morselli, *42100 Reggio Emilia, Italy*
francesco.lolli@unimore.it; rita.gamberini@unimore.it; bianca.rimini@unimore.it; 84942@studenti.unimore.it

[b] Centre of Operations Research and Logistics, Portsmouth Business School, University of Portsmouth, Portland Street – Richmond Building, *Portsmouth PO1 3DE, UK*
Alessio.Ishizaka@port.ac.uk

Abstract

Failure mode and effects analysis (FMEA) is a well-known approach for correlating the failure modes of a system to their effects, with the objective of assessing their criticality. The criticality of a failure mode is traditionally established by its risk priority number (RPN), which is the product of the scores assigned to the three risk factors, which are likeness of occurrence, the chance of being undetected and the severity of the effects. Taking a simple "unweighted" product has major shortcomings. One of them is to provide just a number, which does not sort failures modes into priority classes. Moreover, to make the decision more robust, the FMEA is better tackled by multiple decision-makers. Unfortunately, the literature lacks group decision support systems (GDSS) for sorting failures in the field of the FMEA.

In this paper, a novel multi-criteria decision making (MCDM) method named FlowSort-GDSS is proposed to sort the failure modes into priority classes by involving multiple decision-makers. The essence of this method lies in the pair-wise comparison between the failure modes and the reference profiles established by the decision-makers on the risk factors. Finally a case study is presented to illustrate the advantages of this new robust method in sorting failures.

Keywords: FMEA, Criticality assessment, Flow-Sort-GDSS, MCDM, PROMETHEE

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[1] Corresponding author, Tel 0044(0)23 9284 4171

1. Introduction

The reduction of the non-quality costs is a main concern in all production and service systems because it increases the customer fidelity and reduces the after-sales costs. The FMEA is a long established quality improvement technique that dates back to 1940s. The first step in FMEA is to identify potential or known failure modes of a given system. These modes are then evaluated for their causes and effects, and the final purpose of FMEA is to correct the most critical failure modes. Traditionally, the criticality assessment of the failure modes in FMEA is carried out by calculating their risk priority numbers (or RPNs), which are given by the product of the likeness of occurrence (O), the severity of the effects (S), and the chance of being undetected (D), each one measured on a 1-10 scale, as follows:

$$\mathbf{RPN} = \boldsymbol{O} \times \boldsymbol{S} \times \boldsymbol{D} \tag{1}$$

Based on their RPN ranking, it is decided whether an improvement action needs to be implemented in order to reduce the RPN. The issue is to find the threshold that triggers this improvement action. This problem is therefore better solved with a sorting technique, where failures are sorted into predefined priority classes.

To the best of our knowledge, the most recent review on FMEA has been conducted by Liu, Liu, & Liu (2013) who have summarized a number of major shortcomings in the traditional FMEA approach. They have reviewed a number of academic journal articles published between 1992 and 2012 that aimed at overcoming these shortcomings. It is worth to remark that more than a half of the reviewed paper aim to overcome the following shortcomings:

a) The relative importance of O, S and D is not taken into account.
b) Different sets of the three risk factors can give the same RPN without considering their very different implications.
c) The three risk factors are difficult to be precisely evaluated.

These shortcomings have been solved with multi-criteria decision making methods (see section 2). However, these methods provide only a rank for the failure but do not sort them into priority classes. Having an ordered class of importance of failures allows the managers to focus in priority on all the elements of this class and then to tackle the elements of the next class. This gives a clear indication on which failures to correct first.

Moreover, several experts are generally involved in the FMEA. For example, engineers, process managers, product managers, quality inspectors and inline operators are called to design and monitor the quality of products and processes. As a consequence, the sorting method introduces ad hoc approach for the FMEA and accommodates multiple decision-makers.

This paper proposes a group decision support system, named FlowSort-GDSS, for sorting the failure modes into priority classes. This method belongs to the PROMETHEE family methods and therefore inherits their properties. Particularly to this method is that the decision-makers are asked to provide the reference profiles on the risk factors to define the priority classes according to their experiences and skills. The essence of this method lies in the pair-wise comparison between the failure modes and the reference profiles, either limiting or central profiles, which provides their global net flow, so named according with the PROMETHEE notation. The structure of this paper is as follows: Section 2 reviews the developments of the FMEA. Section 3 proposes the new method termed FlowSort-GDSS. Section 4 describes the application of FlowSort-GDSS for the FMEA in a large company operating in the blow moulding field. Finally, Section 5 concludes the paper with some future research suggestions.

2. Literature review

The FMEA approaches introduced in the last decades can be divided into three categories according to their failure mode prioritization methods: MCDM, mathematical programming, and integrated approaches.

With regard to MCDM methods, Braglia (2000) introduced the multi attribute failure mode analysis (MAFMA), which uses the analytic hierarchy process (AHP) to calculate weights for the risk factors. The same technique was also used later in (Carmignani, 2009). Zammori and Gabbrielli (2012) further decomposed the occurrence, severity and detectability into subcriteria and used analytic network process (ANP) to evaluate their weights. In addition to the multiplication reported in equation (1), other aggregation techniques have also been proposed, e.g. decision making trial and evaluation laboratory – DEMATEL (Seyed-Hosseini, Safaei, & Asgharpour, 2006), grey theory (Chang, Liu, & Wei, 2001) and evidence theory (Chin, Wang, Poon, & Yang, 2009). Liu, Liu, and Liu (2013) reported a trend to incorporate MCDM methods with fuzzy logic in order to overcome the shortcoming c) mentioned in section 1. For a recent review on fuzzy MCDM techniques, reader may refer to (Mardani, Jusoh, & Zavadskas, 2015). Some researchers have in fact merged multi-

criteria techniques and fuzzy logic to accommodate the imprecision of the evaluations: fuzzy technique for order preference by similarity to ideal solution (TOPSIS) (Braglia, Frosolini, & Montanari, 2003; Hadi-Vencheh & Aghajani, 2013; Liu et al., 2011; Liu, Liu, Liu, & Mao, 2012; Vahdani, Salimi, & Charkhchian, 2015); VIKOR (VIsekriterijumska optimizacija i KOmpromisno Resenje) with fuzzy logic (Liu et al., 2012); fuzzy AHP (Hu, Hsu, Kuo, & Wu, 2009; Kutlu & Ekmekçioğlu, 2012); fuzzy logic with grey theory (Chang, Wei, & Lee, 1999); or simply applied fuzzy logic on the risk factors (Petrović et al., 2014). Mandal and Maiti (2014) adopted the similarity measure of fuzzy numbers in order to overcome the drawback of standard de-fuzzification approaches. However, these approaches neither support a group decision nor solve a sorting problem. A group-decision FMEA approach was proposed by (Liu, You, Fan, & Lin, 2014) where grey relational projection and D numbers representing the uncertain information are merged in order to rank the failure modes. Examples of D numbers applications can be read in (Deng, Hu, Deng, & Mahadevan, 2014a; Deng, Hu, Deng, & Mahadevan, 2014b). This approach allows to handle various type of uncertainties and judgmental divergences during the assessment of the failure modes with respect to the risk factors, but, as the other contributions cited before, it does not sort failures by priority classes.

For the mathematical programming methods, Garcia, Schirru, & Frutoso e Melo (2005) used data envelopment analysis (DEA) to optimise the weights in order to measure the maximum risks of each failure mode. Chin, Wang, Poon, & Yang (2009) also used DEA to calculate the weights giving the maximum and the minimum RPN for each failure mode. Then, they used the geometric mean of the two extreme weights. Chang & Sun (2009) used the Charnes, Cooper, and Rhodes (CCR) assurance region DEA model, which introduces weights restrictions in order to prevent unrealistic values. Netto, Honorato, & Qassim (2013) proposed to first find subjective weights and then calculate objective weights in DEA by maximising the subjective weights. Wang, Chin, Poon, & Yang (2009) used a mathematical programming to find the best α cut in defuzzifying the fuzzy weighted geometric means of the fuzzy ratings of O, S and D. As in the previous family of methods, mathematical programming methods do not tackle any group-decision sorting problems.

Integrated approaches have also been proposed for ranking the failure modes. For instance, the DEMATEL approach has been integrated with the ordered weighted geometric averaging operator (Chang, 2009) and with the fuzzy ordered weighted averaging operator (Chang & Cheng, 2011). The fuzzy weighted least square method is integrated with nonlinear programming model (Zhang &

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Chu, 2011). The 2-tuple is combined with the ordered weighted averaging operator (Chang & Wen, 2010). The fuzzy evidential reasoning is integrated with the grey theory (Liu et al., 2011), and fuzzy TOPSIS with fuzzy AHP (Kutlu & Ekmekçioğlu, 2012). Fuzzy logic is used within the integrated approaches to deal with judgmental imprecision and vagueness. Bozdag, Asan, Soyer, & Serdarasan (2015) have highlighted the importance of group decision in the FMEA by measuring both the variation in one expert's understanding (intra-personal uncertainty) and the variations in the understanding among experts (inter-personal uncertainty) by adopting an interval type-2 fuzzy sets. The individual judgments are aggregated into group judgments in form of interval type-2 fuzzy numbers that deal with both intra- and inter-personal uncertainty. However designed for multiple experts, this approach does not sort failures into groups. Moreover, as it is based on fuzzy logic, it requires the definition of membership functions, which is subjective and difficult. Risk assessment of the FMEA is in fact a group exercise that requires cross-functional specialists from various functions (e.g. design, process, production and quality). Thereby, the membership function definition may vary from person to person (Ishizaka & Nguyen, 2013). Unfortunately, in previous researches the same membership function was used for all members of the risks assessment team. For these reasons, in our paper, we avoid to use fuzzy logic as the definition of membership functions is a difficult task. Instead, we have introduced the novel Flowsort-GDSS, a method of the outranking family, which allows us to deal with the inter-personal uncertainty regarding the reference profiles defining the priority classes and therefore reaching the classification of the failure modes as consensual as possible. Furthermore, it is partially compensatory; this means that a bad evaluation on a risk factor cannot be compensated by a good evaluation on other risk factors. The next section will describe the method in details.

3.   FlowSort-GDSS

3.1. Introduction

FlowSort-GDSS is an extension of the FlowSort method, when several decision-makers are involved in the sorting decision process. FlowSort was developed by Nemery & Lamboray (2008) as an adaption of the ranking method PROMETHEE II. The possibility to use FlowSort for group decisions was first mentioned in an oral communication (Nemery, 2008). FlowSort-GDSS is composed of the three following steps:

1) Decision-makers are selected; alternatives, evaluation criteria, classes and their characteristics are defined. The definition step is described in section 3.2.

2) This stage compares one alternative at the time with the reference profiles on each criterion for each decision-maker. The comparison step is described in the section 3.3.

3) The last stage assigns the alternatives to a class defined in step 1, on the basis of their global scores achieved in step 2. The assignment step is described in section 3.4.

3.2. Definition step

The first step is to define $A = \{a_1, \dots, a_i, \dots, a_n\}$ the set of n alternatives to be sorted, with respect to a set $G = \{g_1, \dots, g_j, \dots, g_J\}$ of J criteria, both qualitative and quantitative, into K global classes, i.e. $C_1, \dots, C_k, \dots, C_K$. The term 'global' is used when the sorting decision is based on the whole set of the criteria. A 'local' sorting decision is employed when the process is based on one criterion. The K classes need to be completely ordered ($C_1 \rhd \cdots \rhd C_l \rhd \cdots \rhd C_K$), where $C_h \rhd C_l$ with $h < l$ means that the class C_h is preferred to the class C_l. A set of weights $W_g = \left\{ w_{g_1}, \dots, w_{g_j}, \dots, w_{g_J} \right\}$ is defined for the J criteria and another set of weights $W_d = \left\{ w_{d_1}, \dots, w_{d_t}, \dots, w_{d_T} \right\}$ for the T decision-makers involved in the decision process. The assignment of different weights to the decision-makers permits to take into account to their different expertise and skills, as it often happens in real decision process.

To characterise the K classes, each decision-maker defines a reference profile by a limiting or a central profile. A limiting profile represents the minimum value an alternative needs to achieve on each criterion for belonging to the class. For K classes, a set of T·(K-1) limiting profiles $R^j = \left\{ r_1^{1,j}, \dots, r_k^{1,j}, \dots, r_{K-1}^{1,j}, \dots, r_1^{t,j}, \dots, r_k^{t,j}, \dots, r_{K-1}^{t,j}, \dots, r_1^{T,j}, \dots, r_k^{T,j}, \dots, r_{K-1}^{T,j} \right\}$ given by the T decision-makers on criterion j needs to be defined. When the definition of a limiting profile is difficult, for example when the field of application is new, a typical value on each class may be simpler to represent a class. This typical value is called central profile. In such cases, a set of T·K central profiles , $R^j = \left\{ r_1^{1,j}, \dots, r_k^{1,j}, \dots, r_K^{1,j}, \dots, r_1^{t,j}, \dots, r_k^{t,j}, \dots, r_K^{t,j}, \dots, r_1^{T,j}, \dots, r_k^{T,j}, \dots, r_K^{T,j} \right\}$ are needed.

Without loss of generality, we suppose that all J criteria have to be maximized. To ensure that all classes on each criterion are ordered, the following condition is necessary.

Condition: Dominance on the reference profiles

$$r_k^{t,j} > r_{k+1}^{s,j}; \ \forall r_k^{t,j}, r_{k+1}^{s,j} \in R^j, \forall j = 1, \dots, J \text{ and } \forall t, s = 1, \dots, T.$$

This condition avoids the overlapping of the reference profiles. Figure 1 shows three criteria, three decision-makers and three classes represented by two limiting profiles. In this case, the dominance condition is verified.
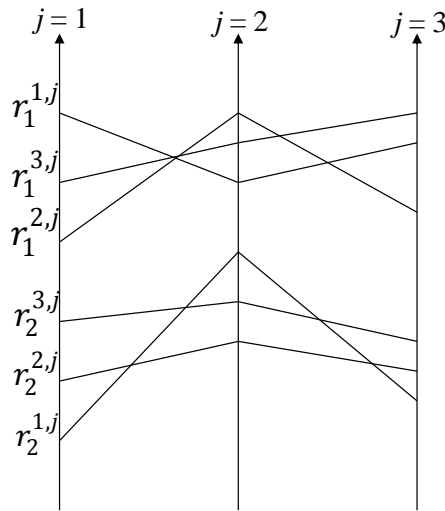
Figure 1. An example of Dominance condition respected

3.3. Comparison step

The comparison stage is based on the PROMETHEE algorithm (Brans & Vincke, 1985). Two alternatives a_1 and a_2 are compared on a criterion g_j by calculating the distance $d_j(a_1, a_2) = g_j(a_1) - g_j(a_2)$ in a uni-criterion preference degree $P_j(a_1, a_2)$, whose proprieties are:

- $0 \leq P_j(a_1, a_2) \leq 1$
- $P_j(a_1, a_2) \approx 0$ if a_1 is indifferent to a_2 on the criterion g_j
- $P_j(a_1, a_2) \approx 1$ if a_1 is strictly preferred to a_2 on the criterion g_j

Six different types of function $P_j(a_1, a_2)$, e.g. linear, step wise, Gaussian and so on, have been proposed (Brans & Vincke, 1985). They are defined by two shape parameters: preference and indifference threshold.

In Flow-Sort, each alternative $a_i \in A$ is compared only to the reference profiles (Nemery & Lamboray, 2008). This technique is also used in Flow-Sort-GDSS but in using all references

profiles of all decision-makers. Therefore, the uni-criterion net flow of a_i on criterion g_j is defined as follows:

$$\Phi_j(a_i) = \frac{1}{|R^j|} \sum_{r_k^{t,j} \in R^j} [P_j(a_i, r_k^{t,j}) - P_j(r_k^{t,j}, a_i)] \tag{1}$$

The net flow is between -1 and 1 depending on the strength (near 1) or the weakness (-1) of the alternative a_i relatively to the reference profiles on criterion g_j. Equation 1 is calculated with one alternative at the time for making $\Phi_j(a_i)$ independent from the other alternatives of the set A.

The global net flow $\Phi(a_i)$ is given by the weighted sum of the uni-criterion net flow:

$$\Phi(a_i) = \sum_{j=1}^{J} w_{g_j} \Phi_j(a_i) \tag{2}$$

where w_{g_j} represents the weight given to criterion j.

In order to situate the global net flow of the alternative a_i regarding the reference profiles, the net flows of the $T \times (K-1)$ limiting profiles or $T \times K$ central profiles on the criterion g_j have to be calculated. Therefore, the uni-criterion net flow of the reference profile $r_\kappa^{\tau,j} \in R^j$ is compared in pairs with all reference profiles and the alternative a_i.

$$\Phi_{j,i}(r_\kappa^{\tau,j}) = \frac{1}{|R^j|+1} \left\{ \sum_{r_k^{t,j} \in R^j} [P_j(r_\kappa^{\tau,j}, r_k^{t,j}) - P_j(r_k^{t,j}, r_\kappa^{\tau,j})] + [P_j(r_\kappa^{\tau,j}, a_i) - P_j(a_i, r_\kappa^{\tau,j})] \right\} \tag{3}$$

The global net flow $\Phi_i(r_\kappa^\tau)$ referred to a_i is given by the weighted sum of the uni-criterion net flow:

$$\Phi_i(r_\kappa^\tau) = \sum_{j=1}^{J} w_{g_j} \Phi_{j,i}(r_\kappa^{\tau,j}) \tag{4}$$

Equations (1), (2), (3) and (4) are calculated for each a_i, $i = 1, .., n$.

Because of the dominance condition on the local classes (Section 3), it is proved that:

Lemma 1: Dominance on the global reference profiles

$$\Phi_i(r_k^t) \geq \Phi_i(r_{k+1}^s); \forall\, k = 1, \dots, K - 2 \text{ (limiting profiles)} \land \forall\, k = 1, \dots, K - 1 \text{ (central profiles)},$$
$$\forall\, t, s = 1, \dots, T \text{ and } \forall\, i = 1, \dots, n.$$

3.4. Assignment step

3.4.1. Introduction

The assignment procedure is composed of rules depending on the value of $\Phi(a_i)$ (Equation (2)) with respect to the global net flows of the reference profiles (Equation (4)). These rules are explained in the sequel by distinguishing between the cases of limiting (section 3.4.2) or central profiles (section 3.4.3). In both cases, an assignment is '*unanimous*' if all decision-makers agree with the assignment of the alternative to the same class. If the assignment is '*non unanimous*', then the total distance between the global net flow of the alternative and the global net flows of the reference profiles is used. The lemma 1 of dominance on the global reference profiles (Section 3.3) always forces the divergence of assignment between decision-makers only between two consecutive classes at most.

3.4.2. Assignment with limiting profiles

Depending on the unanimous agreement or not of the decision-makers, two different assignment procedures are distinguished.

1. *Unanimous assignment:*

   Three cases exist:

   a) If $\exists\, k$, with $1 < k < K - 1$, *such that* $\Phi_i(r_k^t) \geq \Phi(a_i) > \Phi_i(r_{k+1}^t)\ \forall t = 1, \dots, T \Rightarrow$ $C(a_i) = C_k$

   b) If $\Phi(a_i) \geq \Phi_i(r_1^t), \forall t = 1, \dots, T \Rightarrow C(a_i) = C_1$

   c) If $\Phi(a_i) < \Phi_i(r_{K-1}^t), \forall t = 1, \dots, T \Rightarrow C(a_i) = C_K$

   The assignment rules b) and c) are for the highest and lowest class, respectively. The assignment rule a) is for all the other classes.

2. *Non unanimous assignment.*

   If at least two decision-makers t and s exist *such that* $\Phi_i(r_k^t) \leq \Phi(a_i) < \Phi_i(r_k^s)$, which means that t and s assign a_i respectively to C_k and C_{k+1}.

The *non unanimous* assignment consists of two subsequent steps:

i.   The distances $d_i(k)$ and $d_i(k+1)$ between the net flow $\Phi(a_i)$ and the net flows of the global limiting profiles of the decision-makers assigning a_i to C_k and C_{k+1} are calculated as follows (in respective order):-

$$d_i(k) = \sum_{t:\Phi(a_i) \geq \Phi_i(r_k^t)} w_{d_t}[\Phi(a_i) - \Phi(r_k^t)] \tag{5}$$

$$d_i(k+1) = \sum_{s:\Phi(a_i) < \Phi_i(r_k^s)} w_{d_s}[\Phi(r_{k+1}^s) - \Phi(a_i)] \tag{6}$$

where w_{d_t} and w_{d_s} are the weights respectively given to the decision-makers t and s, which represents the experience and knowledge of the decision-maker involved in the sorting process. Thereby, Equation (5) and (6) provide the weighted average distances between $\Phi(a_i)$ and the global limiting profiles of their respective classes. This represents a degree of membership to C_k and C_{k+1}.

ii. The distances $d_i(k)$ and $d_i(k+1)$ are compared in order to conclude the class assignment on the basis of the degree of membership to C_k and C_{k+1}. The smallest the distance to the limiting profile defines the class. In case of equal distance, two assignments are possible according to the vision of the decision-makers. In an optimistic vision, the alternative is assigned to the higher class and in a pessimistic vision it is assigned to the lower class. The three assignment rules are defined as following:

a) If $d_i(k+1) - d_i(k) > 0 \Rightarrow C(a_i) = C_k$

b) If $d_i(k+1) - d_i(k) < 0 \Rightarrow C(a_i) = C_{k+1}$

c) If $d_i(k+1) - d_i(k) = 0 \Rightarrow$ in an optimistic vision $C(a_i) = C_k$

in a pessimistic vision $C(a_i) = C_{k+1}$.

3.4.3. Assignment with central profiles

Depending on the unanimous agreement or not of the decision-makers, two different assignment procedures are distinguished.

1. *Unanimous assignment.*

   If all T global central profiles of class C_k are the closest to the global net flow of a_i, then all decision-makers agree with the assignment of a_i to C_k.

   If $\exists\, k$, with $1 \leq k \leq K$, such that $|\Phi_i(r_k^t) - \Phi(a_i)| < |\Phi_i(r_h^t) - \Phi(a_i)|$, $\forall t = 1, \dots, T$ and $\forall h = 1, \dots, K \setminus \{h\} \Rightarrow C(a_i) = C_k$.

2. *Non unanimous assignment.*

   If at least two decision-makers (t and s) and two different classes (k and h) exist such that $|\Phi_i(r_k^t) - \Phi(a_i)| \leq |\Phi_i(r_h^t) - \Phi(a_i)|$ $\forall h = 1, \dots, K$ and $|\Phi_i(r_k^s) - \Phi(a_i)| \geq |\Phi_i(r_h^s) - \Phi(a_i)|$ $\forall k = 1, \dots, K$, it means that t and s assign a_i respectively to C_k and C_h or have an equal preference for C_k and C_h in case of an equality sign. It is to remark that the lemma of the dominance (Section 3.3) leads to $h = k \pm 1$. Thereby, without loss of generality, in order to simplify the notation let be T_k and T_{k+1} the set of decision-makers assigning a_i respectively to C_k and C_{k+1}.

   As in the case of the limiting profiles, the non unanimous assignment has two steps:

   i. The distances $d_i(k)$ and $d_i(k+1)$ between the net flow $\Phi(a_i)$ and the net flows of the central profiles defined by the decision-makers assigning a_i to C_k and C_{k+1} are respectively calculated as follows:

   $$d_i(k) = \sum_{t \in T_k} w_{d_t} \cdot |\Phi_i(r_k^t) - \Phi(a_i)| \tag{7}$$
   $$d_i(k + 1) = \sum_{s \in T_{k+1}} w_{d_s} \cdot |\Phi_i(r_{k+1}^s) - \Phi(a_i)| \tag{8}$$

   where w_{d_t} and w_{d_s} are the weights respectively given to the decision-makers t and s. Equations 7 and 8 provide the weighted distances between $\Phi(a_i)$ and the global central profiles of their respective classes. They represent respectively the degree of membership to C_k and C_{k+1}.

   ii. The distances $d_i(k)$ and $d_i(k + 1)$ are compared in order to conclude the class assignment on the basis of the degree of membership to C_k and C_{k+1}. The smallest the distance to the limiting profile defines the class. In case of equal distance, two assignments are possible according to the vision of the decision-makers. In an optimistic vision, the alternative is assigned to the higher class and in a pessimistic vision it is assigned to the lower class. The three assignment rules are defined as following:

a) If $d_i(k+1) - d_i(k) > 0 \Rightarrow C(a_i) = C_k$

b) If $d_i(k+1) - d_i(k) < 0 \Rightarrow C(a_i) = C_{k+1}$

c) If $d_i(k+1) - d_i(k) = 0$

4. Case study

This section presents the application of FlowSort-GDSS to the FMEA on plastic bottles manufacturing, through a blow-moulding process. Some features of the operative environment have to be clarified before showing the numerical illustration. When the FMEA is applied to the plastic bottles (i.e. the final products of a blow-moulding process) of an already existing process, failure modes regard the defects occurred in a pre-defined time horizon to the bottles, e.g. oval neck, weak handle welding, and so on. They in turn should be correlated to their causes related to machines and/or technological process. However, as often happens in real industrial contexts, the failure causes are not directly traceable when the failure modes are reported by inline operators without any specific knowledge on the process. In this case, the FMEA is applied to the failure modes of the final products, and FlowSort-GDSS is used for classifying them into priority classes.

4.1. FlowSort-GDSS:

A large dataset consisting of 2673 events of 46 different failure modes (i.e. alternatives with $n = 46$) is registered during one year by visual inspections performed by inline operators. The product, quality and process managers have then agreed on the severity (S) of the failures by using Table 1 and on the detectability (D) by using Table 2. The occurrence (O) is simply given by the number of observed events. Table 3 reports these values for all the alternatives denoted by a_i, with $i = 1, \dots, 46$. The objective of the application of the FlowSort-GDSS to these 46 failures is thus to sort them into 3 priority classes ($K = 3$).

Severity (S_i)	Linguistic judgment
10	Damage to customers
9	Damage to retailers
8	Very frequent line stops leading to the blocking of production
7	Repeated line stops leading to the blocking of production
6	Very frequent line stops leading to the products selection
5	Repeated line stops leading to the products selection
4	Periodic problems of machinability
3	Sporadic problems of machinability
2	Rare problems of machinability
1	The line does not stop without damaging customers/retailers

Table 1. Evaluation scale for assessing the severity

Detectability (D_i)	Linguistic judgment
10	No identifying test
9	A visual test exists and a highly skilled technician can perform it using dedicated tools
8	A visual test exists and expert highly skilled technician can perform it
7	A visual test exists and a fairly skilled operator can perform it using dedicated tools
6	A visual test exists and a fairly skilled operator can perform it
5	A visual test exists and it's easy to identify the failure using dedicated tools
4	A visual test exists and it's easy to identify the failure
3	A visual test exists and the failure is immediately found using dedicated tools (water test)
2	A visual test exists and the failure is immediately found
1	Automatic test

Table 2. Evaluation scale for assessing the detectability

a_i	Failure	O_i	D_i	S_i
a_1	Low weight	2	2	1
a_2	High weight	10	2	1
a_3	Irregular surface on bottle body	3	4	1
a_4	Weak handle	2	4	2
a_5	Hole on bottle bottom	2	2	10
a_6	Black spots on bottle body	15	5	1
a_7	Neck height out of specification	15	2	4
a_8	Hole on bottle shoulder	3	2	10
a_9	Weak bottle shoulder	42	3	2
a_{10}	Excess plastic inside bottle panel	9	4	3

a_{11}	Deformed bottom	14	4	3
a_{12}	Deformed handle	13	4	3
a_{13}	Convex bottom	12	4	3
a_{14}	Lines on bottle body	604	4	2
a_{15}	Dented bottom	17	4	4
a_{16}	Crocked neck	14	8	2
a_{17}	Bottle undeflashed	14	4	4
a_{18}	Dirt on bottle	8	4	5
a_{19}	Colour lines on bottle body	6	4	5
a_{20}	Hole on bottle neck	6	2	10
a_{21}	Damaged thread	40	4	3
a_{22}	Damaged pawl trigger	24	5	3
a_{23}	Deformed bottle	26	4	4
a_{24}	Excess plastic outside the bottle	151	4	3
a_{25}	Handle flash	45	2	8
a_{26}	Handle hole	27	2	10
a_{27}	Stapled neck	35	3	6
a_{28}	Bottle colour out of specification	12	3	10
a_{29}	Handle "V" ring	72	4	6
a_{30}	Stapled bottom	63	4	6
a_{31}	Deformed neck	58	4	6
a_{32}	Excess plastic outside bottle neck	53	6	4
a_{33}	Belly	41	8	6
a_{34}	Bottom Flash	191	4	8
a_{35}	Neck Flash	137	4	8
a_{36}	Handle Ring	412	4	8
a_{37}	Weak shoulder welding	31	7	9
a_{38}	Weak bottom welding	28	7	9
a_{39}	Weak neck welding	62	6	8
a_{40}	Excess plastic inside bottle bottom	49	7	8
a_{41}	Micro holes	19	8	10
a_{42}	Excess plastic inside the neck	107	7	7
a_{43}	Weak Bottom	37	7	9
a_{44}	Weak handle welding	62	7	9
a_{45}	Oval Neck	54	8	8
a_{46}	Small groove inside the neck	26	10	10

Table 3. Criteria performances

Each manager characterises the classes with a limiting profile (Table 4).

Decision-maker	Limiting profiles	Criteria		
		O	D	S
1	$r_1^{1,j}$	98	8	7
	$r_2^{1,j}$	30	5	3
2	$r_1^{2,j}$	110	8	6
	$r_2^{2,j}$	55	5	4
3	$r_1^{3,j}$	80	7	6
	$r_2^{3,j}$	25	6	2

Table 4. The limiting profiles

As the decision-makers have the same importance, the same weight w_d is allocated to them.

4.2. Flowsort-GDSS: comparison step

For the pair-wise comparison, the linear preference function $P_j(a_1, a_2)$ is selected for each criterion j. The indifference and preference thresholds are given in Table 5.

	O	D	S
Indifference threshold	0	0	0
Preference threshold	602	8	9

Table 5. The preference thresholds.

The software Smart-Picker is then used to calculated the net flow of the global limiting profiles $\Phi_i(r_k^t)$, with $k = 1,2$, $t = 1,2,3$ and $i = 1, ...,46$ and the net flow of the failures $\Phi(a_i)$, with $i = 1, ...,46$. The results are reported in Table 6.

Failures	Net Flows of the Global Limiting Profiles						Net Flows of the Failures
	$\Phi_i(r_1^1)$	$\Phi_i(r_1^2)$	$\Phi_i(r_1^3)$	$\Phi_i(r_2^1)$	$\Phi_i(r_2^2)$	$\Phi_i(r_2^3)$	$\Phi(a_i)$
a_1	0.254	0.218	0.151	-0.109	-0.049	-0.106	-0.359
a_2	0.253	0.218	0.150	-0.109	-0.050	-0.107	-0.354
a_3	0.240	0.204	0.137	-0.123	-0.063	-0.120	-0.275
a_4	0.234	0.198	0.130	-0.129	-0.069	-0.126	-0.238
a_5	0.199	0.163	0.095	-0.164	-0.105	-0.162	-0.026
a_6	0.232	0.196	0.128	-0.131	-0.072	-0.129	-0.227
a_7	0.234	0.199	0.131	-0.128	-0.069	-0.126	-0.234
a_8	0.198	0.163	0.095	-0.164	-0.105	-0.162	-0.025
a_9	0.237	0.201	0.133	-0.125	-0.066	-0.123	-0.258
a_{10}	0.227	0.192	0.124	-0.136	-0.076	-0.133	-0.198
a_{11}	0.226	0.191	0.123	-0.136	-0.077	-0.134	-0.195
a_{12}	0.226	0.191	0.123	-0.136	-0.077	-0.134	-0.195
a_{13}	0.227	0.191	0.123	-0.136	-0.077	-0.134	-0.196
a_{14}	0.178	0.143	0.075	-0.184	-0.125	-0.182	0.095
a_{15}	0.220	0.185	0.117	-0.142	-0.083	-0.140	-0.156
a_{16}	0.205	0.170	0.102	-0.157	-0.098	-0.155	-0.065
a_{17}	0.220	0.185	0.117	-0.142	-0.083	-0.140	-0.158
a_{18}	0.215	0.179	0.112	-0.148	-0.089	-0.145	-0.124
a_{19}	0.215	0.179	0.112	-0.147	-0.088	-0.145	-0.125
a_{20}	0.198	0.163	0.095	-0.164	-0.105	-0.162	-0.023
a_{21}	0.224	0.189	0.121	-0.138	-0.079	-0.136	-0.180
a_{22}	0.218	0.183	0.115	-0.144	-0.085	-0.142	-0.148
a_{23}	0.219	0.184	0.116	-0.143	-0.084	-0.141	-0.151
a_{24}	0.214	0.179	0.111	-0.148	-0.089	-0.147	-0.119
a_{25}	0.207	0.171	0.103	-0.156	-0.096	-0.153	-0.076
a_{26}	0.196	0.161	0.093	-0.166	-0.107	-0.164	-0.012
a_{27}	0.213	0.178	0.110	-0.149	-0.090	-0.147	-0.114
a_{28}	0.191	0.155	0.087	-0.172	-0.113	-0.170	0.022
a_{29}	0.203	0.167	0.099	-0.160	-0.100	-0.158	-0.052
a_{30}	0.204	0.168	0.100	-0.159	-0.100	-0.157	-0.057
a_{31}	0.204	0.168	0.100	-0.159	-0.099	-0.156	-0.060
a_{32}	0.203	0.167	0.099	-0.159	-0.100	-0.157	-0.053
a_{33}	0.186	0.151	0.083	-0.176	-0.117	-0.174	0.047
a_{34}	0.179	0.144	0.076	-0.183	-0.124	-0.181	0.088
a_{35}	0.184	0.149	0.081	-0.178	-0.119	-0.176	0.058
a_{36}	0.159	0.124	0.056	-0.203	-0.144	-0.201	0.210
a_{37}	0.167	0.132	0.064	-0.195	-0.136	-0.193	0.162
a_{38}	0.167	0.132	0.064	-0.195	-0.136	-0.401	0.160
a_{39}	0.177	0.142	0.074	-0.185	-0.125	-0.183	0.100
a_{40}	0.172	0.136	0.068	-0.191	-0.131	-0.188	0.135
a_{41}	0.155	0.120	0.052	-0.207	-0.148	-0.205	0.234
a_{42}	0.172	0.132	0.069	-0.190	-0.131	-0.188	0.130
a_{43}	0.166	0.131	0.063	-0.196	-0.137	-0.193	0.165
a_{44}	0.164	0.129	0.061	-0.198	-0.139	-0.196	0.179
a_{45}	0.164	0.129	0.061	-0.198	-0.139	-0.196	0.179
a_{46}	0.141	0.105	0.037	-0.222	-0.162	-0.219	0.321

Table 6. Net Flows

4.3. Flowsort-GDSS: assignment step

The assignment rules described in section 3.4 are applied on the net flows of

Failures	Net Flows of the Global Limiting Profiles						Net Flows of the Failures
	$\Phi_i(r_1^1)$	$\Phi_i(r_1^2)$	$\Phi_i(r_1^3)$	$\Phi_i(r_2^1)$	$\Phi_i(r_2^2)$	$\Phi_i(r_2^3)$	$\Phi(a_i)$
a_1	0.254	0.218	0.151	-0.109	-0.049	-0.106	-0.359
a_2	0.253	0.218	0.150	-0.109	-0.050	-0.107	-0.354
a_3	0.240	0.204	0.137	-0.123	-0.063	-0.120	-0.275
a_4	0.234	0.198	0.130	-0.129	-0.069	-0.126	-0.238
a_5	0.199	0.163	0.095	-0.164	-0.105	-0.162	-0.026
a_6	0.232	0.196	0.128	-0.131	-0.072	-0.129	-0.227
a_7	0.234	0.199	0.131	-0.128	-0.069	-0.126	-0.234
a_8	0.198	0.163	0.095	-0.164	-0.105	-0.162	-0.025
a_9	0.237	0.201	0.133	-0.125	-0.066	-0.123	-0.258
a_{10}	0.227	0.192	0.124	-0.136	-0.076	-0.133	-0.198
a_{11}	0.226	0.191	0.123	-0.136	-0.077	-0.134	-0.195
a_{12}	0.226	0.191	0.123	-0.136	-0.077	-0.134	-0.195
a_{13}	0.227	0.191	0.123	-0.136	-0.077	-0.134	-0.196
a_{14}	0.178	0.143	0.075	-0.184	-0.125	-0.182	0.095
a_{15}	0.220	0.185	0.117	-0.142	-0.083	-0.140	-0.156
a_{16}	0.205	0.170	0.102	-0.157	-0.098	-0.155	-0.065
a_{17}	0.220	0.185	0.117	-0.142	-0.083	-0.140	-0.158
a_{18}	0.215	0.179	0.112	-0.148	-0.089	-0.145	-0.124
a_{19}	0.215	0.179	0.112	-0.147	-0.088	-0.145	-0.125
a_{20}	0.198	0.163	0.095	-0.164	-0.105	-0.162	-0.023
a_{21}	0.224	0.189	0.121	-0.138	-0.079	-0.136	-0.180
a_{22}	0.218	0.183	0.115	-0.144	-0.085	-0.142	-0.148
a_{23}	0.219	0.184	0.116	-0.143	-0.084	-0.141	-0.151
a_{24}	0.214	0.179	0.111	-0.148	-0.089	-0.147	-0.119
a_{25}	0.207	0.171	0.103	-0.156	-0.096	-0.153	-0.076
a_{26}	0.196	0.161	0.093	-0.166	-0.107	-0.164	-0.012
a_{27}	0.213	0.178	0.110	-0.149	-0.090	-0.147	-0.114
a_{28}	0.191	0.155	0.087	-0.172	-0.113	-0.170	0.022
a_{29}	0.203	0.167	0.099	-0.160	-0.100	-0.158	-0.052
a_{30}	0.204	0.168	0.100	-0.159	-0.100	-0.157	-0.057
a_{31}	0.204	0.168	0.100	-0.159	-0.099	-0.156	-0.060
a_{32}	0.203	0.167	0.099	-0.159	-0.100	-0.157	-0.053
a_{33}	0.186	0.151	0.083	-0.176	-0.117	-0.174	0.047
a_{34}	0.179	0.144	0.076	-0.183	-0.124	-0.181	0.088
a_{35}	0.184	0.149	0.081	-0.178	-0.119	-0.176	0.058
a_{36}	0.159	0.124	0.056	-0.203	-0.144	-0.201	0.210
a_{37}	0.167	0.132	0.064	-0.195	-0.136	-0.193	0.162
a_{38}	0.167	0.132	0.064	-0.195	-0.136	-0.401	0.160
a_{39}	0.177	0.142	0.074	-0.185	-0.125	-0.183	0.100
a_{40}	0.172	0.136	0.068	-0.191	-0.131	-0.188	0.135
a_{41}	0.155	0.120	0.052	-0.207	-0.148	-0.205	0.234

a_{42}	0.172	0.132	0.069	-0.190	-0.131	-0.188	0.130
a_{43}	0.166	0.131	0.063	-0.196	-0.137	-0.193	0.165
a_{44}	0.164	0.129	0.061	-0.198	-0.139	-0.196	0.179
a_{45}	0.164	0.129	0.061	-0.198	-0.139	-0.196	0.179
a_{46}	0.141	0.105	0.037	-0.222	-0.162	-0.219	0.321

Table 6. Some examples illustrating the assignment procedure are described in the following:

For the unanimous assignment:

- Failure a_8 is assigned to C_2 because a class exists (C_2) such that its global net flow (-0.025) lies between the global net flows of all the limiting profiles of the classes C_1 and C_3 (Condition (a) of Section 4.2).

- Failure a_{45} is assigned to C_1 because its global net flow (0.179) is greater than or equal to all the global net flows of the limiting profiles of the class C_1 (Condition (b) of Section 4.2).

- Failure a_1 is assigned to C_3 because its global net flow (-0.359) is less than all the global net flows of the limiting profiles of the class C_3 (Condition (c) of Section 4.2).

The non unanimous assignment is performed whenever at least two decision-makers would assign the alternative to different classes. For instance, the assignment of failure a_{27} is non unanimous because decision-makers 1 and 3 would assign it to C_2 ($-0.114 \geq -0.149$ $and -0.114 \geq -0.147$), whilst decision-maker 2 to C_3 ($-0.114 < -0.090$). Thereby, Equation 5 and 6 have to be respectively applied to decision-makers 1 and 3 and to decision-maker 2, where the decision-makers are equally weighted (i.e. 0.33). They respectively provide these values: $d_{27}(2) = (0.33 *
0.035) + (0.33 * 0.033) = 0.02264$; $d_{27}(3) = 0.33 * 0.024 = 0.00799$. Since $0.02264 -
0.00799 > 0$, then a_5 is assigned to C_2 (Condition (d) of Section 4.2).

Table 9 reports the final sorting either by unanimous ("U" in 2th column) or non unanimous assignments ("NU" in the 2th column).

Failures	*Type of assignment*	*Assigned to class*
a_1	U	C_3
a_2	U	C_3
a_3	U	C_3
a_4	U	C_3
a_5	U	C_2
a_6	U	C_3
a_7	U	C_3
a_8	U	C_2
a_9	U	C_3
a_{10}	U	C_3

a_{11}	U	C_3
a_{12}	U	C_3
a_{13}	U	C_3
a_{14}	NU	C_2
a_{15}	U	C_3
a_{16}	U	C_2
a_{17}	U	C_3
a_{18}	NU	C_2
a_{19}	NU	C_2
a_{20}	U	C_2
a_{21}	U	C_3
a_{22}	U	C_3
a_{23}	U	C_3
a_{24}	NU	C_2
a_{25}	U	C_2
a_{26}	U	C_2
a_{27}	NU	C_2
a_{28}	U	C_2
a_{29}	U	C_2
a_{30}	U	C_2
a_{31}	U	C_2
a_{32}	U	C_2
a_{33}	U	C_2
a_{34}	NU	C_2
a_{35}	U	C_2
a_{36}	U	C_1
a_{37}	NU	C_1
a_{38}	NU	C_1
a_{39}	NU	C_2
a_{40}	NU	C_1
a_{41}	U	C_1
a_{42}	NU	C_1
a_{43}	NU	C_1
a_{44}	U	C_1
a_{45}	U	C_1
a_{46}	U	C_1

Table 7. Sorting of the failures with Flowsort-GDSS.

In this case study, ten failures are C_1 classified and thus prioritised for improvement interventions. As shown in Table 7, twelve non unanimous assignments exist. In these cases, decision-makers would remain in a conflicting state without such a group decision support system. FlowSort-GDSS reveals its strength exactly when an individual sorting method fails.

5. Conclusion

FMEA is recognised in industrial settings as an operative tool for quality improvement of both the products and the processes. Although several shortcomings of the traditional FMEA have already been addressed, we have seen that some of them are still unsolved. The ranking of the failure modes does not directly provide clear classes of risk levels. In particular, when dealing with a large number of failure modes, classifying them into priority classes by an expert and intelligent system allows managers to be focused on the most critical ones. Therefore, this qualifies to be a multi-criteria sorting problem. Furthermore, the FMEA generally involves several decision-makers with different experiences and skills. However, literature lacks of contributions on expert and intelligent group decisions systems, especially for the FMEA. In this paper, a novel MCDM approach named FlowSort-GDSS has been introduced for facing such a group decision sorting issue. It requires that the decision-makers establish the reference profiles on each risk factor for defining each priority class. Thereby, the global classification of the failure modes incorporate multitude of experiences and several points of view coming from multiple decision-makers.

FlowSort-GDSS incorporates the generic advantages of the MCDM methods, which are able to overcome the standard FMEA shortcomings (e.g. different degree of importance may be assigned to the risk factors, construction of a risk function) and the specific advantages of the outranking methods: it does not require any normalisation. This addresses the problem of the choice of the normalisation method which may lead to different outcomes. As a consequence, the classification does not depend on the failure modes stored into the dataset. This feature represents a relevant advantage in real settings, when FMEA is periodically reviewed and new types of failure modes eventually appear into the dataset. In fact, the already classified failure modes will not change their priority classes because they are only compared to the same reference profile. Moreover, FlowSort-GDSS avoids compensatory effects. A low score on one risk factor cannot be compensated by a high score on another risk factor and therefore problems cannot be hidden and ignored. Furthermore, FlowSort-GDSS is highly flexible, that is it can be customised by adopting different preference (risk) functions, as well as by assigning different weights to the decision-makers. The practical advantages of FlowSort-GDSS have been confirmed in the industrial case study of the blow moulding process, where a large dataset of product failures have been collected. Sorting these failures into priority classes allowed the company to focus the improvement actions only on the

most critical ones. It is worth to remark that FlowSort-GDSS is generic enough to be used in other sorting problems involving several decision-makers.

It is to note that the advanced information provided by FlowSort-GDSS also require more inputs from the decision-makers, which can be time-consuming. Other limitations of FlowSort-GDSS exists and they require further research. The economical dimension is not taken into account. This is an important further research direction because budget are often limited. Moreover, the improvements are not necessarily linear correlated with the investments, which means that a non-linear optimisation problem needs to be solved. The FMEA has been considered as a snapshot of the quality production. This does not take into account that the different improvement and degradation rate over time. FMEA could benefit from continuous improvement theory by introducing quality-based learning curves. It is also to note that we have assumed that the failures are independent. This is not always the case, for example one improvement action can solve several failures. Therefore, further research would be to take into account the interdependent failures while building the model.

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