

Assessing Non Conformities in Quality Management Systems from Customer perspective and Firm perspective

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Abstract: Quality has been recognized broadly as one of the key factors for success in global market for all kind of business. Quality management practices and programs, such as total quality management, six sigma, statistical process control and ISO 9001 certification have been extensively researched. Several studies explored the relationship between quality management practices and competitive performances in manufacturing companies. This work is focused on the problem of quality Non Conformity (NC) assessment and characterization. A comprehensive approach for NCs analysis is presented aimed to i) characterize an NC based on multiple perspectives, ii) define intervention priorities with respect to NC characterization. NC are classified with respect to multiple features, and through the use of Failure Mode Effects and Criticality Analysis (FMECA) methodology and a fuzzy inference engine. A Ranking Criticality Index (RCI) is defined, which allow to address the appropriate intervention priorities. Within a case study, the fuzzy engine is tuned and the whole approach is developed.

Keywords:

1. Introduction

Quality management policies in majority of companies evolve continuously over a number of years by focusing on quality issues that are critical at any given instant of time (Shetwan et al., 2011), since quality is widely recognized broadly as one of the key factors to success in global market for all kind of business (Leong et al., 2012). Quality management practices and programs such as total quality management (TQM), six sigma, statistical process control and external certification programs such as the ISO 9000 series have been extensively researched in almost any industry sector (Wiengarten and Pagell, 2012). Actually, Academics and Manager agree that Quality and production control are fundamental functions to improve competitiveness in industrial firms. This kind of link between Quality and firms' performances is confirmed by Colledani and Tolio (2012), and before Chi Phan et al. (2011), who explored the

relationship between quality management practices and competitive performance in manufacturing companies. Again, Colledani and Tolio (2011) affirm that Quality control allows to meet high product quality standards, also reducing scraps and reworks. Usually, manufacturing systems start in an ‘in-control’ state, producing conforming items of acceptable quality and, after a random span, they shift to the ‘out-of-control’ state and start producing non-conforming items (Dhouib et al., 2012). Ahire and Dreyfus (2000) state that “Product quality is the result of manufacturing resources – people, processes, materials, and equipment – oriented to varying degrees for achieving customer satisfaction and low deficiencies” and the consensus of results from other empirical studies is that quality management practices effectively improve product quality and overall performance (Kull and Wachter, 2010). In light to these studies, it seems fundamental to drive firm efforts and resources towards a prioritization of interventions aimed to front quality problems and to reduce wastes, with related production losses and costs. The present research work can be so configured within the thread of Quality Assurance and Quality Management. The approach developed aims to define a new NC classification and evaluation encompassing firms’s and customers’ perspective. The work uses FMECA analysis and fuzzy inference engine to search insights on NC evaluation and related Corrective Actions (CA) prioritization. Our findings provide the following insights: i) Which can be the most important features that can characterize a Quality NC, ii) How a quality NC can be ranked with respect to its features, to appraise the correct priority of the relative CA.

The work is organized in six sections: the second section analyses the topic of quality and quality management approaches emerging from literature. The third section provides an overview about the spirit of the research and its methodology while the fourth section

2. Literature review

2.1 Quality Management and Non-Conformities

Quality Assurance (QA) is acted to verify conformance of products according to quality manuals and product design specifications, and to control six factors affecting quality such as man, machines, material, methods, environments and measurements (De Chiaro et al., 2013). QA aims at monitoring actions and processes, and at analyzing the states and conditions to solve quality problems (Tang and Yun, 2008). A complete definition of quality that somewhat reaches a consensus in products and services domain can be given by international standards (Boer and Blaga, 2012), where EN ISO 9000/2004 defines quality as the measure by which intrinsic features meet requirements. The concept of quality may have different definitions and applications, depending on the specific work area (Del Castillo and Sardi, 2012). In particular, Murthy and Ravi Kumar (2000) proposed three definitions of quality, i.e. (i) quality of performance, (ii) quality of conformance, (iii) quality of service (repairs during post-sale period) where quality of conformance is

determined by quality of manufacturing e.g. technologies and quality control schemes used by the manufacturer. The concept of quality along product lifecycle gained attention by the application of Quality Function Deployment (QFD) which is a product development method dedicated to translating client requirements into activities to develop products and services by the use of appropriate matrixes (Carnevali and Miguel, 2008). Quality in product lifecycle is a new focus in quality management, which holds the promise of seamlessly integrating all quality data produced throughout the life of a product (Tang and Yun, 2008).

More in general, Quality Management (QM) encompasses a set of mutually reinforcing principles, each of which is supported by a set of practices and techniques (Dean and Bowen, 1994). It can be defined as an holistic management philosophy that fosters all functions of an organization through continuing improvement and organizational change (Kaynak and Hartley, 2005). Sousa and Voss (2002) state that QM has become an all-pervasive management philosophy, finding its way into most sectors of today's business society, while Pyzdek (2003) divides QM into four dimensions, i.e. (i) Quality planning, (ii) Quality control, (iii) Quality assurance and (iv) Quality improvement. In this context Six Sigma was considered as a new QM method (Zu et al., 2008) "for strategic process improvement and new product and service development that relies on statistical methods to make dramatic reductions in customer defined defect rates" (Linderman et al., 2003). Similarly, Total Quality Management (TQM) is a widely recognized quality management philosophy. It has become the key slogan for organizations that strive for competitive advantage in markets (Sureshchandar et al., 2001) favoring excellence in a sustainable development approach (Todorut, 2012). TQM provides a set of practices emphasizing among others, continuous improvement, meeting customers' requirements, reducing rework, long-range thinking, increased employee involvement and teamwork, process redesign, competitive benchmarking, team-based problem-solving, constant measurement of results, and closer relationships with suppliers (Agus and Hassan, 2012). Forza and Filippini (1998) analyzed the impact of TQM on quality conformance and customer satisfaction identifying four critical aspects for its implementation in companies. The concept of quality conformance is strictly related to non-conformity (NC) of Quality Management Systems (QMSs) where a NC is a mistake that is found in some phases of a production process and/or on the finished product, or something that did not go as planned (Lillrank and Kujala, 2006). Savino et al. (2008) developed a QMS methodology defining a set of finalised pointers to measure production improvements and to deal with (attenzione all'uso del verbo TO FRONT. Non esiste in questa accezione, è usato in questo modo molte volte in maniera errata!) quality NCs. An extension of such work based on fuzzy logic is proposed by Savino and Seklouli Sekhari (2009). According to practical findings (Lari et al., 2002), without an effective corrective and preventive action program, problems will occur again, continuous improvement will be difficult and any of the other quality system elements might not work properly. QMS

are essentially based on the requirements of ISO 9001 standard where its audits are used to evaluate the level of compliance to the requirements of relevant standards (Maglić et al., 2007); Maglić (2002) analysed the difficulties during implementation of QMS according to these international requirements. Wu et al. (2006) developed an information analysis system to isolate the causes of non-conformity and quickly identify the causes of problems thereby reducing the time taken to solve quality-related problems.

Under manufacturing perspective, good internal process quality management means fewer scrap, defects and rework, and leads to a better operational performance (e.g. lower manufacturing costs, more reliable processes), and substantial production improvement (Yaqiong et al., 2011). Boer and Blaga (2012) presented the strategy for the joint use of quality tools and human resources management to achieve positive results in terms of production capacity and product quality. This task can be achieved through direct executive staff motivating as an effect of the usage and application of the main seven quality tools (Tague, 2004) including cause-and-effect diagram (Ishikawa diagram), Shewart control charts, check sheet, histogram, Pareto chart, scatter diagram, and stratification. Taking into account the fact that there is no such a think as a company able to operate with infinite resources, and that new problems are continuously emerging in every context, we may argue that in QM a key role is played by Non Conformities (NC), the relative Corrective Actions (CA) and by the evaluation of their impact on productivity and production costs. In fact, especially in case of shortage of resources, every company needs to have sound criteria to prioritize NCs and CAs. According to Love et al. (1995), costs of Non Conformities (NC) are typically broken down into two areas: (i) cost of internal failures (scrap, rework and other excesses before the product is shipped) and, (ii) cost of external failures (warranty services, costs of product failures during its use). While in conformity costs we may also include those ones relative to fault prevention, within NC costs are encompassed all the direct and indirect costs of faults (Winkler, 1995). An interesting finding of Khana et al. (2011a) relates the new cost of the product to the probability that a defectiveness may be found by the inspector or by the buyer. On the same line, the works of Wahab et al (2010) and Khana et al, (2011b) inspired us in modeling our approach. In their works, Wahab et al. appraise the learning effects related to poor quality and related holding costs of defective items, while Khana et al. revise the use of fuzzy sets in modeling the effect of product defectiveness on costs and customer dissatisfaction.

This study is focused on the research stream illustrated above, aiming to investigate on: i) the core features of an NC that can define its criticality; ii) How these features can impact on NC criticality and; iii) for each NC, the correct appraisal of CA priority.

2.2 Fuzzy techniques for Quality Management

Regarding the above objectives, Fuzzy Sets can be used as a practical tool to guarantee objectivity in features evaluations and priorities appraisal, being widely acknowledged as a suitable mathematical tool to deal with information of different origin and affected by uncertainty and subjectivity (Peche and Rodriguez, 2012). In recent years fuzzy theory has been considered a key technique for QM within manufacturing system (Yaqiong et al., 2011). In some previous work, it has been used to control the key quality parameters, grade product quality to reduce parameters variability and better adjust specification limits (Taylan, 2011).

The core of a fuzzy model is the Fuzzy Engine (FE), in which an inference process is developed to have output from a set of fuzzy rules and from one or more given conditions (Bukowski and Feliks, 2005). Fuzzy theory was developed based on the premise that key elements in human thinking are not numbers, but linguistic terms or fuzzy sets that are not precisely defined. The fuzzy approach has been explored in Quality Function Deployment (QFD) for modeling customer preferences/attributes and engineering characteristic that are expressed in linguistic terms (Chougule et al., 2013). Earlier, Lao et al. (2012) developed an Intelligent Food Quality Assurance System (IFQAS) facilitating the selection of the most appropriate quality control operations and suggesting the best storage environment. Here fuzzy techniques are applied to extract critical quality assurance information in terms of fuzzy rules. Syn et al. (2011) developed an expert system using fuzzy logic model to predict the effect of carbon dioxide on laser cutting quality (non sono sicuro ma così com'era non era chiaro) and to improve its cutting quality. Fuzzy techniques have been also applied by Kumru and Kumru (2013) to Failure Mode and Effects Analysis (FMEA), as one of the well-known techniques of quality management used for continuous improvements in product or process designs or to Failure Mode Effects and Criticality context (FMECA) by Brunet al. (2011). Another example of applying Fuzzy Sets to QMS can be found in the work of Lau et al. [25] (Come standard usiamo nomi autori e anno? Nel qual caso questi numeri in parentesi quadre vanno uniformati), who addressed the hidden relationships among process variables through an intelligent QMS with fuzzy association rules. Conversely, Deshpande and Raje [7] introduced fuzzy logic applications for water quality management.

3. Industrial context

The development of the proposed model is based on a real life industrial application in a production plant characterized by a wide product range with more than 30 different products. The analysis is focused on a production line of components for boilers (Figure 1) realizing around the 25% of overall production of the plant. The line is able to

produce two types of components for boilers at different production costs, due to product requirements and to the incidence of setup times for changeover activities.

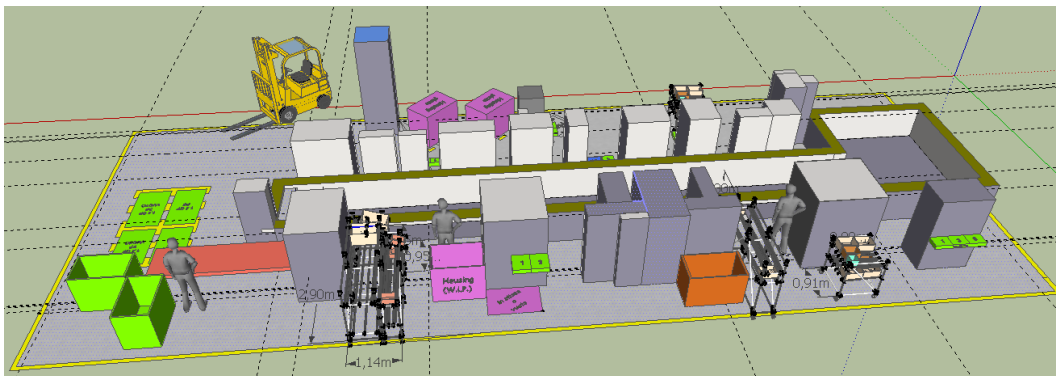


Figure 1 – The production line of the case study

The line operates on two working shifts per day with a cycle time of about 20 seconds. It is composed of 15 automatic stations and three manual ones, managed by a dedicated operator. A subset of five automatic stations are in charge to perform quality control along the production line and at its final station, e.g. leak or welding tests. Such quality gates perform 100% quality tests assuring the compliance of output products which are then shipped to the customers. Additional quality gates are available in material acceptance and before shipment in accordance to a statistical sampling program. Despite of these quality gates, claims can be raised from customers in case of product defectiveness, implying expensive recovery, repairing or replacement activities.

4. Research questions and research framework

Qui vedo ancora riferimenti bibliografici. Non sarebbe stato meglio contenerli tutti nella section dedicata, e qui focalizzarsi solo su RQ e framework?

In QMS, NC are usually classified based on their frequency and, in some cases, on their impact on final product. Currently, approaches dedicated to NC classification and coding are mostly related to product features and defectiveness reduction. In this context, Sun and Li (2011) focused on reduction of surface quality-related problems of large plastic products through product design, raw material selection, forming method, structural design of mode, and debugging of shaping process. Similarly, Di Foggia and D'Addona (2013) chased the “zero defects” goal through the control of critical parameters related to the performances of casting process. They obtained a defectiveness reduction by limiting manual operations to help the repeatability of the process through automation and introducing on-line measurements along the production process. Both authors faced NCs based on the analysis of design measures or geometrical product conformity. Similarly, Savino et al. (2008) defined a set of pointers to front quality NCs and to

measure production improvements. Based on these works, we can assert that such techniques of Quality Control are post-process based, i.e. Quality controllers and process verification engineers inspect final products (Lou and Huang, 2003). In contrast to the mentioned works, we aim to decompose NC in its main features, evaluating the impact that these features may have on the final product, stressing the importance of process control as the new QC concept (Lou and Huang, 2003). According to the previous findings we may argue that an NC (sempre an se vogliamo fare riferimento all'acronimo ("EN SI" inizia con vocale)) can have different impact on costs, and it may have a different criticality, depending on where it is detected (in production line or by the customer), or if it can compromise the correct working of the final product. Based on this assumption, different aspects should be selected to completely characterize an NC. Then, these aspects should offer the possibility to proceed with a further deeper analysis of related causes and to appraise the CA priority for each NC.

According to these considerations, the work is mainly aimed at answering the following research questions:

RQ1 What are the main factors that may characterize a quality NC?

RQ2 How such factors can be combined together to rank a certain NC and prioritize CA?

This empirical study was conducted to investigate which can be the most important features of an NC and how they can impact on NC criticality and their prioritization for Corretive Actions To achieve this goal, we started from audit development and NC control (Bernardo et al, 2009) The research framework and the research methodology developed is structured in five steps (Figure 2).

With the data of the NC detected on the production line, RQ1 was investigated by addressing each NC for a set of features with respect to elements of resource that were related to the traditional and strategic definition of Quality [36], [47]. The investigation of RQ2 resulted in a set of features based on the above literature review and through the analysis of claims and quality problems detected in the industrial context.

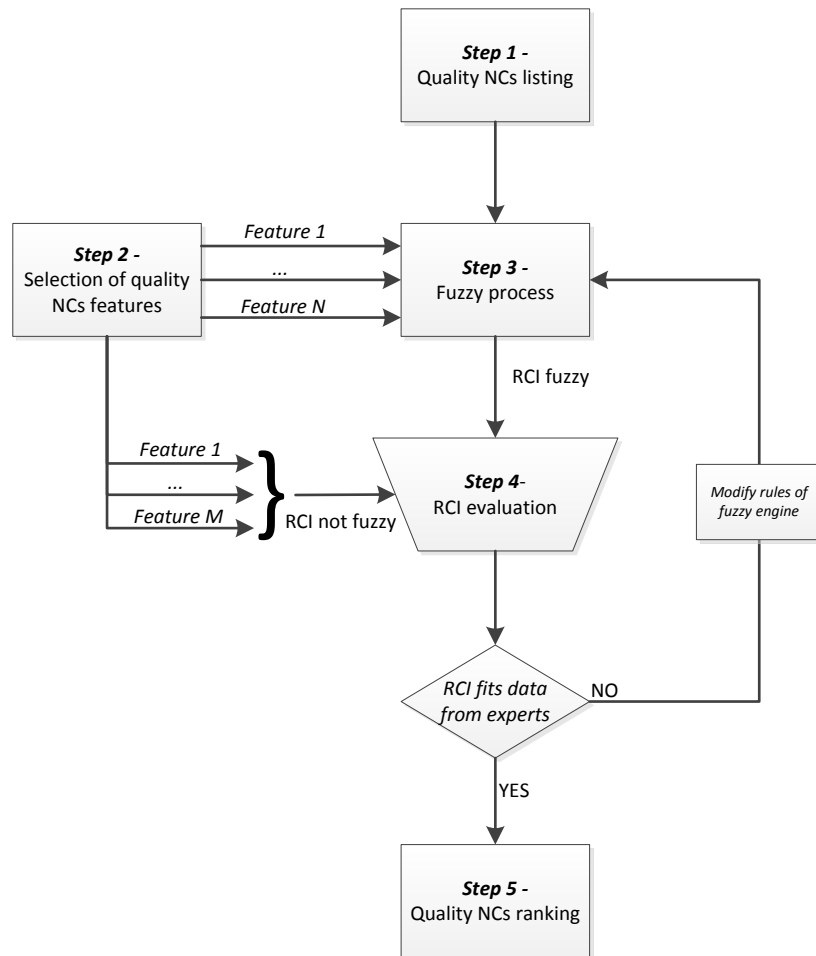


Figure 2 – Research methodology

The portion of research to answer RQ2 requires the development of a quality definition for NC gravity in the QMS. This goal was pursued by means of a Fuzzy Inference Engine (FIE). The main objectives are: i) to address the linguistic definitions used by NC auditors for classification and ii) to evaluate the gravity of the NCs for the QMS with *Ranking Criticality Index – RCI*. computed combining Risk Priority Number (RPN) of Failure Mode Effect Analysis (Yang et al, 2011; Bai and Yang, 2009) along with the approach of Liukkonen et al (2011).

In this portion of the research we are consistent with Brun et al. (2011), who ranked failures criticality and with Liukkonen et al.(2011) who developed an approach to rank the costs of poor quality and with the findings of Link and Naveh (2009) who demonstrated the importance of an effective NC ranking and a corrective and preventive action program to effectively solve NCs.

In our approach *RCI* is considered as function of the main factors on which an NC can impact (...), (cosa manca qui?), i.e. the *Cost* of the product, the *Probability* (è sempre una percentuale, ma io parlerei per chiarezza di “probabilità” o “frequenza”) of the defectiveness and the *NC Gravity*.

$$RCI = f(P, C, G, DP) = f(P, C, G \sum n_{occ@DP} * DP) \quad (1)$$

Where

- DP is the Detection Point, giving a measure of the NC gravity with respect to where, within the production process, the NC has been detected. (nella formula che segue penso che manchi un simbolo di appartenenza. Tra l'altro decidiamo uno standard per esprimere l'appartenenza ad un intervallo: più Avanti si usano duepunti, o trattino, o punto e virgola. Diciamo che “da uno a cinque” lo esprimiamo con il punto e virgola? [1; 5])

$DP \in [1 - 5]$

- $n_{occ@DP}$ is the number of occurrences of that NC for each DP.

The later the NC is detected, the higher is the contribution to increase RCI (...). The gravity scale for DP has been defined using the Likert five point-scale 1:5, usually used to assist practitioners for prioritizing service attributes when attempting to enhance service quality and customer satisfaction (Zhao et al, 2004; Al-Khalili and Subari, 2013) and for performances analysis (Deng and Pei, 2009). Table 1 reports the possible values proposed for DP within the NC analysis of the case study.

Dunque. Qui si spiega in dettaglio la tabella del DP (che peraltro viene poi ripetuta più Avanti.)

Forse conviene PRIMA dire che DP e gli altri parametri si comportano in modo diverso; quindi prima facciamo vedere come si attribuisce il valore (in scala 1-5) a DP, e poi facciamo vedere gli altri 3 con il motore fuzzy. Solo dopo questa premessa ha senso iniziare a descriverli.

DP value	Detection Point
1	Material acceptance
2	Along production line
3	Output quality gate of the production line
4	Final Quality Control
5	@ Customer

Table 1 – NC Detection points

The suitability of the fuzzy sets for linking linguistic definitions used by NC auditors to Costs, Percentage and Gravity classification (Figure 3) was suggested by its previous use in the QMS to process the audit data [25], [37] and to model uncertainty and the imprecision that results from the human mental phenomena [22].

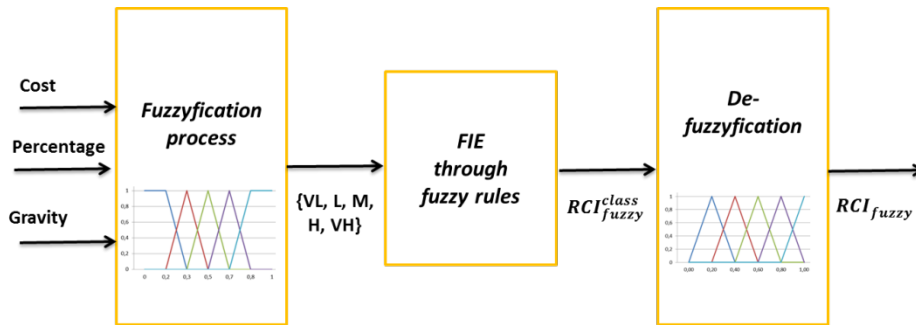


Figure 3 – Fuzzy Inference Engine

The FIE receives, in input, the classes shown in Figure 4, linked to C, P and G crisp values by triangular (attenzione – qui I temi sono un po’ mescolati. Il fatto che il MD sia triangolare lo citerei dopo, spiegandone le ragioni; qui dobbiamo trattare la procedura a più alto livello) membership degree (MD). The FIE is realised with the fuzzy toolbox of Matlab r2010a. FIA has been tuned with respect to the experimental data retrieved from the application case; its rules can be customised for the different industrial contexts in which it is applied. To design the FIE, we followed the empirical research results of Wiengarten and Pagel [42], who demonstrated that environmental (environmental? Questa citazione qui non c’entra nulla. Se vogliamo salvarla, eventualmente, va spostata in letteratura) practices can lead to high quality practices. In addition, we were consistent with the findings of Wu et al. [44], who interpreted QMSs as a source for competitive advantage. Ranges for each of the five fuzzy levels have been associated through the use of mixed trapezoidal-triangular functions (Figure 3) already used by Savino and Sekhari (2009) to model Quality NC evaluation and by Savino and Mazza (2013) to model linguistic evaluation of NC gravity.

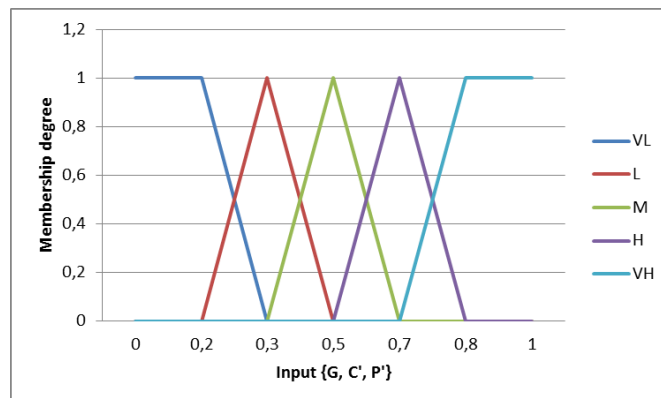


Figure 4 – MF and classes

5. Data development and results

The proposed methodology was tested by means of a set of Quality audits within the production line, in which around 1000 NCs have been detected and classified during a production period of six ????. Table 2 provides an example of the different types of NC detected.

<i>NC #</i>	<i>Description</i>
1	Welding error
2	Leak of hydraulic circuit
3	Scratches on panels
4	Non-compliant gauge
5	Wrong wiring
6	Wrong fastening of gasket
7	Not compliant hole

Table 2 – Types of NCs detected

NCs are analysed through the Risk Priority Number (RPN) by Failure Mode Effects Analysis (FMEA). In FMEA, the RPN encompasses three main characteristics of a failure, namely severity, occurrence and detectability (Yang et al., 2011) In the present approach we characterize an NC through the following basic features: (i) Percentage - P, (ii) Cost - C, (iii) Gravity – G and (iv) Detection Point – DP, defined as follows:

- *Percentage* – P, it addresses the incidence of that NC in a certain time period with respect to all the other ones.

It is evaluated by

$$\sum_{i=1}^n NC_i^j / NC_{tot} \quad (2)$$

qui

qui (o dopo) spiegare che il nostro approccio non è basato sulle NC ipotetiche o potenziali, e la loro probabilità di accadimento (anche teorica) ma sulla effettiva frequenza di accadimento riscontrata durante il period di osservazione.

Where NC_i^j is the number of occurrences of the NC^j and NC_{tot} is the total number of NCs occurred on the production lines

- *Cost* – C, is the production cost of the finished product affected by the NC;
- *Gravity* – G, is related to the perception and consequences of the non-conformity. G values can range from 0 if the defect is not detectable by the customer to 1 if the NC causes product disposal. Intermediate values

within the range [0,1] can be used, e.g. when the NC generates a certain degree of dissatisfaction to the customer

Detection Point- (tutto questo è già stato scritto prima. In effetti sembra che stia meglio qui) DP aims to give a measure of the NC detection. The basic concept is based on the finding of ... ; starting from material acceptance, up to the distribution chain, the concept is that the later the NC is detected, the higher is the associated criticality. Based on this concept, the scale for DP is taken from linear Likert five point-scale 1:5, as in surveys (surveys? Audits?) for quality management (Zhao et al, 2004; Al-Khalili and Subari, 2013) or for Importance-Performance Analysis (Deng and Pei, 2009), i.e. in assisting practitioners for prioritizing service attributes when attempting to enhance service quality and customer satisfaction. Table 3 gives the possible values of DP.

DP value	NC detection point
1	Material acceptance
2	Along production line
3	At Quality Control point
4	Product testing
5	Customer

Table 3 – DP values and detection points

5.1 Fuzzy Inference Engine

The Inferential rules of the FIE have been set through a survey in which five different quality managers (QM), provided their own values relative to the criticality of each NC, in the range [1-100] (vedi sopra. Quale standard usiamo?). Table 4 shows the values obtained from the survey.

NC Description	Auditor				
	Quality manager #1	Quality manager #2	Quality manager #3	Quality manager #4	Quality manager #5
Non- compliant gauge	20	15	25	20	20
Leak of idraulic circuit	50	60	40	50	40
Scratches on panels	65	60	60	50	65
Welding error	70	65	75	80	75
Wrong wiring	65	60	60	55	60
Wrong fastening of gasket	75	70	80	90	80
Not compliant hole	15	20	25	25	20

Table 4 – Criticality Survey results

(ho tolto la questione della distribuzione normale perchè mi sembra difficile da dimostrare) we adopted as value of criticality index the mean of the five different values given by the QM. Table 5 reports the values of each parameter and the corresponding value of the Criticality index

#	NC Description	Gravity [0,1]	Cost [€]	Occurrences - Detection Point					Criticality Index [1-100]
				DP1	DP2	DP3	DP4	DP5	
1	Non- compliant gauge	0,4	3,00	32					20
2	Leak of idraulic circuit	0,5	7,00		17	13			48
3	Scratches on panels	0,3	7,00				27		60
4	Welding error	0,2	3,00		47				73
5	Wrong wiring	0,9	9,95				20		60
6	Wrong fastening of gasket	0,5	13,00					4	79
7	Not compliant hole	0,3	6,00	10					21

Table 5 Output of the data processing

Input values of fuzzy functions for P and C, named P' and C', are obtained by dividing for the corresponding maximum values as follows:

- $P' = \frac{P}{P_{max}}$ where P_{max} represents the percentage of the most common NC observed by the firm in a given observation period;
- $C' = \frac{C}{C_{max}}$ where C_{max} represents the higher production cost among the finished products of the firm.

The fuzzyfication process works as follows:

- Values P and C of all NCs must be dimensionless, i.e. divided by the corresponding maximum ranges; by assuming $P_{max} = 4,2\%$ and $C_{max} = 13$, column P' and C' are obtained;
- According to G, P' and C' it is possible to evaluate the membership degree and the corresponding membership class. As an example, for the NC#1:
 - (qui occorre forse già fare un rimando / riferimento a fig.4) $G=0,4$ implies that this NC belongs to L class ($NC1G'_{class}=L$) with membership degree of 0,5 ($NC1G'_{md}=0,5$) and to M class ($NC1G''_{class}=M$) with membership degree of 0,5 ($NC1G''_{md}=0,5$);
 - $P'=0,50$ implies that the NC belongs to M class ($NC1P_{class}=M$) with membership degree of 1 ($NC1P_{md}=1$);
 - $C'=0,23$ implies that the NC belongs to VL class ($NC1C'_{class}=L$) with membership degree of 0,78 ($NC1C'_{md}=0,78$) and to L class ($NC1C''_{class}=L$) with membership degree of 0,22 ($NC1C''_{md}=0,22$).

Table 6 shows the fuzzy classes for all NCs, while in Table 7 the MD are shown

#	Non conformity description	Gravity -G	Percentage -P [%]	Cost -C [€]	P'	C'
1	Non- compliant gauge	0,4	<u>2,1</u>	<u>3</u>	0,50	0,23
2	Leak of Hydraulic circuit	0,5	<u>2,0</u>	<u>7</u>	0,48	0,54

3	Scratches on panels	0,3	<u>1,8</u>	<u>7</u>	0,43	0,54
4	Welding error	0,2	<u>3,1</u>	<u>3</u>	0,75	0,23

Table 6 – NC values (perché i valori di due colonne sono sottolineati?)

NC#	Gravity –G	MD and Class - G	P'	MD and Class – P'	C'	MD and Class – C'
1	0,4	NC1G' _{md=0,5} NC1G' _{class=L}	0,50	NC1P' _{class=M} NC1P' _{md=1}	0,23	NC1C' _{md=0,78} NC1C' _{class=VL}
		NC1G'' _{md=0,5} NC1G'' _{class=M}				NC1C'' _{md=0,22} NC1C'' _{class=L}
2	0,5	NC2G' _{class=M} NC2G' _{md=1}	0,48	NC2P' _{class=L} NC2P' _{md=0,05}	0,54	NC2C' _{md=0,77} NC2C' _{class=M}
				NC2P'' _{class=M} NC2P'' _{md=0,95}		NC2C'' _{md=0,23} NC2C'' _{class=H}
3	0,3	NC3G' _{class=L} NC3G' _{md=1}	0,43	NC3P' _{class=L} NC3P' _{md=0,4}	0,54	NC3C' _{md=0,77} NC3C' _{class=M}
				NC3P'' _{class=M} NC3P'' _{md=0,6}		NC3C'' _{md=0,23} NC3C'' _{class=H}
4	0,2	NC4G' _{class=VL} NC4G' _{md=1}	0,75	NC4P' _{class=H} NC4P' _{md=0,5}	0,23	NC4C' _{md=0,78} NC4C' _{class=VL}
				NC4P'' _{class=VH} NC4P'' _{md=0,5}		NC4C'' _{md=0,22} NC4C'' _{class=L}

Table 7 – MD values

Once variables P', C' and G have been fuzzyfied, one of the five fuzzy classes is associated to RCI_{fuzzy} , according to a set of fuzzy rules obtaining RCI_{fuzzy}^{class} . By fixing a class for G, fuzzy rules matrixes allow to get the class assignment for RCI_{fuzzy}^{class} according to membership classes of C' and P'.

The five matrixes are shown in Table 8a, 8b, 8c, 8d, 8e for gravity values VL, L, M, H, VH, respectively

P' \ C'	VL	L	M	H	VH
VL	VL	VL	L	M	H
L	VL	L	M	M	H
M	L	L	M	M	H
H	M	M	M	H	H
VH	M	M	H	H	H

Table 8a - Fuzzy rules - G=VL

P' \ C'	VL	L	M	H	VH
VL	L	L	L	M	H
L	L	L	L	M	H
M	L	L	L	M	H
H	M	M	M	H	H
VH	M	M	M	H	H

Table 8b - Fuzzy rules - G=L

P' \ C'	VL	L	M	H	VH
VL	L	M	M	H	H
L	L	M	M	H	H
M	M	M	M	H	H
H	M	M	M	H	H
VH	H	H	H	H	H

Table 8c - Fuzzy rules - G=M

P' \ C'	VL	L	M	H	VH
VL	M	M	H	H	H
L	M	M	H	H	H
M	M	M	H	H	VH
H	M	H	H	H	VH
VH	M	H	H	VH	VH

Table 8d - Fuzzy rules - G=H

P' \ C'	VL	L	M	H	VH
VL	H	H	VH	VH	VH
L	H	H	VH	VH	VH
M	H	H	VH	VH	VH
H	H	VH	VH	VH	VH
VH	H	VH	VH	VH	VH

Table 1e - Fuzzy rules - G=VH

The rules are aimed to weight: i) gravity, ii) frequency and iii) cost of NC, giving high priority to those NCs that generate high dissatisfaction in customers and that are most frequent. With respect to this principle, we started from a set of five master matrixes, which were modified to guarantee a good correspondence between experimental data (i.e. criticality index of Table xxx) and the output of the proposed model (i.e. RCI).As an example, we obtained the following implications:

- $\{G'=VH, P'=VL, C'=VL\}$ implies $RCI_{fuzzy}^{class} = H$;
- $\{G'=VL, P'=VH, C'=VL\}$ implies $RCI_{fuzzy}^{class} = H$;
- $\{G'=VL, P'=VL, C'=VH\}$ implies $RCI_{fuzzy}^{class} = M$.

With reference to the NC#1 of Table:

- The term $\{NC1G'_{class}=L, NC1P_{class}=M, NC1C'_{class}=VL\}$ implies $RCI1'^{class}_{fuzzy} = L$ with a membership degree $MD1' = 0,5 \times 1 \times 0,78 = 0,39$;
- The term $\{NC1G'_{class}=L, NC1P_{class}=M, NC1C''_{class}=L\}$ implies $RCI1''^{class}_{fuzzy} = L$ with a membership degree $MD1'' = 0,5 \times 1 \times 0,22 = 0,11$;
- The term $\{NC1G''_{class}=M, NC1P_{class}=M, NC1C'_{class}=VL\}$ implies $RCI1'''^{class}_{fuzzy} = M$ with a membership degree $MD1''' = 0,5 \times 1 \times 0,78 = 0,39$;
- The last term $\{NC1G''_{class}=M, NC1P_{class}=M, NC1C''_{class}=L\}$ implies $RCI1''''^{class}_{fuzzy} = M$ with a membership degree $MD1'''' = 0,5 \times 1 \times 0,22 = 0,11$.

Scenarios of remaining NCs are shown in Table 9

NC#	MD and Class – G	MD and Class – P'	MD and Class – C'	MD and Class – RCI _{fuzzy}
1	NC1G' _{md} =0,5 NC1G' _{class} =L	NC1P _{class} =M NC1P _{md} =1	NC1C' _{md} =0,78 NC1C' _{class} =VL	$RCI1'^{class}_{fuzzy} = L, MD1' = 0,5$
	NC1G'' _{md} =0,5 NC1G'' _{class} =M		NC1C'' _{md} =0,22 NC1C'' _{class} =L	$RCI1''^{class}_{fuzzy} = M, MD1'' = 0,5$
2	NC2G _{class} =M NC2G _{md} =1	NC2P' _{class} =L NC2P' _{md} =0,05	NC2C' _{md} =0,77 NC2C' _{class} =M	$RCI2'^{class}_{fuzzy} = M, MD2' = 0,26$
		NC2P'' _{class} =M NC2P'' _{md} =0,95	NC2C'' _{md} =0,23 NC2C'' _{class} =H	
3	NC3G _{class} =L NC3G _{md} =1	NC3P' _{class} =L NC3P' _{md} =0,4	NC3C' _{md} =0,77 NC3C' _{class} =M	$RCI3'^{class}_{fuzzy} = L, MD3' = 0,31$
		NC3P'' _{class} =M NC3P'' _{md} =0,6	NC3C'' _{md} =0,23 NC3C'' _{class} =H	$RCI3''^{class}_{fuzzy} = M, MD3'' = 0,14$

4	NC4G _{class} =VL NC4G _{md} =1	NC4P' _{class} =H NC4P' _{md} =0,5	NC4c' _{md} =0,78 NC4c' _{class} =VL	$RCI4_{fuzzy}^{class} = M, MD4' = 0,39$
		NC4P'' _{class} =VH NC4P'' _{md} =0,5	NC4C'' _{md} =0,22 NC4C'' _{class} =L	$RCI4_{fuzzy}^{class} = H, MD4'' = 0,11$

Table 9 – RCI values

5.2 RCI evaluation and Ranking

By assuming that one of the key Continuous Improvement issues is the management of the NCs and their intervention priorities [37], the potential prioritisation of NCs was investigated starting with the IG values and its related classes. Based on previous findings, the research uses the IG classes of VL, L, M, H, and VH once they are transformed into triangular MFs (Figure 5). The triangular MF that was used by Savino and Sekhari [32] in their QMS procedure was chosen because of its properties that priority variables with linguistic ones.

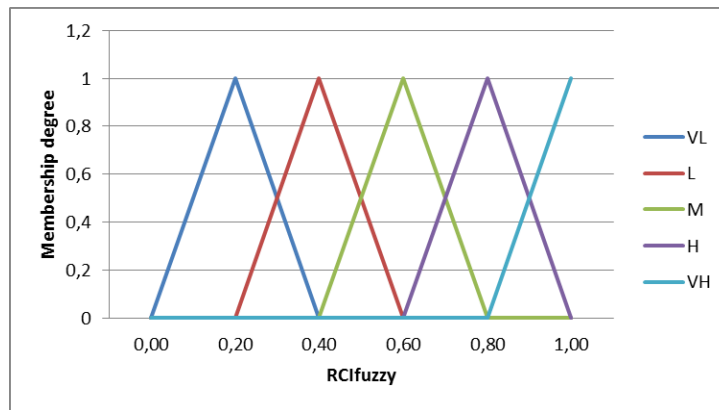


Figure 5 – MF for RCI_{fuzzy} value

Still referring to the example of NC#1 the de-fuzzyfication process that allows to obtain the crisp values works as follows

- $RCI1_{fuzzy}^{class} = L$ with the membership degree of 0,5 provides a partial contribution to the criticality index labeled as $CI' = 0,3$;
- $RCI1_{fuzzy}^{class} = M$ with the membership degree of 0,5 provides a partial contribution to the criticality index labeled as $CI'' = 0,5$;
- The overall priority number is obtained as the weighted average of the two contribution respect to the respective membership degree:

$$NC\#1 \rightarrow RCI_{fuzzy} = \frac{0,5 \times 0,3 + 0,5 \times 0,5}{0,5 + 0,5} = 0,40$$

Table 10 shows the RCI_{fuzzy} values for the all the NCs.

NC#	MD and Class – QPN_{fuzzy}	RCI_{fuzzy} value
-----	------------------------------	---------------------

1	$QPN1_{fuzzy}^{class} = L, MD1' = 0,5$	0,4
	$QPN1_{fuzzy}^{class} = M, MD1'' = 0,5$	
2	$RCI2_{fuzzy}^{class} = M, MD2 = 0,26$	0,43
3	$RCI3_{fuzzy}^{class} = L, MD3' = 0,30$	0,30
	$RCI3_{fuzzy}^{class} = M, MD3'' = 0,14$	
4	$RCI4_{fuzzy}^{class} = M, MD4' = 0,39$	0,51
	$RCI4_{fuzzy}^{class} = H, MD4'' = 0,11$	

Table 10 – RCI_{fuzzy} values

The assignment of the RCI as in (1) (che cos'è? Attenzione a numerazione formule) by considering the detection points DP and the RCI_{fuzzy} according to the relation (2):

$RCI = f(RCI_{fuzzy}, RCI_{notFuzzy}) = RCI_{fuzzy} \sum n_{occ@DP} * DP$ (2) (numero 2 per una formula era già stato usato. Numerare equazioni correttamente!)

Where $n_{occ@DP}$ is the number of occurrences of the NC at the given detection point DP. In this sense, DP is in charge to weight differently the term RCI_{fuzzy} referred to a certain NC according to the DP where such NC has been detected.

As an example, NC#1 has been detected along the production line (DP=2) and in a final delivery test (DP=4) providing $RCI = 2,4$. (ma questo non è coerente con la tabella 10!)

NC#	RCI_{fuzzy} value	Detection points					RCI	Criticality Index [1-100]
		1	2	3	4	5		
1	0,4	32					$0,4 \times 32 = 12,8$	20
2	0,43		17	13			$0,43 \times (17 \times 2 + 13 \times 3) = 31,39$	50
3	0,30				27		$0,30 \times 27 \times 4$	60
4	0,51		47				$0,51 \times 47 \times 2$	75

Table 10 – RCI values

According to the RCI thus obtained, it is possible to select NCs requiring priority attention defining a ranking which favors those NCs with the higher priority number. From table (?) we can see how NC#1 has the least criticality; more in details, it has a lower criticality with respect to NC#3 despite its higher RCI_{fuzzy} . This is due to detection points of NC#3 which increase RCI; more in general, detection points strongly impact on the overall criticality, modifying the ranking. If compared to the ranking imposed by the criticality index of the experimental case study, we can notice how our assessment is able to reflect the same criticality order through RCI. It is worth mentioning that differently from the

[1-100] scale of the criticality index, RCI can assume values higher than 100 (it has no upper bound) depending on the number of occurrences of the NC at the different detection points.

(non vogliamo provare a riscalarli 0-100?)

5. Discussions and managerial implications

The present work is intended to offer an integrated approach for a comprehensive assessment of quality NCs. It has been developed within an industrial case, where it has also been tuned and tested. Both membership functions and the FIE can be adapted in several industrial realities since they encompass quality features and indicators which are generally collected and monitored in a large variety of enterprises. The whole approach has been raised from a specific requirement related to the definition of an objective and flexible criteria related to NCs characterization and prioritization. In this sense, the present approach assigns to (i) *cost*, (ii) *percentage*, (iii) *gravity* and (iv) *detection point* the function of NC description and characterization. Table ... and table ... (NUMERARE) empirically support RQ1. The NCs are now analyzed along their lifecycle through the use of specific detection points, a fact that is usually neglected from current approaches present in literature. In answering to RQ1, we may argue that the detection points have to be included in a quality assessment since a different criticality can be assigned to a certain NC with respect to the related detection point, starting from material acceptance to customer delivering. Figure ... and table ... (NUMERARE) may give an answer to RQ2. The four features have been combined in accordance to a fuzzy logic and following the work of Liukkonen et al. (2011) in obtaining an RCI. Such RCI is in charge to assess a given NC and define an overall ranking for an intervention priority answering to our second research question and being consistent with the importance of NC ranking to effectively solve NCs stated by Link and Naveh (2009). An interesting aspect of the proposed assessment relies in its dynamicity and flexibility. By appropriate changes on the FIE, it has the possibility to update and modify NCs ranking in different industrial environments. Such changes can have different impacts on production costs, improvement or worsening of quality performances or production mix with the introduction or elimination of products or other changes in the production process. In those cases, by simply updating variables boundaries it is possible to adapt the assessment to the new modified environment. As an example, C_{\max} is dependent on firm production mix and market conditions which can modify production costs by the introduction of new machines or additional management costs, while P_{\max} depends on the ability of the firm to properly deal with NCs in reducing such factor, measuring quality performances. In this way, a continuous updating of fuzzy functions boundaries according to the data collected in the firm allows to modify NCs ranking configuring the assessment as a dynamic quality approach following the continuous improvement theory.

In addition, from eq. (2) (check numerazione) it is clear that an important contribution to *RCI* is provided by the detection points due to their weight. As an example, an NC with high production cost, high percentage and high gravity but detected in raw material acceptance (DP=1) will be ranked below an NC with a low production cost, low percentage and low gravity but detected by the customer (DP=5). As anticipated in section 3, the work is consistent with process control oriented and reactive QC approaches (Lou and Huang, 2003), i.e. it stresses the importance to anticipate the detection of NC along the stages of product lifecycle for reduction of criticality by avoiding the NC propagation toward the customer. Clearly, the proposed methodology is still based on an ex-post NC analysis once it is revealed and detected. However it is able to support an intervention priority where corrective actions must be mainly aimed to anticipate detections through more appropriate quality gates.

6. conclusions. Mettere in questa sezione (breve): meriti del paper (in cosa abbiamo innovato), limiti (da discutere con franchezza), sviluppi futuri.

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