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Using Fuzzy Cost-Based FMEA, GRA and Profitability Theory for Minimizing Failures at a Healthcare Diagnosis Service

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Abstract. This paper proposes an integrated approach to identify, evaluate, and improve the potential failures in a service setting. This integrated approach combines FCS-FMEA, GRA and profitability theory for better prioritization of the service failures by considering cost as an important issue and using the profitability theory in a way that the corrective actions costs are taken into account. Considering profitability with FCS-FMEA and GRA reduces the losses caused by failure occurrence. Besides, a maximization linear mathematical problem is used to select the best mix of failures to be repaired. We apply our approach to an academic example concerning the potential failures diagnosis of the Internal Medicine service of a hospital located in Seoul, Korea. We applied our approach and solved the associated maximization problem by a commercial solver, producing an optimal solution which indicates the most convenient mix of failures to be repaired by considering available budget.

Keywords. Service failures, FMEA (Failure Modes and Effects Analysis), GRA (Grey Relational Analysis), PC-FMEA (Priority Cost-Failure Modes and Effects Analysis).

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1. Introduction

Failure analysis (FA) is the process of collecting and analyzing data to determine the cause of a failure. The major concern of FA is to emphasize the prevention of problems linked to the proactive treatment of the system rather than finding a solution after the failure occurs [1]. FA is particularly interesting in service systems, because failures are directly linked to loyalty destruction [2], customer dissatisfaction and negative word of mouth [3,4,5], or customer defection [6,7].

The most popular methodology dealing with this FA is FMEA, the Failure Modes and Effects Analysis [8]. FMEA is an inductive failure analysis for analysis and classification of potential failure modes (FM) based on the severity and likelihood of the failures. It provides therefore a systematic approach for identifying potential failures before they occur [9]. FMEA has been widely used in various manufacturing areas as a solution to many reliability problems [10,11,12]. However, the main literature regarding FMEA is still devoted to manufacturing applications, neglecting the increasing importance of service areas [8]. Nonetheless, several applications of FMEA in the service context have been proposed in the last years, proposing some generic guidelines to apply FMEA to service applications [1], applying FMEA to the service context [13] and applying a systematic approach to manage the service failures using a *service-specific FMEA* (S-FMEA) and *Grey Relational Analysis*, GRA [8]. GRA is a method for decision making, which is suitable for solving problems with complicated interrelationships between multiple factors and variables [14]. It is a simple and data-driven method useful for making decisions by analyzing various relationships [15].

Despite these attempts, traditional FMEA still shows some drawbacks. In particular, no attention is paid to the economic aspects of service failures. Also, it is not possible to consider various experts' ideas. Even S-FMEA, that seems to be more realistic in identifying service failures, doesn't cover these disadvantages appropriately.

In this context, this paper proposes a *Fuzzy cost-based service-specific FMEA* (FCS-FMEA) which uses GRA and *Profitability theory* for diagnosing service failures. To overcome some shortcomings of cost associated with service failures, in this paper at the first step, the estimated cost of faults based on each expert's idea is employed to evaluate each factor of *Risk Priority Number* (RPN). The RPN is the product of *S* (severity), *O* (occurrence) and *D* (detection) and is often used to determine the relative risk of a FMEA.

In addition, different weights are assigned to each expert's idea based on their experience and knowledge. Also, weights are assigned to RPN factors to consider cost and time criteria. Then, following the S-FMEA methodology, the risk priorities of each FM are evaluated using GRA to highlight the multilateral perspective of S-FMEA. Finally, by using profitability theory, taking into consideration the corrective action cost and using the simplex algorithm, we have found an optimal mix of faults to be repaired. To summarize, the proposed approach suggests how to adapt FC-FMEA to incorporate the service characteristics, together with how to prioritize the FMs in a service setting using profitability evaluation. To illustrate the application procedure and effectiveness of our integrated approach, a numerical example is illustrated based on case study in Geum et al. [8]. This paper concludes with a discussion on the major contribution and limitations of this work, as well as recommendations for future studies.

2. Service failure

A service failure is defined as service performance that falls below a customer's expectations [16]. Because of the many uncontrollable factors surrounding a service delivery, service failures appear to be inevitable [3]. It is very important for the service designer to identify the potential service failures and take the required actions in advance to prevent the failure from occurring. Meanwhile, and because of the limited resources, the service designer should prioritize the potential service FMs in order to take the preventive actions before the service is delivered [13].

Service failure generally encompasses any problematic situation during service while service is delivered to a customer, causing significant damage to customer satisfaction [6,17,18]. Whether customers are satisfied or not depends on their perception of the service provided in comparison with their expectations. It is assumed that service failures lead to dissatisfaction. While some failures do not impact the customer's well-being and do not result in financial loss, others may have severe consequences. The acceptability of service failure is influenced by the criticality of the service provided and by the magnitude of the failure. Satisfaction with the service will be lower if the acceptability of the failure is lower [3].

Service failures may vary considerably across the dimensions of timing, severity, and frequency[19]. They can occur anytime during the customer's relationship with a service provider. Since service failure is closely related to the customers, its significance can vary between customers. The perceived significance of service failure is also different depending on the circumstances. Some service failures are more serious than others, for example, serving the wrong soft drink is trivial in comparison to administering the wrong medication, showing high severity in the hospital service [8]. Also, a service failure can be treated differently depending on the industry. For example, in healthcare services, inaccurate appointment is negligible in comparison to inaccurate medication. Therefore, managers who are in charge of failure management or service quality management should measure the severity of service, providing different actions to service failures. Nevertheless, the occurrence or frequency of failure should be measured to provide different actions to each failure, since it is also linked with the triviality of service failures [8].

Preventing service failure from happening, or in other words, identifying service failure in advance, is a very important job in the service sector despite being difficult to achieve [8]. The greatest barrier to identifying service failure is the fact that only 5% to 10% of unsatisfied customers choose to complain following a service failure. Instead, most of them silently switch providers or attempt to get even with the firm by making negative comments to others [20]. As a result, identifying failures in a service setting should be thoughtfully investigated prior to its emergence. The methodology dealing with this problem is FMEA. The next section explains the principles of FMEA.

3. Failure Mode and Effects Analysis

FMEA is a reliability analysis tool widely used in the manufacturing sectors, such as automotive, aerospace, and electronics industries, to identify, prioritize, and eliminate known potential failures, problems, and errors from systems [13]. The goal of FMEA is to predict how and where systems that were designed to detect errors and alert staff might fail [21]. The FMEA process is depicted in Figure 1. FMEA procedure starts with determining all potential FMs of the system. Following determination, all possible effects, causes, and current control process are identified. In order to quantify this procedure, RPN is used, which is the multiplication of severity of failure S, their probability of occurrence O, and possibility of detection D. The RPN number is used to determine the risk of potential failures and prioritize the needed preventive actions and the resource allocations before the service is delivered [13]. Since the main goal of FMEA is to find, prioritize, and minimize the failure, it has been widely used in various manufacturing areas, helping reliability-related problems [10,11,12].

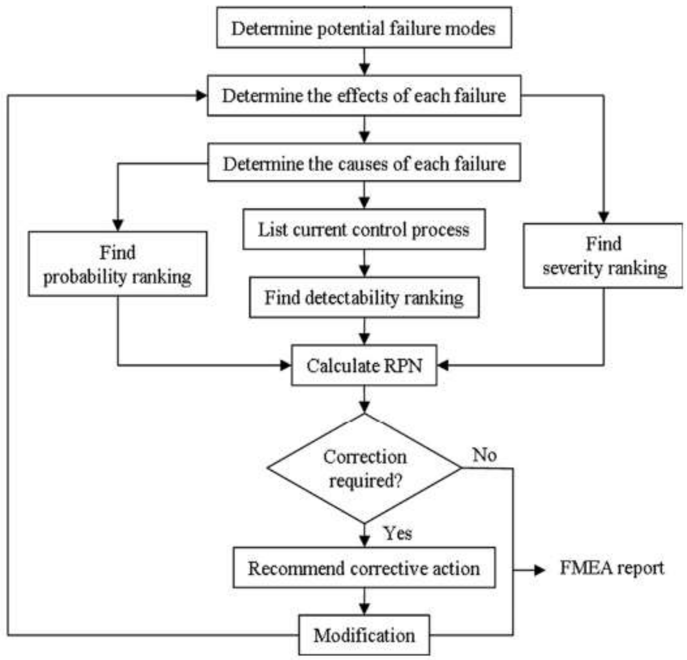

Figure 1. FMEA process.

In the recent decades, the scope of FMEA has started to be extended and applied to the service sector [15]. Service FMEA was proposed, together with system FMEA, design FMEA, and process FMEA [1], providing the generic guidelines required to apply it to the service setting. In addition, various methods to integrate the customer's needs are mentioned such as benchmarking, quality function deployment, market research, and focus groups. Another approach was proposed to combine service blueprint and FMEA in order to provide reliability control in a service setting [13]. Recently, S-FMEA was proposed, together with GRA [8].

Much debate has taken place regarding risk prioritization [22,23] which is related to the appropriateness of the relation, consideration of different impacts of S, O, and D in risk implication, and the appropriateness of multiplication [22]. In order to cope with these problems, a number of researches have been conducted to provide more multilateral consideration for prioritization such as fuzzy logic [22,24,25,26], grey theory [8,22,25,27], life cost-based analysis [10], Analytic network process (ANP) [28], and Analysis Of Variance (ANOVA) [9].

Despite these attempts, previous works don't cover all the disadvantage of service FMEA. For example, no attention is still paid to economic aspects of service-specific failures. In addition, there is no attention to consider various experts' ideas and so on. Since S-FMEA seems to be more realistic among other integrating methods in identifying service failures, our proposed method will be based on this approach. Then, in the next section for better understanding of our proposed method, S-FMEA based on Geum et al.'s method [8] will be explained briefly.

3.1. Service-specific failure mode and effects analysis

The characterizing variable of traditional FMEA consists of three factors: S, O, and D. However, risk in a service setting cannot be measured by a simple judgment due to the inherent intangibility of services. Therefore, Geum et al. extended the traditional 3 dimensions in FMEA by adding 19 sub-dimensions, as shown in Table 1.

Table 1. Key considerations for each constituent for risk priority (Geum et al., 2011).

Dimension	Criteria	Sub-dimension	Description
S	Basic	Impact	How much the impact of failure is
		Core process	How much the customer considers it a core process
		Typicality	How typical the failure is
		Affected range	How broad the affected range is
	Customer	Customer participation	How much the customer participates in the service process
		Customer contact	How closely the failure process contacts the customer
		Service encounter	How closely the failure process is located to the service encounter
	Process	Interdependency	How closely the process is linked with other processes
		Bottleneck possibility	How possible is it that this process works as a bottleneck
		Hardness of isolation	How possible that this process can be isolated
		Resource distribution	How much the process occupies the resources
O	Frequency		How frequently the failure happens
	Repeatability		Does the failure happen repeatedly
	Failure visibility		Is the failure visible to the customer or not
	Single point failure		Does the system fail if a single service failure occurs
D	Chance of non-detection		How severe is the failure detected
	Method of systematic detection		Does the periodical and systematic method exist for detection
	Customer/Employee detection		Is the failure detected by employees or customers
	Hardness of proactive inspection		How the failure modes can be inspected proactively

Note that some dimensions should be considered in reverse scale, since the main objective of these criteria is to prioritize the risk. Therefore, the higher the score of the individual dimension, the more hazardous the FM should be. This is the reason why some sub-dimensions are defined as the inverse of the original ones; for example, the isolation possibility is measured by the difficulty of isolation. Similarly, controllability is measured by difficulty of control, and customer intolerance is used as the measure of how customers are tolerable 8. The genuine preventive characteristic of FMEA lies in that it identifies all potential FMs in a system and prioritizes them in a systematic manner, prior to the outbreak of failure. The preventive efforts of FMEA still remain in S-FMEA, because the main activities for conducting FMEA are identical to the traditional FMEA. In the next section, Utility Theory (UT) and Fuzzy Utility Theory (FUT) will be introduced.

4. Utility Theory (UT) and Fuzzy Utility Theory (FUT) based Failure Mode and Effects Analysis

Dimensions *S*, *O* and *D* determine the failure cost, and they can be seen as cost drivers in the context of UT. UT is an attempt to infer subjective value, or utility, from choices. In this case, each cost driver is ranked from 1 to 10. Cost values are converted into utility values by dividing the cost value of the highest level for each cost driver, i.e. [29]:

$$U_i = C_i / C_{10} \tag{1}$$

FMEA involves normally a team effort in which several experts contribute. During the early product development stage, for example, the effects of potential FMs are not very clear. Thus, different opinions will arise in ranking and evaluating them. In order to account for the differences between experts, we use FUT. In FUT, the utility values are expressed by membership functions instead of real numbers. The cost value for level *i* given by expert *j* is denoted as Cs_{ij} (i = 1…10, j = 1… n), where *n* is the number of experts [29]:

$$Us_{ij} = Cs_{ij} / Cs_{10,j} \tag{2}$$

The cost and utility values for D can be derived in the same approach as the one shown for severity. The evaluation of *O* is different from the evaluation of *S* and *D*, since the probability of failure is given [29]. These probability values are converted to the utility values using the expression:

$$U_o = -1/logP_0 \quad (3)$$

Where P_o is the probability that a FM occurs. In previous works, U_s and U_d have been defined as:

$$U_s = {Cs_{ij}}\Big/{\sum_{i=1}^{n} Cs_{ij}} \quad (4)$$

$$U_d = {Cd_{ij}}\Big/{\sum_{i=1}^{n} Cd_{ij}} \quad (5)$$

where i = 1, 2, 3 …, n corresponds to the expert number, j = 1, 2, 3, … (FMs) and P_o is the failure event probability.

Benefits of this modification are that it produces normalized numbers, it is not time consuming and working with these new functions is very easy and there is no need to draw utility values diagram *D* and *S*. It should be mentioned that particular weights can be assigned to experts based on their experience and knowledge. Weights should be in the zero to one interval and total weights for all experts should sum one. In addition, a pairwise comparison among S, O and D has been done to obtain the comparison matrix. After assigning weights for each expert and each dimension, we have the new fuzzy membership function called RPI [24]:

$$\mu(RPI) = \sqrt[3]{W_{ij}[0.358 \times \mu(\frac{Cs_{ij}}{\sum_{i=1}^{n} Cs_{ij}}) + 0.1652 \times \mu\left(\frac{-1}{\log Po}\right) + 0.4809 \times \mu(\frac{Cd_{ij}}{\sum_{i=1}^{n} Cd_{ij}})]} \quad (6)$$

In the following, this equation will be applied to the case study in [8] to consider RPI factors in cost terms and assign weights to each expert based on their knowledge. After that, we will use grey analysis relational theory to obtain risk score for each dimension. Finally, we will use profitability evaluation to choose the optimum mix of failures to be repaired.

5. Grey relational analysis (GRA) as a tool for risk prioritization

In this section, a new integrated method for risk prioritization is introduced with the help of GRA and our proposed new membership function. Contrary to the traditional FMEA which consists of only three dimensions, S-FMEA has multiple sub-dimensions describing each dimension, and showing the complicated relationships between them [8]. Therefore, a GRA characterized by multiple criteria in a complicated decision making interrelated situation, is proposed to solve this problem. Unlike the previous studies, application of GRA in this paper consists of a two-phase application in order to highlight the multilateral perspective of S-FMEA. The first phase deals with the calculation of risk score for each dimension, and the second phase covers the calculation of overall risk priority by using Equation (6). In the first phase, the risk score for each dimension is calculated and referred to as *S* score, *O* score, and *D* score respectively. These scores are then used as the inputs to the second phase, where the final risk priority is computed. Section 5.1 illustrates the calculation of risk score for each dimension whereas section 5.2 covers the calculation of the overall risk score.

5.1. The calculation of risk score for each dimension

Step 1. Calculating the comparative series for FMs for each dimension.

As the first stage, all values for each FM are processed into a comparability sequence. If there are *m* FMs and *n* attributes in a dimension, the *ith* FM can be expressed as a comparative series $x_i = (x_{i1}, x_{i2}, \dots, x_{in})$ as below [8].

$$x_{ij} = \frac{y_{ij} - Min(y_{ij}, i = \{1,2,\dots m\})}{Max(y_{ij}, i = \{1,2,\dots m\}) - Min(y_{ij}, i = \{1,2,\dots m\})} \qquad i = \{1,2,\dots m\},\ j = \{1,2,\dots n\} \tag{7}$$

Step 2. Setting the reference sequence (standard series) definition.

Since the FMs with higher value should be selected, the reference set should be set as:

$X_o = (x_{o1}, x_{o2}, \dots, x_{on}) = (1, 1, 1, \dots, 1)$.

Step 3. Calculating the grey relational coefficient for each dimension. This step is used for determining how close x_{ij} is to x_{oj}. The larger the coefficients, the closer x_{ij} and x_{oj}. Let ζ be the distinguishing coefficient, $\zeta \in [0,1]$, which affects the relative value of risk without changing the priority. The relational coefficient can be expressed as:

$$\gamma(x_{0j}, x_{ij}) = \frac{\Delta_{min} + \zeta\Delta_{max}}{\Delta_{ij}\zeta\Delta_{max}} \tag{8}$$

where :

- $x_{o(k)}$ is the standard series, and $x_{i(k)}$ is the comparative series,
- $\Delta_{ij} = |x_{0j} - x_{ij}|$
- $\Delta_{min} = Min\{\Delta_{ij}, i = 1, \dots, m; j = 1, \dots, n\}$
- $\Delta_{max} = Max\{\Delta_{ij}, i = 1, \dots, m; j = 1, \dots, n\}$

ζ is usually set to 0.5 [28].

Step 4. Calculating the grey relational grade (the risk score):

Using the weighting coefficient of the decision factors, the final grey relational grade is calculated according to:

$$\Gamma(X_0, X_i) = \sum_{j=1}^{n} w_j \gamma(x_{0j}, x_{ij}) \qquad for\ i = 1,\dots,\ m \qquad (9)$$

where w_j is the weighting coefficient of factors, and $\sum_{j=1}^{n} w_j = 1$.

Therefore, scores for each dimension can be obtained using the grey relational grade framework as shown in Table 2.

Table 2. Risk scores for each dimension.

Dimension	Grey relational grade (Risk score)
S score	$\Gamma(X_o, X_i) = \sum_{j=1}^{n_s} w_j\, \gamma(x_{oj}, x_{ij})$ for i = 1, 2, . . . ,m (n_s : Total number of attributes for S dimension)
O score	$\Gamma(X_o, X_i) = \sum_{j=1}^{n_o} w_j\, \gamma(x_{oj}, x_{ij})$ for i = 1, 2, . . . ,m (n_o : Total number of attributes for O dimension)
D score	$\Gamma(X_o, X_i) = \sum_{j=1}^{n_r} w_j\, \gamma(x_{oj}, x_{ij})$ for i = 1, 2, . . . ,m (n_r : Total number of attributes for D dimension)

In Table 2, $\Gamma(X_0, X_i)$ is the grey relational grade between x_i and x, representing the level of correlation between the reference sequence and the comparability sequence. It means that if the degree of relation is stronger, this FM is more risky, and is thus prioritized as the urgent one. Until now, the risk score of each dimension is evaluated. After calculating scores for each dimension, the overall risk score can be calculated under the framework of profitability theory.

5.2. The calculation of overall risk score using profitability evaluating

5.2.1. The profitability evaluation

After finding the risk scores for each dimension in the previous step, in order to consider economic aspects in prioritizing of the failures we use profitability theory. Figure 2 reports a complete framework to evaluate profitability.

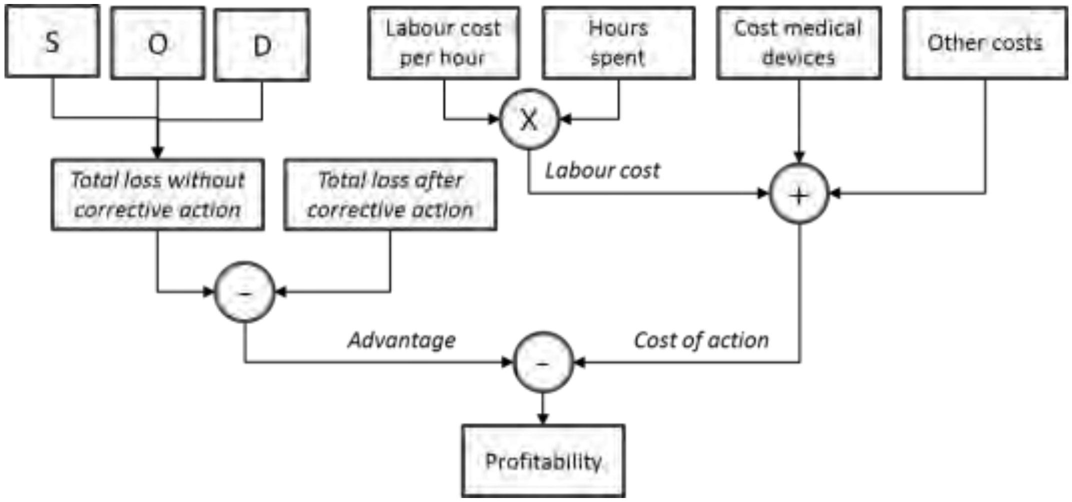

Figure 2. The profitability evaluation framework.

In calculating the fault profitability, the corrective action cost is evaluated by means of the following relation:

$$Cost\ of\ action = C_1 \times h_1 + C_2 + C_3 \tag{10}$$

where, C_1 is the personnel cost per hour, h_1 the hours spent for each activity, C_2 is the cost related to the improvement of medical devices, and C_3 encompasses all the other costs associated to the improvement action.

5.2.2. The priority–profitability diagram

At this point a given priority and a given potential profitability are associated with each fault. We draw a graph where the abscissa represents the FM priority, evaluated with the new RPI, while the ordinate represents the profitability. The points in this graphic are the single FMs and their disposition in the quadrant provides information about their priority, economic opportunities of intervention and advantages. Then a straight line passing through the origin, and called *strategy straight line*, can be drawn. The straight line slope indicates the adopted planning policy and expresses the expected relation between the action urgency and the economic convenience intervention. To identify this slope, [30] stated the policy into four fundamental terms :

1. *PR*: This term expresses the trend of an organization to accept one or more unconformities.
2. *SR*: This term expresses the trend of an organization to accept rejects (internal unconformities).

3. *PT*: It expresses the trend of an organization to make a profit; it shows how profit is important in the organization policy.
4. *IL*: This term reveals the trend of an organization to risk its own image on the market. In fact, there is a correlation between a potential FM prevention and the organization image.

To each element of the adopted planning policy is attributed a score from 1 to 10 depending on the preference of the manager. After attributing a score to the four elements, the value M is given by:

$$M = \left[\frac{PR + SR + PT + IL}{4}\right] \tag{11}$$

The obtained score is then turned into the slope of the strategy straight line (*t*) using a conversion relation. If the organization decides to assign more importance to fault criticality, the straight line will have a low slope. On the other hand, if profitability is assumed to be more important, higher slopes are obtained. See [30] for detailed explanation of this process.

5.2.3. Failure classification

The strategy straight line defines a local coordinate, on whose basis we create a classification of the considered faults in the FMEA analysis. This coordinate is the distance from the axes origin to the projection points on the line indicating the failures, called Critical Index CI [30] and is calculated by:

$$CI_j = \sqrt{\frac{(m \times Pr_j + RPI_j)^2}{1 + m^2}} \tag{12}$$

where CI_j is the Critical Index of generic fault j, Pr_j is the profitability of generic fault j, RPI_j is the risk priority index of generic fault j, and *m* is the strategy straight line's slope. Since the RPI is dimensionless, we need to normalize the profitability values before calculating the CI. Then, we calculate a score for each potential design fault, which identifies its priority, and at the same time we calculate another score, which identifies the profitability in accomplishing the correct actions. All the potential failures are considered through priority and profitability criteria. Furthermore, we use an algorithm of optimization to choose the optimum mix of failures to be repaired taking into account the firm budget as a bound for the execution of corrective actions.

6. Optimal mix of failure selection

As a matter of fact, not all the failures can be repaired or avoided due to the limited available budget allocated to corrective actions. Only a specific mix of FMs can be modified according to the available budget. Therefore, we propose to use an optimization model to find the optimal mix of faults to be repaired maximising the sum of their C.I., in such a way that the firm budget is respected. The optimization problem is formulated as follows [30]:

$$\text{Max.} \quad \sum_{j=1}^{n} x_j CI_j$$

$$\text{s.t.} \quad \sum_{j=1}^{n} x_j \times cost\ of\ action_j \leq Budget$$

$$x_j \in \{0,1\} \tag{13}$$

where j is a generic fault, x_j takes the value 1 if the action is selected and 0 otherwise, C.I. is the Critical Index of the j-th fault. Needless to say, Budget is the available budget for the corrective actions.

7. Numerical example

In this section, a numerical example proposed by Geum et al. [8] is used to illustrate the proposed approach. The example in [8] concerns the potential failure diagnosis for a hospital located in Seoul, Korea. The activities or the tasks performed in a hospital might be quite different depending on the specific department. In particular, Geum et al. elected the department of internal medicine since it has a high level of interaction between customers and staff.

7.1. Construction of service-specific FMEA

Considering the hospital service, S-FMEA is constructed. Firstly, FMs are identified and listed. 5 FMs were identified in this numerical example. The identification of FMs includes the possible errors which might occur during the service delivery process. Table 3 shows the list, types and characteristics of the FMs used by Geum et al [8]. Each RPI factor is estimated based on a 1 to 10 scale [29]. Assigned ranks for each RPI factor, according to the opinions of five experts (identified by *Eng 1* to *Eng 5*), are shown in Table 4. These numbers were thrown from a discrete uniform distribution within the interval [1,10]. Cost values provided by the 5 experts for dimensions S and D are given in Figure 3. Costs to severity functions in Figure 3 were suggested in [24].

Table 3. FMs in the Internal Medicine case.

	FM	Type	Description
FM1	Inaccurate check-in	Wrong employee actions	Incorrect reservation, inaccurate prioritization
FM2	No availability of doctor	Service delivery system failures	Long doctor consultation, inaccurate allocation of customers
FM3	Long waiting time	Service delivery system failures	Unexpected arrival of customer, long processing time
FM4	Order forgotten	Wrong employee actions	Inaccurate allocation of customers
FM5	Wrong prescription	Wrong employee actions	Wrong prescription due to a mistake, Wrong communication between doctor and nurse

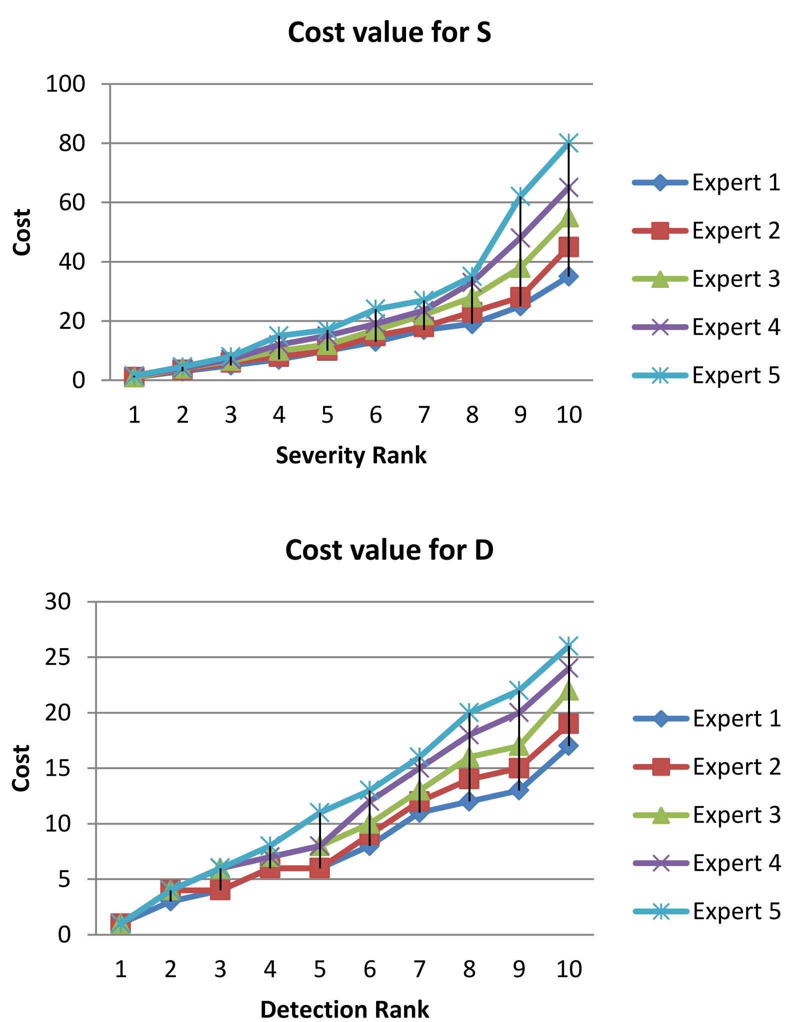

Figure 3. Cost values given by experts to S and D.

Table 4. Assigning ranks for each RPI factor.

FM	Eng	S1	S2	……	S11	O1	O2	O3	O4	D1	D2	D3	D4
	1	6	5	……	5	8	3	7	3	10	9	5	4
	2	8	4	……	4	7	2	8	2	10	9	8	6
1	3	5	3	……	3	8	3	9	3	10	10	8	2
	4	6	4	……	3	7	4	9	1	10	9	7	7
	5	7	3	……	5	6	2	7	2	9	9	5	1
	1	10	4	……	9	7	10	9	1	10	8	8	9
	2	10	6	……	8	7	10	9	2	9	7	6	6
2	3	9	5	……	8	7	9	9	2	9	7	7	9
	4	8	6	……	7	7	9	9	2	9	3	7	9
	5	9	5	……	8	7	10	9	3	5	6	7	7
	1	5	6	……	5	10	9	10	8	8	9	7	3
	2	3	5	……	6	9	9	6	10	10	9	7	7
3	3	4	7	……	7	8	8	7	9	9	8	6	6
	4	4	6	……	7	9	9	6	9	8	7	5	5
	5	3	6	……	6	10	10	10	10	8	7	6	6
	1	7	5	……	9	9	10	7	7	10	3	5	4
	2	8	6	……	7	10	9	8	8	8	5	4	6
4	3	7	6	……	8	8	8	9	6	10	4	5	4
	4	6	5	……	8	10	9	10	7	9	4	4	5
	5	7	4	……	7	9	10	9	8	9	3	3	6
	1	10	10	……	8	2	8	8	4	4	2	10	3
	2	9	10	……	9	3	9	9	5	7	2	9	3
5	3	9	10	……	8	3	10	9	5	2	1	8	1
	4	8	10	……	9	4	9	9	4	5	2	8	2
	5	9	9	……	7	8	8	8	4	7	3	7	1

Using values in Table 4 and costs-to-severity functions from Figure 3, we evaluate costs (see Table 5) for S and D factors according to each expert's opinion. The value W in Table 5 refers to the weight of experts' opinion, which is assigned according to their experience and knowledge. In our case, we set them arbitrarily in such a way that they sum up to 1.

Using Equations 3, 4 and 5, cost values for each sub criteria (in Table 5) are converted into utility values (see Table 6). In addition, Table 6 reports the experts' assignment of weights to utility values of each dimension of RPI.

Now we convert the fuzzy membership functions numbers into numerical values. To this end, we used the *COM* defuzzification method. In the COM defuzzification method, the fuzzy logic controller first determines the typical numerical value for each scaled membership function. The typical numerical value is the mean of the numerical values corresponding to the degree of membership at which the membership function was scaled.

Table 5. Assigning Costs to each RPI factor.

FM	Eng	W	CS1	CS2	……	CS11	O1	O2	O3	O4	CD1	CD2	CD3	CD4
1	1	0.15	12	10	……	10	8	3	7	3	16	14	11	14
	2	0.2	25	10	……	10	7	2	8	2	18	16	15	10
	3	0.3	13	21	……	21	8	3	9	3	20	20	15	18
	4	0.25	19	13	……	7	7	4	9	1	22	19	14	14
	5	0.1	24	24	……	18	6	2	7	2	23	23	11	11
2	1	0.15	36	9	……	24	7	10	9	1	16	13	13	14
	2	0.2	44	16	……	25	7	10	9	2	16	12	10	10
	3	0.3	40	13	……	32	7	9	9	2	18	13	13	18
	4	0.25	36	19	……	22	7	9	9	2	19	5	14	19
	5	0.1	60	18	……	36	7	10	9	3	11	13	16	16
3	1	0.15	10	12	……	10	10	9	10	8	13	14	11	14
	2	0.2	19	12	……	16	9	9	6	10	18	16	12	12
	3	0.3	11	21	……	21	8	8	7	9	18	15	11	11
	4	0.25	13	19	……	22	9	9	6	9	17	14	9	9
	5	0.1	24	20	……	20	10	10	10	10	19	16	13	13
4	1	0.15	16	10	……	24	9	10	7	7	16	14	11	14
	2	0.2	25	16	……	19	10	9	8	8	15	8	7	10
	3	0.3	21	17	……	32	8	8	9	6	20	13	18	13
	4	0.25	19	16	……	36	10	9	10	7	19	7	7	9
	5	0.1	24	14	……	24	9	10	9	8	23	11	11	13
5	1	0.15	36	36	……	20	2	8	8	4	14	14	16	14
	2	0.2	30	44	……	30	3	9	9	5	12	3	16	4
	3	0.3	40	57	……	32	3	10	9	5	18	18	15	18
	4	0.25	36	67	……	50	4	9	9	4	9	3	17	3
	5	0.1	60	60	……	24	8	8	8	4	16	11	16	11

Table 6. Weights assigned by experts to utility values.

FM	Eng	W	W*US1	W*US2	......	W*US11	W*UO1	W*UO2	W*UO3	W*UO4	W*UD1	W*UD2	W*UD3	W*UD4
1	1	0.15	0.019	0.009	......	0.001	0.088	0.045	0.075	0.045	0.024	0.023	0.025	0.031
	2	0.20	0.054	0.012	......	0.002	0.100	0.050	0.118	0.050	0.036	0.035	0.045	0.030
	3	0.30	0.042	0.037	......	0.006	0.176	0.091	0.230	0.091	0.061	0.065	0.068	0.081
	4	0.25	0.051	0.019	......	0.002	0.125	0.083	0.192	0.050	0.056	0.052	0.053	0.052
	5	0.10	0.026	0.014	......	0.002	0.043	0.025	0.050	0.025	0.023	0.025	0.017	0.016
2	1	0.15	0.025	0.018	......	0.026	0.075	0.150	0.115	0.030	0.030	0.035	0.030	0.027
	2	0.20	0.041	0.043	......	0.036	0.100	0.200	0.154	0.050	0.040	0.043	0.030	0.026
	3	0.30	0.056	0.052	......	0.069	0.150	0.230	0.230	0.075	0.068	0.070	0.059	0.070
	4	0.25	0.042	0.063	......	0.040	0.125	0.192	0.192	0.063	0.059	0.022	0.053	0.062
	5	0.10	0.028	0.024	......	0.026	0.050	0.100	0.077	0.030	0.014	0.023	0.024	0.021
3	1	0.15	0.019	0.021	......	0.017	0.150	0.115	0.150	0.088	0.023	0.028	0.029	0.036
	2	0.20	0.049	0.029	......	0.036	0.154	0.154	0.087	0.200	0.042	0.043	0.043	0.041
	3	0.30	0.043	0.075	......	0.071	0.176	0.176	0.150	0.230	0.064	0.060	0.059	0.056
	4	0.25	0.042	0.057	......	0.062	0.192	0.192	0.109	0.192	0.050	0.047	0.040	0.038
	5	0.10	0.031	0.024	......	0.022	0.100	0.100	0.100	0.100	0.022	0.021	0.023	0.022
4	1	0.15	0.023	0.021	......	0.027	0.115	0.150	0.075	0.075	0.026	0.040	0.031	0.036
	2	0.20	0.048	0.044	......	0.028	0.200	0.154	0.118	0.118	0.032	0.030	0.026	0.034
	3	0.30	0.060	0.070	......	0.071	0.176	0.176	0.230	0.130	0.065	0.074	0.100	0.066
	4	0.25	0.045	0.055	......	0.067	0.250	0.192	0.250	0.125	0.051	0.033	0.032	0.038
	5	0.10	0.023	0.019	......	0.018	0.077	0.100	0.077	0.059	0.025	0.021	0.020	0.022
5	1	0.15	0.027	0.020	......	0.019	0.038	0.088	0.088	0.050	0.030	0.043	0.030	0.042
	2	0.20	0.030	0.033	......	0.038	0.060	0.154	0.154	0.074	0.035	0.012	0.040	0.016
	3	0.30	0.059	0.065	......	0.062	0.091	0.300	0.230	0.111	0.078	0.110	0.056	0.108
	4	0.25	0.045	0.063	......	0.080	0.083	0.192	0.192	0.083	0.033	0.015	0.053	0.015
	5	0.10	0.030	0.023	......	0.015	0.059	0.059	0.059	0.033	0.023	0.022	0.020	0.022

Table 7. List of S-FMEA for the Internal Medicine case.

		FMs	FM1 Inaccurate check	FM2 No availability of doctor	FM3 Long waiting time	FM4 Order forgotten	FM5 Wrong prescription
Characteristics of failure		Cause of failure	Communication error	No existing free doctor	Wrong planning to reservation	Putting wrong information of reservation	Miscommunication between doctor and nurse
		Effect of failure	Giving up the reservation	Giving up the reservation, dissatisfaction	Taking long time to check-in	Impossible to check the reservation	Receiving wrong prescription
Rating	S	**S1: Impact (5)**	19.33628	42.36865	15.67359	21.27343	40.06250
		S2: Core process (5)	17.29124	15.78	18.14195	15.55915	56.21735
		S3: Typicality (1)	17.74371	47.83142	26.64188	16.36845	36.22301
		S4: Affected range (3)	33.94262	22.61437	16.25958	15.13245	27.55735
		S5: Customer participation (5)	11.55758	13.80365	17.79414	11.31841	17.23531
		S6: Customer contact (1)	54.25649	47.10143	54.39658	38.58727	13.77493
		S7: Service encounter (5)	15.08449	18.51221	39.7044	24.93618	17.46556
		S8: Interdependency (5)	18.76429	14.75262	33.7543	14.36264	19.27408
		S9: Bottleneck possibility (3)	13.27118	35.50909	16.73276	16.74843	27.74883
		S10: Hardness of Isolation (1)	19.95247	18.56893	14.12591	14.09159	15.78645
		S11: Resource distribution (1)	15.87512	28.17595	19.43236	29.83794	36.71038
	O	**O1: Frequency (5)**	7.415009	7	9.095337	9.334311	4.027832
		O2: Repeatability (3)	3.028047	9.515818	8.896365	9.095337	9.193036
		O3: Failure visibility (5)	8.447218	9	7.931799	8.976527	8.79668
		O4: Single point failure (1)	2.329245	2.000807	9.261288	7.091196	4.526316
	D	**D1: Chance of undetection (5)**	20.0555	17.16024	17.29244	18.7833	14.63632
		D2:Method of systematic detection (3)	18.7330	11.85192	14.94628	11.22003	14.34675
		D3: Customer/Employee detection (5)	13.9454	13.17768	11.04586	13.23011	15.98433
		D4: Hardness of proactive inspection (3)	14.7304	16.55837	11.59911	11.8831	14.20197

The fuzzy logic controller then uses the following equation to calculate a weighted average of the typical values.

$$X_{final} = \frac{x_1\mu_1 + \cdots + x_n\mu_n}{\mu_1 + \cdots + \mu_n} \tag{14}$$

Where x_n is the typical numerical value for the scaled membership function n, and μ_n is the degree of membership at which membership function n was scaled.

After defuzzification of Table 6 by COM method, and based on the identified FMs given in Table 3, the CS-FMEA is constructed, as shown in Table 7. The value in parentheses refers to the weight of each dimension.

7.2. Application of grey relational analysis

This section illustrates the application of GRA to the numerical example in [8].

Step1. Based on Table 7 and Equation 7, the first step of GRA is applied. Table 8 shows the comparative series for S dimension.

Table 8. Comparative series for S dimension.

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11
FM1	0.178	0.133	0.143	0.503	0.005	0.956	0.083	0.165	0.043	0.192	0.101
FM2	0.691	0.099	0.813	0.251	0.055	0.796	0.160	0.076	0.538	0.161	0.375
FM3	0.097	0.151	0.341	0.110	0.144	0.959	0.632	0.499	0.120	0.062	0.180
FM4	0.221	0.094	0.112	0.084	0	0.607	0.303	0.067	0.120	0.061	0.412
FM5	0.640	1	0.554	0.361	0.131	0.054	0.136	0.177	0.365	0.099	0.565

Step 2. Working with the reference set and using Equation 8, the grey relational coefficients for each dimension are calculated. They are reported in Table 9. In this case, we set $\zeta = 0.5$.

Table 9. Grey relational coefficients for S dimension.

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11
FM1	0.378	0.366	0.368	0.502	0.334	0.92	0.353	0.375	0.343	0.382	0.357
FM2	0.618	0.357	0.728	0.401	0.346	0.711	0.373	0.351	0.52	0.373	0.444
FM3	0.356	0.371	0.432	0.36	0.368	0.925	0.576	0.5	0.362	0.347	0.378
FM4	0.391	0.356	0.36	0.353	0.333	0.56	0.418	0.349	0.363	0.347	0.459
FM5	0.581	1	0.529	0.439	0.365	0.346	0.367	0.378	0.441	0.357	0.535

Step 3. After calculating the grey relational coefficients, grey relational grade for each dimension is calculated using the weighted average of each grey relational grade. Table 10 shows the weight vector for dimension *S*.

Table 10. Weight vector for each sub-dimension of S dimension.

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11
Weight	0.0541	0.052	0.011	0.043	0.0478	0.0267	0.0505	0.0536	0.03	0.011	0.0104

Step 4. Using the weighting coefficients in table 10, Equation 9 and the risk score expressions given in Table 2, the final grey relational grade is calculated for S, O and D dimensions. Results of the grey relational grade for each dimension are given in Table 11.

Table 11. Grey relational grades for each dimension.

	S	O	D
FM1	0.035	0.1525	0.168667
FM2	0.04	0.1914	0.121242
FM3	0.039	0.2057	0.1125
FM4	0.034	0.2222	0.124234
FM5	0.047	0.1681	0.11733

By using Equation 6, the overall grey relational grades are calculated and the resulting values are reported in Table 12.

Table 12. Overall grey relational grades.

	S*W1	O*W2	D*W3	SUM	SUM^(1/3) (RPI)	Rank
FM1	0.012	0.025	0.081	0.118	0.491	1
FM2	0.014	0.031	0.058	0.104	0.470	3
FM3	0.014	0.034	0.054	0.102	0.467	4
FM4	0.012	0.037	0.059	0.108	0.477	2
FM5	0.016	0.027	0.056	0.101	0.465	5

According to the results in Table 12, the most important and critical FMs are FM1, FM4, FM2, FM3 and FM5, respectively. Profitability is obtained in Figure 2 as the difference between *Advantage* and *Cost of action* from. Moreover, Equation 10 allows computing *Cost of action* based on the values provided in Table 13. Assuming PR=3, SR=4, PT=6 and IL=6, the slope of the strategy straight line is evaluated by using Equation 11, leading to $M = 5$ and $m = 45^{\circ}$.

Table 13. C.I. values using Profitability.

	Cost of action	Total loss without corrective action	Total loss after corrective action	Profitability	Normalized Profitability	C.I.
FM1	7	5872	1046.3	4818.7	0.245	0.477
FM2	2	5872	2050.6	3819.4	0.194	0.423
FM3	16	5190	1323.5	3850.5	0.196	0.423
FM4	5	5000	1100	3895	0.198	0.430
FM5	3	5300	2000	3297	0.168	0.398

Figure 4 shows the profitability- RPI diagram. By using Equation 12, we compute C.I. for each FM, leading to the values shown in Table 13.

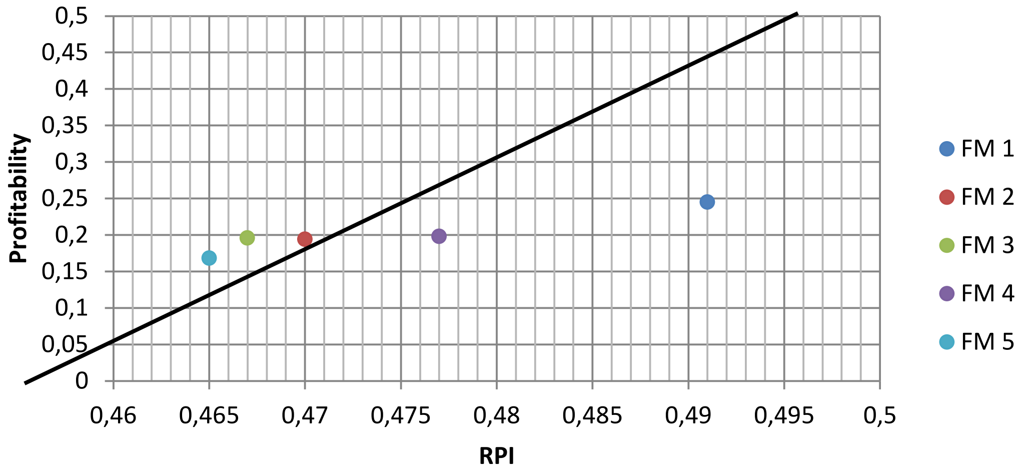

Figure 4: Profitability- RPI diagram for the numerical example.

Finally, the manager has to select the best mix of failures. In the numerical example, it is assumed that a maximum budget of 30 currencies is available. By solving the linear program (13) with the commercial software Lingo 13.0, we found that the optimal corrective action under the present budget constraint consist in implement actions related to FMs 1, 4, 2, and 3.

Since precise and accurate prioritization of failures has a key role in their selection for corrective actions in order to reduce service failures and related costs, we conducted a sensitivity analysis to evaluate possible changes in prioritizations of failures. As shown by Table 14, the prioritization of failures for corrective actions changes according to the available budget. If budget is decreased by 10%, the prioritization of failures becomes 1, 4, 2, 5 while, if the budget is increased by 10%, all the five consider failures (1, 4, 2, 3, 5) could be afforded.

Table 14. Sensitivity analysis for budget factor

Budget Factor	Prioritization of failures
27(10% decrease)	FM1,FM4,FM2,FM5
30	FM1,FM4,FM2,FM3
33(10% increase)	FM1,FM4,FM2,FM3,FM5

8. Discussion and conclusions

This paper proposes an integrated approach to identify, evaluate, and improve the potential failures using FCS-FMEA, GRA and profitability theory. In this paper a new integrated approach is developed to improve the method of S-FMEA from an economic perspective. Accordingly, at the first step, the estimated cost of faults based on an arbitrary number of expert's (5 experts in the case here considered) was employed to evaluate each factor of RPI. In addition, different weights were assigned to each expert's opinion and each RPI factor. Doing so, a more comprehensive and realistic evaluation of potential effects is possible. In the second step, each FM was evaluated using GRA. GRA is applied by using a two-phases scheme. In the first phase, the risk score of each dimension (S, O, and D) is calculated. Then, the final risk priority is computed in the second phase. Since precise and accurate prioritization of failures has a key role in their selection for corrective actions, we propose two measures (fuzzy RPI and profitability evaluation) in the second phase to achieve better results. This integrated method is an original and innovative approach based on combining FCS-FMEA, GRA and profitability theory. In particular, FCS-FMEA has been combined with GRA in order to consider many inter-related different dimensions and weights. On the other hand, considering profitability with FCS-FMEA and GRA, reduces the losses caused by failure occurrence. Besides, a maximization problem has been used to select the best mix of failures to be repaired. This constrained maximisation problem is solved by a standard tool, leading to the most convenient mix of failures to be repaired under available budget constraint.

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