AARHUS UNIVERSITY
UNIVERSITY OF CAMBRIDGE
PMA
WWW.PERFORMANCEPORTAL.ORG

CONFERENCE PROCEEDINGS

PERFORMANCE MANAGEMENT:
DESIGNING THE HIGH-PERFORMING ORGANIZATION

25-27 JUNE 2014, AARHUS, DENMARK

PMA2014

CONFERENCE PROCEEDINGS

0014	THE USES OF MEASURES IN PERFORMANCE PRISM IN DIFFERENT ORGANIZATIONAL CULTURES	Unchan Youngbantao, Nopadol Rompho
0015	When does it pay to be good? - Moderators and Mediators in the Corporate Sustainability Performance - Corporate Financial Performance Relationship: A Review	Sylvia Grewatsch, Ingo Kleindienst
0016	A English handbell ensemble resonate you more by strategic consulting (Practical application)	Yasunori Mori, Taiko Ohtsubo, Eri Koyama, Reina Endo, Daisuke Fukuhara
0017	Dynamic system crisis's detecting using big data flow	Svetlana Maltseva, Andrey Dmitriev
0018	DUALITY SOLUTION IN PLS SATISFACTION SURVEYS	John Vestergaard Olesen, Jacob Kjær Eskildsen
0019	Analysis of visualization techniques supporting performance measurement process	Aki Jääskeläinen, Juho-Matias Roitto
0020	Corporate sustainability reports in the apparel industry: An analysis of reported indicators	Anika Kozlowski, Michal Bardecki, Cory Searcy
0022	Life Long Lean Learning – Case Sweden	Raine Isaksson, Rickard Garvare, Mikael Johnson, Christer Kuttainen, Jörg Pareis
0023	PERFORMANCE MEASUREMENT EFFECTS ON ORGANIZATIONAL RESPONSES TO THREATS	George Huber
0024	Enhancing Prioritisation of Technical Attributes in Quality Function Deployment	Zafar Iqbal, Nigel Grigg, K Govindaraju, Nicky Campbell-Allen
0025	Relevance and Responsibility: Obligatory Components in Commercial Innovation	Gregory H. Watson
0027	Current Trends in Strategic Management and Performance Measurement	Michaela Blahova, Parissa Haghirian, Premysl Palka
0028	Employee job satisfaction and quit behavior	Anders Frederiksen
0029	Performance Measurement System design: Developing a new system for Danish emergency departments.	Anders Møllekær, Jacob Eskildsen
0030	Ultra-organizational Co-opetition Dynamics: Designing micro-foundations of organizational performance	Audrey Depeige, Stavros Sindakis, Konstantinos Biginas
0031	Managing Inter-Organizational Networks for Customer Value: Constructing Networks in the Experience Economy	Jean-Paul Peronard

0033	Management Tools for the New Workplace	Lukas Michel
0034	An empirical evaluation of a sustainable strategy model	Ole Friis, Jacob Eskildsen, Jens Holmgren
0035	Increasing flexibility and performance orientation with Relative Performance Contracting	Franz Wirnsperger
0036	Exploring the Impact of National Culture on Performance Measurement (PM)	Ihssan Jwijati, Umit Bititci
0037	The service of performance measurement of public service	Christian Lystbaek
0039	Disciplined Collaborative Performance as the Road to Results	Mary Jo Hall
0040	The crippled bottom line - measuring sustainability	Raine Isaksson, Rickard Garvare, Mikael Johnson
0041	Inter-organizational knowledge transfer as a driver of network performance	Harri Laihonen, Sanna Pekkola
0042	Impacts of Unified Communications on Work	Joseph Williams, Ryan LaBrie, Gerhard Steinke, Al Erisman
0043	Triple Bottom Line and Firm's Sustainable Performance Measurement	Flavio Hourneaux Junior, Marcelo Gabriel, Dolores Gallardo-Vázquez
0044	Role of performance measurement in developing industrial services	Sanna Pekkola, Minna Saunila, Tero Rantala, Juhani Ukko
0045	Exploring Performance Measurement Systems in a Service Context	Juhani Ukko, Sanna Pekkola, Oona Takala, Hannu Rantanen
0046	Multi-level strategic alignment within a complex organisation	Gavin Lawrie, Nur Anisah Abdullah, Christopher Bragg, Guillaume Varlet
0047	Beyond Performance Measurement: Contribution Measurement	Farhad Shafti
0049	Divide and conquer? Integration and firm performance in the newspaper industry	Tor Bøe-Lillegraven, Paulina Junni
0050	Performance management systems in universities: do governance structures matter?	Ana I. Melo, Cláudia S. Sarrico, Zoe Radnor
0051	Growth and Impact of Performance Engineering in the U.S. Government	David Paschane
0055	From Belts to Baldrige - A Case Study	Charles Aubrey
0058	Exploring Lean deployment in New Zealand apple pack-houses.	Johan Theodoor Doevendans, Nigel Grigg, Jane Goodyer

0059	Grand Global Challenges in Relation to Superior and Sustained Enterprise Performance & Impact	Rick Edgeman
0063	Developing a neuropsychological measurement instrument to capture working-environment	Yvonne Lagrosen, Fred Travis
0064	What about municipal strategic management and preformance measurement	Krister Bredmar
0065	Evidence for the Performance Prism in Higher Education	Stacy Smulowitz
0066	Designing the approach for assessment the implemented Performance Management Systems	Tarmo Kadak
0068	Lean target communication in SMEs	Carina Larsson, Kristina Säfsten, Anna Syberfeldt
0071	Using guest feedback for improving performance in a hotel	Joachim Sandt, Christoph Hoffmann
0072	Culture and management styles' influence on PMS's lifecycle.	Fateha Shaheen, Sai Nudurupati, David Petty
0073	Accelerating a Company's Sustainability Performance through a Safety, Health and Environmental Culture	Cathy Hansell
0074	Measurement Beyond Financial Performance: Security and Privacy	Barbara Krumay, Stefan Bauer, Sebastian Margiol
0075	Synergetic effects of performance concepts on financial performance of companies	Adriana Knapkova, Drahomira Pavelkova, Lubor Homolka
0076	Future of Performance Measurement and Management: an Empirical Evidence	Sai Nudurupati, Patrizia Garengo, Umit Bititci
0077	Strategic decisions creation-implementation process: An empirical study	Samer Abdulhadi, Andrey Pavlov
0078	Uncertainty assessment of performance indicators	Marcello Cavallare, Sergio Sousa, Eusébio Nunes
0079	How managers use performance measurement in strategy making	Gillian Pratt, Mike Bourne

0080	Review of Factors Affecting Performance Measurement System Implementation	Heather Keathley, Eileen Van Aken
0081	Chronology of the Organizational Performance Measurement Research	Julio Carneiro da Cunha, Flávio Hourneaux Jr., Hamilton Corrêa
0083	Extended enterprise performance management: a value co-creation perspective	Wilma (M.L.) Bobbink, Andreas Hartmann
0084	Integration of Sustainable Development Goals (SDG) in Measures for Sustainability Performance in Corporate Value Chains reported to Multi-stakeholder Standards	Thomas Kjærgaard
0085	Performance Measurement Systems and Organisational Performance: literature review	Magdalena Partac, Lester Lloyd-Reason, Francis Greene
0090	Sustainability Assessment Vs Building Performance; an Innovative Review	Fodil Fadli
0091	Managing Organizational "fit" for Successful Service Alliance	Bianca Keers
0092	The Role of Performance-Driven Behaviour in the High Performance Organisation	André A. de Waal, Béatrice I. J. M. van der Heijden
0093	New Organisation Forms and Reorganisation in a Modern World	Børge Obel
0095	Variations in the Circumplex Model of Affect Across Contexts	Dan Mønster, Jacob Kjær Eskildsen, Dorthe Døjbak Håkonsson, Børge Obel, Richard Burton, Linda Argote

BEST PAPER AWARDS

BEST PAPER

Impacts of Unified Commucations on Work

Joseph Williams, Albert Erisman, Ryan LaBrie, Gerhard Steinke

BEST PAPER IN INNOVATION

The Benefits of Taking a Radical Approach to Continuous Innovation

Jacob Brix, Lois Peters

BEST PAPER IN SUSTAINABILITY

The Crippled Bottom Line - Measuring Sustainability

Raine Isaksson, Mikael Johnson, Rickard Garvare

0078

UNCERTAINTY ASSESSMENT OF PERFORMANCE INDICATORS

MARCELLO A. L. CAVALLARE, SERGIO D. SOUSA, EUSÉBIO P. NUNES

Uncertainty assessment of performance indicators

Authors

Marcello A. L. Cavallare[1*], Sergio D. Sousa[1], Eusébio P. Nunes[1]

[1]Centro Algoritmi, University of Minho, Campus de Gualtar, Braga, Portugal

*malc@dps.uminho.pt

Abstract

Purpose: This paper defines a model to evaluate the uncertainty in performance indicators (PIs) based on Uncertainty Components (UCs).

Methodology: The proposed work consists, in a first stage, of an assessment of the level of influence that each UC has in a given PI. Based on the questionnaire responses a matrix of UCs *vs* PIs is presented to show the relevance of the contribution of each UC to the uncertainty associated with a PI. The second stage of the methodology consists on the development of a model to infer the uncertainty level on a PI based on the uncertainty level of the identified UCs.

Findings: A questionnaire referring to the assessment of PIs was applied, and the results provide evidence that UCs influence the PI. A model was developed based on logical relations between the UCs and the overall PI uncertainty, and the number of empirical analyses contribute to validate it.

Originality/value: This paper presents a model to infer the uncertainty level of a PI based on UCs. The model can also be applied to propagate uncertainty among multiple related PIs. UCs definitions can guide the development of actions to reduce uncertainty in PIs, thus reducing the risk in the decision-making process.

Keywords

Uncertainty, performance indicators, uncertainty components, fuzzy logic

1. Introduction

Organizations have the need to process information to express measurements at different levels of management. For this, performance measures systems (PMSs) are used that provide performance indicators (PIs) to measure organization's performance (Verweire & Berghe, 2003).

PIs can be considered a particular type of information and some authors suggest several classifications of Information/Data Quality (Lee & Wang, 2002). Requirements associated with the design, implementation and use of PIs have been proposed in the literature (Bourne, Mills, Wilcox, Neely, & Platts, 2000), but may not be fulfilled, causing uncertainty on the "true" value of a PI. In the traditional formulation of a PMS, most PIs are affected by uncertainties.

Galway and Hanks (2011) classify the quality problems of PIs as operational, conceptual and organizational. PIs are often associated with multidimensional concepts that may be considered as sources of uncertainty on its value. In this approach, the dimensions are identified according to the specific application contexts. For example, O'Reilly (1982) uses the accessibility, accuracy, specificity, timeliness, relevance and amount of data to evaluate the PI in the context of decision-making. Ballou and Pazer (1985) employ the accuracy, timeliness, completeness and consistency modeling deficiencies of the PI.

A variety of methods are proposed to evaluate the PI. These methodologies can be categorized as objective evaluation and subjective evaluation (Pipino et al., 2002). The objective evaluation makes use of software as a tool to measure the PI as a set of rules for the quality. The methodologies for subjective evaluation are based on the veracity of the information for use and use surveys and interviews to assess the PIs.

Sousa, Nunes and Lopes (2012) propose a set of seven Uncertainty Components (UCs) that may affect PIs. These UCs are Measurement Method, Precision and Accuracy, Human Assessment, Data Collection, Definition/Measuring, Environment and PIs Aggregations.

Generally, each PI is represented by a value (number) that is unable to represent uncertainty. The problem addressed in this work is to assess the uncertainty of PIs. Associated with problems of operational data there is an implicit assumption that, if the data are correct, the user can use them directly in making decision (Lopes, Sousa, & Nunes, 2013). The inability to cope with this uncertainty results in simplified models of reality that may increase the risk of decision-makers.

This paper is organized as follows. Section 2 describes a comprehensive methodology of assessing of PI. Section 3 presents a case example to demonstrate the propose approach. Section 4 presents some concluding remarks.

2. METHODOLOGY

The proposed work consists of a methodology comprised of five steps. The first step assesses the degree of influence that each UC has on the PI uncertainty. The second step evaluates the overall uncertainty present in the PI. The third phase, is created the input and output variables which receive the result of the influence of the UC in PI uncertainty. A fourth step is defined by the creation of rules for treatment of input and output variables and the fifth step, provides an estimate of PI uncertainty. The Figure 1 summarizes the stages of the model.

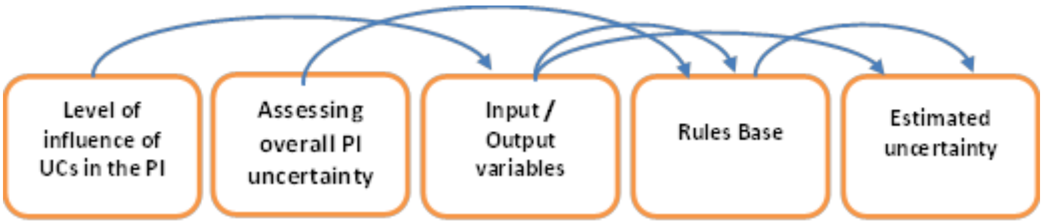

Fig. 1. Steps in the evaluation of PI

2.1. Level of influence of the UC in PI

This step starts with the presentation of the study to the specialist contacted the company, and the definition of a PI by the specialist, who will be assessed. To evaluate the influence of each UC on the PI uncertainty a questionnaire was developed and is used to guide semi-structured interviews. The questionnaire presents UCs that are the basis for the survey responses. The assessment questionnaire uses a Likert scale with three levels (Without/NA, Some or Much) that is designed to assess such influence. For a given UC, higher number of responses at the highest level of the uncertainty means that the component strongly influences the PI uncertainty.

Subjective criteria and expectations of the questionnaire responses vary from person to person; each user generates an individual report. Therefore, in the analysis phase of the PI, the results of the subjective evaluation of multiple users need to be coordinated, because, when there is no coincidence of responses among raters for the same IP rated, the choice should be made by using the consensus of the evaluators or doing choosing the worst scenario for the PI reported.

2.2. *Assessing overall PI uncertainty*

The general perception of uncertainty in the PI is also recorded in the questionnaire using a five-point scale. This provides a means to capture the uncertainty through experts' perception that designed and/or use the PI.

Based on the questionnaire responses a matrix of UCs vs PIs is presented to show the relevance of the contribution of each UC to the uncertainty associated with a PI.

2.3. *Input / Output variables*

This stage of the methodology consists on the development of a model to infer the uncertainty level of a PI based on the uncertainty level of the identified UCs. To treat the questionnaire answers the method was based on Fuzzy Logic Theory since it allows dealing with uncertain, qualitative, and in some cases, contradictory data. The concept of linguistic constant is very useful in dealing with situations that are complex or not well-defined to be reasonably described by conventional quantitative or numerical expressions.

In this work, the uncertainty present in the PI is defined by linguistic constants given by the questionnaire responses (High, Low and Without). For treating the linguistic constants fuzzy set methodology was used.

The fuzzy method is fed with normalized input variables. Normalization is defined from the linguistic constants of table Ucs *vs* PI previously generated. The first input variable is defined as Relevant Components (RC), it describes the sum of UCs with answers that have value "High" answered in the questionnaire, the second input variable is defined as Influent Component (IC) the second variable, which is set to receive the value of the sum of the Ucs answered "Low" uncertainty.

2.3.1. Fuzzy logic method

In order to solve the problem of the evaluation of PI through the fuzzy logic approach, the following operations are performed (Figure 2):

- Definition of the fuzzy set of the input and output variables (*fuzzification*);
- Definition of the rules that correlate the input and output variables (Fuzzy Rule Base);
- *Defuzzification* of the results.

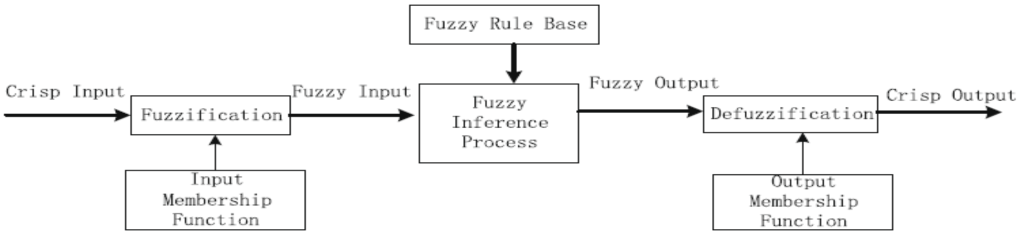

Fig. 2. Stages of Fuzzy Logic

Source: Li et al. (2010)

2.3.2. Definition of the membership function of the input and output variables *(fuzzification)*

For each input variable, the fuzzy set generates a normalized range of values between [0,7]. This range is due to the maximum number of UCs. In each input variable fuzzy sets are represented by a membership function element (MFE) triangular or trapezoidal. The choice of the type of membership function and number of elements depends on the characteristics of the available data. In order to make a general procedure a number of five MFEs is considered appropriate to use in fuzzy sets (Very Low, Low, Medium, High and Very High).

Tables 1 and 2 presents the definition of the range for each membership function elements of the input variables RC and IC respectively.

Table 1. Membership function elements – input variable RC (Relevant components)

MFE	Range
Very Low	(0; 0; 0.5)
Low	(0.25; 0.65; 1.0)
Medium	(0.75; 1.25; 1.65)
High	(1.25; 1.75; 2.25)
Very High	(2.0; 2.5; 7; 7)

Table 2. Membership function elements – input variable IC (Influent components)

MFE	Range
Very Low	(0; 0; 1.5)
Low	(0.5; 1.5; 2.5)
Medium	(1.5; 2.5; 3.5)
High	(2.5; 3.5; 4.5)
Very High	(3.5; 5; 7; 7)

The references of the membership function elements for defining fuzzy set are show in Figures 3 and 4.

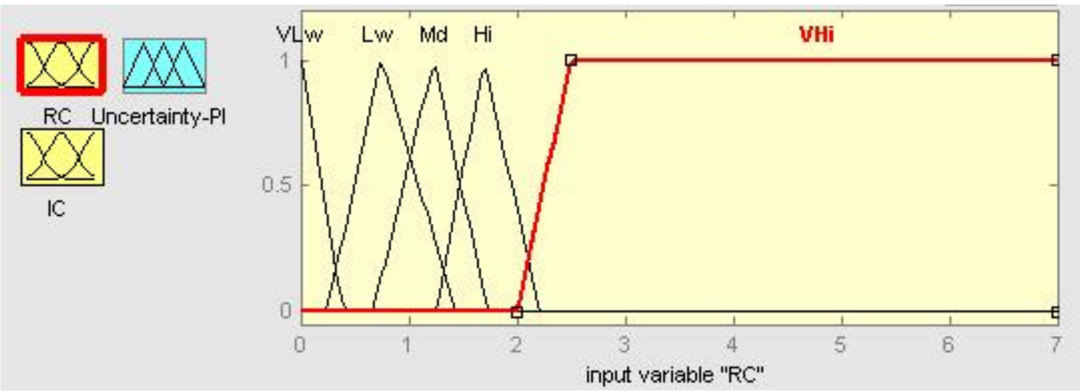

Fig. 3. Membership function elements – input variable RC

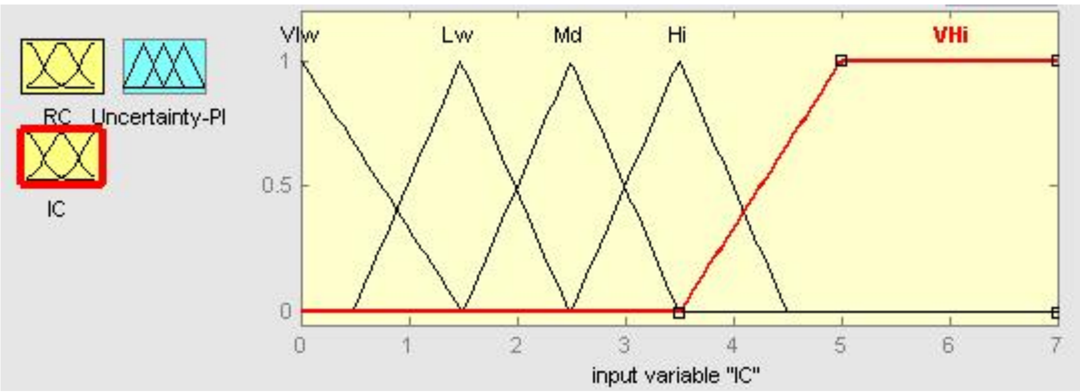

Fig. 4. Membership function elements – input variable IC

For the output variable it is defined a fuzzy set in a range that varies between [0 -100]. The use of this interval defines clarity in the outcome area facilitating the data interpretation. The form of representation of the output variable is triangular or trapezoidal. Table 3 shows the definition of the range for the MFE and Figure 5 graphically shows the output variable "Uncertainty".

Table 3. Membership function elements – output parameter Uncertainty

MFE	Range
Very Low	(0; 0; 15)
Low	(10; 22.5; 35)
Medium	(30; 40; 50)
High	(45; 56.5; 70)
Very High	(65; 80; 100; 100)

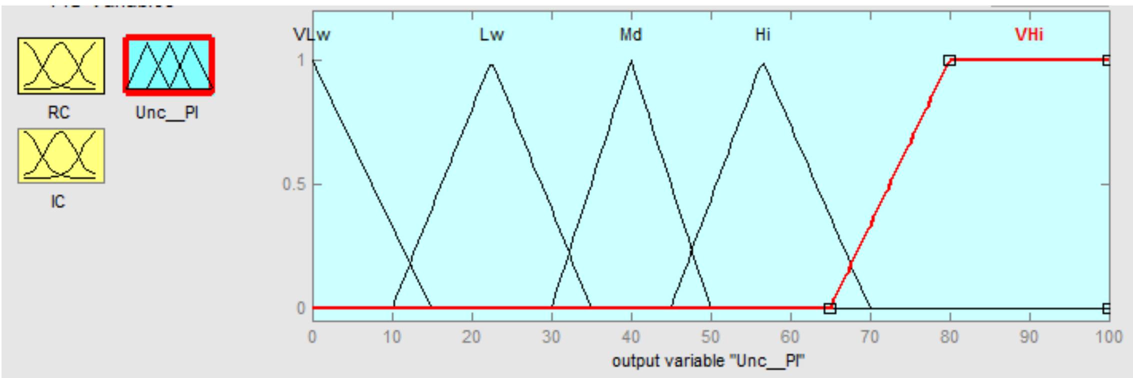

Fig. 5. Membership function elements – output variable Uncertainty

2.4. Definition of the rules that correlate the input parameters to the output (Fuzzy Rule Base)

The fuzzy rules represent the logic correlation between the input and output parameters. They correspond to decisions "if… then", on the premise that the consequences of decisions occur only if the premise is true.

Logical operations between terms of MFE can be made through the operators AND or OR.

If fuzzy logic uses the logical operator AND, the maximum number of rules is equal to m^n, where n = number of input variables and m = the number of fuzzy sets for each of the input parameters (Zadeh, 1965). In this case, the number of rules generated for the fuzzy logic is 25, where: n = 2 (RC and IC) and m = 5 (VeryLow, Low, Medium, High, VeryHigh).

Table 4 presents the rules are defined for the logical operations between terms of MFE.

Table 4. Fuzzy Rule Base

RC / IC	VLw	Lw	Md	Hi	VHi
VLw	VLw	Lw	Lw	Md	Hi
Lw	Lw	Lw	Lw	Md	Hi
Md	Lw	Lw	Md	Hi	VHi
Hi	Md	Md	Hi	Hi	VHi
VHi	Hi	Hi	VHi	VHi	VHi

2.5. Estimated uncertainty

The evaluation of uncertainty in PI using the fuzzy logic approach can be described by different rules. The final result is determined by adding each rule. This adding depends on the aggregation fuzzy inference process of (FIP) adopted. This study is based on the Mamdani method (Mamdani, Assilian, 1975). They claim that, as the degree of truth of assumptions and the minimum correlation method, each active rule is a part of a specific set of fuzzy output. Thus, the result of the fuzzy problem is the union of several portions of areas activated at the same time (Zadeh, 1965). The result is obtained by the union of several portions of selected areas. The defuzzification method used to extract the results is the centroid method. In particular, the Mamdani FIP associated with the centroid method of defuzzification is the most appropriate technique to solve a widespread and pervasive problem (Cammarata, 1994).

3. CASE STUDY

3.1. Context

Companies were contacted to participate in the evaluation study of uncertainty in PIs. As a result 5 companies have shown themselves willing to participate. The next step consisted of a semi-structured interview based on a questionnaire with the person responsible for designing or using a given PI. The interviewee provides his perception about how UCs affect the uncertainty of the PI.

When the interviewee has full confidence in the PI, and the PI is well defined, it uses the option *Without / NA*, this means that the PI has no uncertainty or this component does not apply to PI reported. When the user realizes that the PI contains some uncertainty, he uses the *Some* or *Much* to define what level of uncertainty that exists in PI. After the interviewee has answered the seven UCs, he completes the questionnaire evaluating overall the PI, providing his general perception of the PI uncertainty using a five-point scale.

3.2. Data Results

The questionnaire was applied to seven persons referring to seven PIs, and results provide evidence that the UCs influence PI. A brief summary of seven PIs is presented in table 5.

Table 5. Evidence that the UCs influence PI

Uncertainty components (UC)	Frequency index	Number of days without accidents	Incident Tickets close	Time to Resolve	Quantity produced	Capacity Utilization days	Overall Equip. Effectiveness
Measurement method	High	High	Without	Low	Low	NA	Low
Precision and accuracy of measurement	Without	Low	Without	Without	Low	Low	Low
Human assessment	Low	Low	Low	Low	Low	NA	NA
Data collection	High	High	High	High	Without	Low	High
Definition / Measuring	Low	Low	Low	Low	Low	Low	Low
Environmental	Low	Low	Low	Without	Without	NA	NA
IDs Aggregating	Low	Low	Low	Low	Without	NA	NA
PI overall uncertainty perception	**High**	**High**	**Low**	**Low**	**Low**	**Low**	**Low**

The model is based on logical relation between the UCs and the overall PI uncertainty, and the number of empirical analysis contributes to validate the proposed model.

Completed the stage of data gathering and the creation of the matrix the next step is the treatment of the data presented in the matrix. To evaluate the PIs it was used software (Matlab v. 8) that possesses a tool to treat linguistic constants using the fuzzy logic method.

Based on the matrix (Table 5), treatment was made for each individual PI, to assess the level of uncertainty through the model studied. A structure was created with two input variables RC and IC to receive the total sum of the values that each of these two variables is answered in the questionnaire and the output variable (defuzzification) shows the level of uncertainty present in the PI. The results obtained in the output variable are defined by the set of rules (FIP).

The Figure 6 shows the model used for treatments of language constants through the fuzzy method.

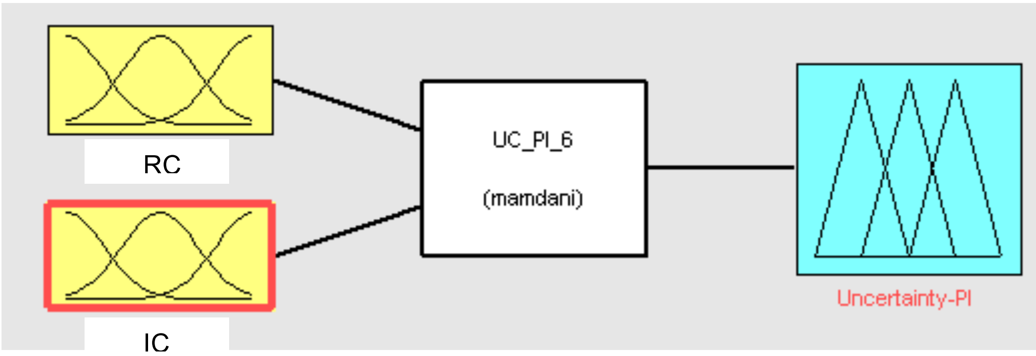

Fig. 6. Model used for treatment of uncertainty in the PI

This study used ten performance indicators proposed by companies that participate in the study. These are indicators used by business managers from various areas and, some them, simultaneously, as element to meet legal requirements. Then a brief discretion of two indicators are presented and the evaluation result of the uncertainty in PI.

Assessment of PI - Frequency Index

The PI *Frequency index* represents the number of absences of employees in a given period of time. To the respondents the overall evaluation the PI has a high level of uncertainty.

Observing Table 5 the PI has four UCs classified as "Low" and two UCs classified as "High" and one a UC with the answer "Without". With these results the RC input variable is assigned with the value 2, which corresponds to a value of “High” according to Table 1 and Figure 3, and the IC input variable, is assigned the value 4 which corresponds to a value of High / Very High, according to Table 2 and Figure 4.

With the values of variables RC and IC assigned, the method is applied for assessment of uncertainty based on the rules defined (Table 4) as the report is show in Figure 7.

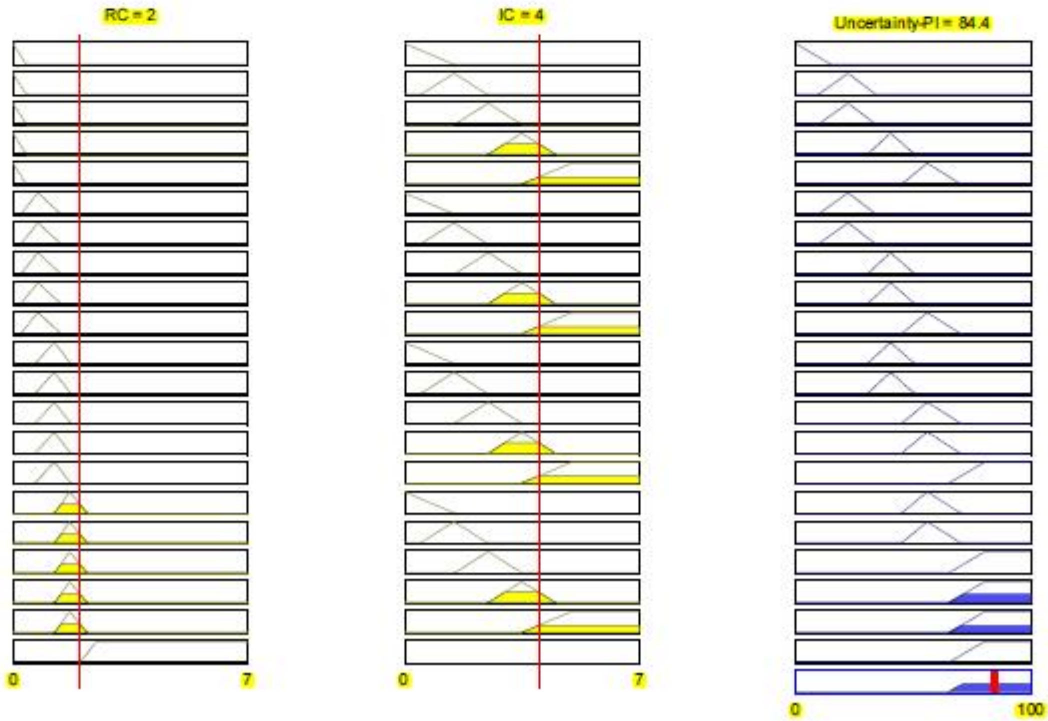

Fig. 7. Results of the evaluation obtained by the fuzzy logic method

Based on RC=2 five inference rules were positioned in "High" (Figure 2). Similarly for IC=4 eight inference rules were active representing the function elements "High" and "Very High" (Figure 3). The result shows an uncertainty level of 84.4 (0 to 100 scale) or a linguistic term of Very high.

Based on the overall evaluation of the PI provided by the respondent apparently, the result obtained by the proposed method was similar to the interviewee where both refer to the presence of uncertainty in the PI as being of “high” to “very high” uncertainty.

Applying the method presented in other PIs in Table 5 we obtain the results shown in Table 6.

Table 6. PIs uncertainty level

PI name	RC	IC	Uncertainty %	Global evaluation method	Global assessment of the expert
Number of days without	2	5	84.6	Very High	High

accidents					
Incident Tickets close	1	4	71.8	Very High	High
Time to Resolve	1	4	71.8	Very High	Low
Quantity produced	0	4	48.4	Medium / High	Low
Capacity Utilization days	0	3	30.2	Low / Medium	Low
Overall Equipment Effectiveness	1	3	49.7	Medium / High	Low

3.3. Analysis and discussion of results

Analyzing Table 5 resulting from the questionnaires applied in different areas and companies, shows that the influence of UCs has different weights according to the PI reported. This happens because of a strong subjective component of evaluations or judgments by experts. Different interpretations of concepts influenced by social or cultural issues introduce uncertainty and complicate the assessment of PIs.

One aspect to note is that in the evaluations in some cases when respondents are not convinced of the uncertainty in PI a particular UC, he replies that this uncertainty is low.

In general, the results are obtained directly through basic steps of diagnostic expert, with significant and subjective data, collected over a period of structured work processes.

Figures 6 and 7 represent the level of uncertainty associated with the data and contextual factors in PIs. They represent the result of a measurement of PI which can also be seen as a tool for decision support to the management, suggesting a revision of the PI to improve the data quality.

4. CONCLUSIONS

This paper presents a model to infer the uncertainty level of a PI based on analysis of UCs. The model is based on the logical relationship between PIs and the uncertainty of PI where, the first step of this study begins by presenting the level of influence that the uncertainty components (UCs) has on the performance indicators (PIs), the following was done to develop a method based on fuzzy logic approach to assess quantitatively PIs uncertainty.

Through the case studies evidence suggests that: i) PIs are affected by various components of uncertainty previously defined; ii) PIs uncertainty can be estimated by a model based on Fuzzy Logic; iii) UCs definitions can guide the development of actions to reduce uncertainty in PIs, thus reducing the risk in the decision-making process.

This work is part of a larger project that aims propose study evaluation method of PIs uncertainty.

AKNOWLEDGMENTS

This work was financed with FEDER Funds by Programa Operacional Fatores de Competitividade – COMPETE and by National Funds by FCT – Fundação para a Ciência e Tecnologia, Project: FCOMP-01-0124-FEDER.

REFERENCES

Ballou, D.P., Pazer, H.L. (1985). Modeling Data and Process Quality in Multi-input. Multi-output Information Systems. Management Science 31(2), 150–162

Bourne, M.C., Mills, J.F., Wilcox, M., Neely, A.D., & Platts, K.W. (2000). Designing, implementing and updating performance measurement systems. *International Journal of Operations & Production Management, 20*(7), 754-771.

Cammarata, S. (1994). Sistemi fuzzy: un'applicazione di successo dell' intelligenza artificiale. Milano: Etaslibri.

Galway, L. A., & Hanks, C. H. (2011). "Classifying Data Quality Problems." Information and Data Quality Newsletter 7(4): 1-3: IAIDQ's Information and Data Quality Newsletter 7(4): 1-3.

Kahn, B., Strong, D., Wang., R.Y. (2002). Information Quality Benchmarks: Product and Service Performance. Communications of the ACM 45(4), 184–192

Lee, Y. W., D. M. Strong, Beverly K. Kahn, & Wang, Richard Y. (2002). "AIMQ: a methodology for information quality assessment.": Information and Management 40(2): 133-146.

Li P., Chen G., Dai L., Zhang L. (2010). Fuzzy logic-based approach for dentifying the risk importance of human error. Journal Safety Science. 48, 902 – 913.

Lopes, I. S., Sousa, S., & Nunes, E. (2013). *Quantification of uncertainty of performance measures using graph theory*. Proceedings of XI Congreso Galego de Estatística e Investigación de Operacións, Coruna, Spain, 24-26 October 2013, pp264-269.

Mamdani, E. H., & Assilian, S. (1975). An experiment in linguistic synthesis with a fuzzy logic controller. International Journal of Man-Machine Studies, 7(1), 1–13.

O'Reilly III, C.A.(1982). Variations in Decision Makers: Use of Information Source: The Impact of Quality and Accessibility of Information. Academy of Management Journal 25(4), 756–771

Pipino, L., Lee, Y.W., Wang, R.Y. (2002). Data Quality Assessment, Communications of the ACM. Communications of the ACM. 45(4), 211–218

Pipino, L., Lee, Y.W., Wang, R.Y.: Data Quality Assessment, Communications of the ACM. Communications of the ACM. 45(4), 211–218 (2002)

Sousa, S. D; Nunes, E. P. and Lopes, Isabel (2012), "Data Quality Assessment in Performance Measurement", Lecture Notes in Engineering and Computer Science: Proceedings of the World Congress on Engineering 2012, WCE 2012, London, UK 4-6 July, 2012, pp. 1530-1535.

Verweire, K., & Berghe, L.V.D. (2003). Integrated performance management: adding a new dimension. Management Decision 41(8), pp. 782-790.

Wand, Y., Wang, R.Y. (1996). Anchoring Data Quality Dimensions in Ontological Foundations.Communications of the ACM 39(11), 86–95

Wang, R.Y., Strong, D.M. (1996). Beyond Accuracy: What Data Quality Means to Data Consumers. Journal of Management Information System. 12(4), 5–34

Zadeh, L. A. (1965). Fuzzy sets. Information and Control, 8, 338–353.

Aarhus University
Business and Social Sciences
ICOA
Fuglesangs Allé 20
8210 Aarhus V

Marianne Sejthen
Tel.: (+45) 8716 5492
E-mail: ms@asb.dk
www.icoa.dk