ON THE CHARACTERISATION OF UNCERTAINTY IN PERFORMANCE MEASUREMENT SYSTEMS

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INTRODUCTION

Performance measurement systems (PMSs) are receiving increasing attention from academics and practitioners particularly after the development of the Balanced Scorecard (BSC) [1], and many PMSs are available nowadays [2]. Nevertheless, this subject is not new and, for example, quality gurus such as Crosby, Feigenbaum, or Deming recognized the importance of performance measurement as an activity within quality management. Recently, there are many publications on the design of PMSs, (developed for industries, services, SMEs, public services, non-for profit organizations) and about their implementation and use, however there is a lack of investigation on the uncertainty measurement of such performance measures (PMs)

The PMS purpose is to contribute to both the goals and the sustainability of the organisation [3]. This contribution is the result of actions taken given the values of PMs, however, when measuring the same parameter using the same device and method, a variation in the reading will be apparent due to inaccuracies inherent in the measurement system. This variation and other types of inaccuracies or uncertainty are present in physical systems and it should be reflected in the PMS. Furthermore, there are many measurement capability studies of “hard” variables, but there are few attempts to deal with attribute data and “soft” PMs (based on subjective assessment), such as customer satisfaction.

Failure to deal with such uncertainty will result in simplified models that could lead to worse decisions.

The first contribution of this work is to provide a general classification of sources of uncertainty that could affect PMs. This would allow the establishment of a common theoretical framework to classify uncertainty in the field of Performance Measurement. Secondly, it would provide a basis for practitioners to provide evidence about the uncertainty of existing PMSs.

The hypothesis is that organisations need to reflect the uncertainty of its systems and contextual factors in their PMs to improve their models. This identification of uncertainty in PMS is the first step to reduce such uncertainty. This work is part of ongoing research, which is being carried out on world-class organisations and subsequently will do longitudinal case studies to ascertain their applicability.

Methodology

The research methodology to characterise PMs’ uncertainty will comprise both deductive and inductive stages. It starts with a literature review on the field of performance measurement, quality management and uncertainty to develop through deductive logic a conceptual and theoretical structure about the classification of uncertainty in PMs. This paper presents the findings of this deductive research which will later be tested through case studies, to allow another step of inductive research to support, change or refute the proposed characteristics of the performance measure (PM).

LITERATURE REVIEW

Background on TQM and Business Excellence

There is a plethora of quality improvement paradigms to help organisations improve their products or services [4]. Overall, Business Excellence is replacing the narrow objective of meeting customer specifications; the focus is on the performance of the whole system, and not just the outputs.

Based on quality management principles such as the ones of ISO 9000 series of standards and quality awards, one common element emerges:

the process approach. It emphasises on the need to measure critical variables and to quantify process effectiveness and efficiency.

Prajogo and Sohal [5] argue that TQM will remain an essential part of developing and maintaining a competitive advantage for organisations. Excellence models and quality awards have highlighted the importance of performance measurement in achieving Business Excellence.

Scholarly academic research strives to conceptually and empirically extract the components of quality management and their linkages to performance, such as the BSC [1], the performance prism [6] and Kanji's Business Excellence Model [7].

Performance measurement systems

Juran and Godfrey [8] argue that "the choice of what to measure and the analysis, synthesis, and presentation of the information are just as important as the act of measurement itself" and emphasise the system to which the measurement process belongs. The measurement process consists of steps needed to collect data and present results. The larger measurement systems also embrace the decisions that are made and the framework in which the process operates.

A thorough understanding of the existing measurement systems, formal and informal, spoken and unspoken, as they are perceived [9] must be achieved, i.e. the overall framework in which the PMS operates should be understood [8].

According to Macpherson [10] there are two approaches to identifying PMs: top-down and bottom-up. Using the first approach, the search for PMs is based on the mission and vision of the organisation. The latter, on the other hand, is determined by what data is currently available and has the advantage of being cost effective by only focusing on visible data [10]. A third approach [11] is outside (or customer) - inside (or internal processes), endorsing the argument about the importance of looking at the organisation from the customer's viewpoint [12].

Critical Success factors of PMS

To contribute to the planning phase of the PMS, critical success factors (CSF) about data quality are identified in the literature. PMs should be [10, 13, 14, 15]: Relevant (C1); Credible (C2); Precise (C3); Valid (C4); Reliable (C5); and Frequent (C6).

Other CSFs are discussed in the performance measurement literature are:

- Data collection and methods for calculating the PMs must be clearly defined [16] (C7);
- Presentation of PMs must be simple [12] (C8);
- PMs must be flexible [14], including being tied to desired results [15] (C9);
- More extensive use should be made of subjective data [13] (C10);
- Ratio-based performance criteria are preferred to absolute numbers [16] (C11).

Several frameworks have been proposed to develop and use PMSs in organisations [17], a sample of which will be summarised in the next section.

Performance Measurement Frameworks

There are two basic types of PM in any organisation – those related to results, and those that focus on the determinants of the results [9]. This suggests that it should be possible to build a performance measurement framework (PMF) around the concepts of results and determinants. The EFQM model also supports this concept.

Perhaps the best know PMF is Kaplan and Norton's BSC [1, 9]; it seems to be the most influential and dominant concept in the field. The authors of the BSC suggested [18] the definition of strategy maps to describe the cause-and-effect relationships between the identified measures, but according to Wilcox and Bourne [19] these relationships are outdated. The collaborative culture of the integrated supply chain has triggered the emergence of new measures [20].

Kanji and Sá [21] started with the BSC and integrated TQM principles and CSFs resulting in a model which focussed on measuring how an organisation is performing from an outside perspective. Bititci et al. [17] developed a model for an integrated and dynamic PMS. As the previous framework it should have: an external and internal monitoring system. Basu [20] also argued that the PMs should be more externally focused for the total network and a formal senior management review process with two-way communication to all partners was essential to success.

Integrative approaches to performance evaluation, including auditing, self-assessments, benchmarking and performance measurements are still required [21]. Self-assessment against quality award models has gained prominence in areas where quality audits were lacking, most importantly in performance improvement [20, 21].

The Performance Prism' authors [6] refer to the importance of identifying stakeholders' contributions, as they are part of a reciprocal relationship with the organisation. They also argue that it is necessary to start to think about measurement as the process of gathering management intelligence.

UNCERTAINTY OF PERFORMANCE MEASURES

Characterising uncertainty

Any measurement is subject to imperfections; some of these are due to random effects. Repeated measurements will show variation because of such random effects.

When uncertainty is evaluated and reported in a specified way it indicates the level of confidence that the value actually lies within the range defined by the uncertainty interval.

"The definition of uncertainty (of measurement) is a parameter, associated with the result of a measurement, that characterizes the dispersion of the values that could reasonably be attributed to the measurand" [22]:2. Thus the uncertainty, in metrology, is a quantitative indication of the quality of the result. It gives an answer to the question, how well does the result represent the value of the quantity being measured? It allows users of the result to assess its reliability, for example for the purposes of comparing results from different sources or with reference values. Confidence in the comparability of results can help to reduce barriers to trade.

Uncertainty is a consequence of unknown random and systematic effects and is therefore expressed as a quantity, i.e., an interval about the result.

"When reporting the result of a measurement of a physical quantity, it is obligatory that some quantitative indication of the quality of the result be given so that those who use it can assess its reliability. Without such an indication, measurement results cannot be compared, either among themselves or with reference values given in a specification or standard. It is therefore necessary that there be a readily implemented, easily understood, and generally accepted procedure for characterizing the quality of a result of a measurement, that is, for evaluating and expressing its uncertainty." [22]:viii. This is common knowledge in metrology but it is not being applied in ordinary PMs. Thus the quality of a result can be expressed through the uncertainty associated with such PM.

According to ISO 2003 [23], section 7.3, the measurement uncertainty shall be estimated for each measurement process covered by the measurement management system and all known sources of measurement variability shall be documented. If these requirements are to be applied in all PMs of the organization there would be the need to identify all sources of variability. However, few works [24, 25, 26, and 27] report the inclusion of such variability in their studies.

There is a wide variety of reasons why uncertainty is present in PMSs. Particularly, to reliability studies Coolen [28] presents three main reasons: (i) in many reliability applications, there may be few, if any, statistical data available, implying stronger dependence on subjective information in the form of expert judgments; (ii) the relaxation of dependence on precise statistical models justified by physical arguments; (iii) an assumption underlying most mathematical work in the study of system reliability is that the exact system structure and dependence relations between components are known, which may well be unrealistic in many applications for all but the simplest systems.

These relationships are conditioned by the system's environment and may generate contradictory information, vagueness, ambiguity data, randomness, etc. In reliability studies, the vagueness of the data have many different sources: it might be caused by subjective and imprecise perceptions of failures by a user, by imprecise records of reliability data, by imprecise records of the tools appropriate for modeling vague data, and suitable statistical methodology to handle these data as well [29].

Both [24] and [25] considered uncertainty in manufacturing systems and argue that reducing it is a means to improve the system. Other studies have included uncertainty in project scheduling [27], inventory control [26], or supply chain management [30].

Specific components of PMS's uncertainty and its classification, to facilitate systematic studies, are not known.

Methods to deal with uncertainty of PMs

Traditionally, uncertain parameters in inventory control and supply chain management problems have been treated as stochastic processes and described by probability distributions [30]. A probability distribution is usually derived from evidence recorded in the past [26]. This requires a valid hypothesis that evidence collected are complete and unbiased, and that the stochastic mechanism generating the data recorded continues in force on an unchanged basis [30]. However, there are situations where all these requirements are not satisfied and, therefore, the conventional probabilistic reasoning methods are not appropriate [30]. In this case, uncertain parameters can be specified based on the experience and managerial subjective judgment. Often, an expert may feel that a given parameter is within a certain range and may even have an intuitive feel for the best value within that range [26].

It may be convenient to express these uncertainties using various imprecise linguistic expressions [30]. Fuzzy sets are found to be useful in representing these approximate qualifiers, due to their conceptual and computational simplicity. The typical membership functions that can represent fuzzy customer demand, fuzzy external supplier reliability and the fuzzy lead time [30]. They can be derived from subjective manager belie.

To deal with uncertainty in scheduling environment 3 other approaches (apart from stochastic and fuzzy) are presented: reactive, proactive and sensitivity analysis [27], while [25] argue that for complex processes, methodologies based on artificial intelligence and simulation should be used.

On production planning, a need for further research is identified [25]:

- development of new models that contain additional sources and types of uncertainty, such as supply lead times, transport times, quality uncertainty, failure of production system and changes to product structure, etc.
- investigation of incorporating all uncertainty in an integrated manner;
- development of empirical works that compare the different modelling approaches with real case studies.

Lee et al. [31] propose a fuzzy AHP approach to assign weights to BSC perspectives, while [32] used the same approach to calculate the weights of questionnaire criteria, Hu et al. [33] applied it to determine the relative weightings of four risk factors, while [34] used it to obtain weights in multicriteria multifacility location problems.

The costs incurred by organisations to manage uncertainty should not be ignored, and different methods to deal with uncertainty have different requirements and associated costs. In risk management a parallel situation can be established because identified risks are not all subject to the same detailed subsequent treatment, for example qualitative methods for risk assessment (less expensive than quantitative methods), may be enough for lower level risks, while quantitative techniques would be economically reasonable for higher level risks. Similarly, methods to deal with uncertainty have associated costs, and if some components of uncertainty, are small compared to others, it could be unjustifiable to make a detailed determination of all its components. This idea is also expressed in ISO 10012 (section 7.3.1).

Nunes and Sousa [35] studied some instances of the propagation of uncertainty in PMSs and its effects in the decision criterion, which also contains uncertainty. This will not be the focus of this paper.

Having reviewed performance measurement systems and uncertainty, the next section will address the classification of PMs' uncertainty.

UNCERTAINTY COMPONENTS OF PM

Components of uncertainty can be classified according to the following three categories: Measurement process; Data collection; and PM.

Measurement process

The uncertainty associated with the measurement process can be introduced by: the measurement method and the tools and/or criteria (when assessment is made by human perceptions) used to carry out assessment. Therefore in this category, the next components of uncertainty can be distinguished.

UC_MM – Measurement method uncertainty component

This uncertainty is related with errors in the method used to perform the measurement. The procedure to perform the measurement may be wrongly defined or may not be clear, originating misinterpretation. Wrong measurement methods can also be introduced by the measurement performer.

Examples of UC_MM:

- Errors in measuring setup time due to bad misinterpretation of a procedure may lead to inconsistent data;
- Productivity indicator may be affected by defective products or parts, rework and work-in-process, if they are considered in the number of good units.

UC_PA - Precision and accuracy of measurement tool

Precision is how Repeatable and Reproducible the measurement is. This is what is calculated during a gage R&R study. Accuracy, also referred to as "bias", is how close the data is to the "real" value. Usually, accuracy is assured by the calibration of the measurement tool.

UC_H - Human uncertainty component

Frequently, in turbulent systems, the available information is scarce, which implies stronger dependence on subjective information in the form of expert judgement. According to CSF C10, more extensive use should be made of subjective data [13], but if the measurement system relies on human judgement, it can be assumed that some uncertainty will result. The existence of several methods (AHP, Delphi technique, etc.) to overcome such ambiguity supports this component.

Examples of UC_H:

- In quality control one person identifies defects. If that person is replaced by another the classification may differ;
- The Risk Priority Number calculated in FMEA methodology is based on three subjective indicators.

Data Collection

In the process of data collection to subsequently calculate a PM, error can be introduced due to human failure or to the data collection system (software).

UC_DC – Data collection (equipment/ operator) uncertainty component

This component includes errors in the introduction of data in database, a bad calibration of an automated data acquisition system, the absence of data whose release was planned.

Examples of UC_DC:

- Assigning a defect to a wrong product;
- The maintenance technician registers the beginning of the corrective maintenance task, but forgets to register the end of the action.

Performance Measure

Uncertainty may be introduced by the selected PM which may not adequately represent the reality to be measured. The difference between what is measured and what it is intended to be measured may be present originally, when the PM is firstly defined, or may appear due to changes in the environment. For PMs or indicators calculated based on other PMs, uncertainty in the PM of high level may be originated by the propagation of uncertainty present in the PMs of low level.

Therefore, in the of PM category, three uncertainty components are identified, as presented below.

UC_D - Definition / Measurand uncertainty component

PM are often tied to desired results (C9) and its presentation must be simple (C8), this may lead to provide a simpler definition of what is to be measured while the reality is more complex.

PMs, to be understandable, should be related to shop floor operations and product and service characteristics (C8 – understandable variables). Their construction should be bottom-up which would make them more cost-effective. However, to be simple and tied to desired results (C8 and C9) they should derive from strategy (top-down), or from customer's requirements. These alternatives mean that any given solution has to increase uncertainty to comply with these requirements.

Examples of UC_D:

- The detection of different defects if added can ignore differences between them, showing to top management a simplistic view of the organisation;
- The assessment of customer satisfaction implies that the definition of customer is clear.

UC_E - Environmental uncertainty component

Uncertainty can increase if some environment characteristics change, particularly if System Complexity increases. CSF C7 requires that methods for calculating the PMs must be clearly defined, but any environmental change (maintenance policy, layout, or weather conditions) could cause a revision in data collection methods. Changes in PMs are to be simple, but the system may not. Stakeholders' needs may change and the relationships between variables will also vary.

Examples of UC_E:

- Changes in the procedure of verifying incoming parts in warehouses, excluding defects' detection, may cause defective parts to be considered as good once it is supposed that this inspection is done;
- Introduction of a new product, different from an existing one, could cause variation in the PM "percentage of defective units" (C11 – Ratio based PM can no longer make sense if different products are added).

UC_A – Aggregating uncertainty component

When two or more PMs are combined to generate one new PM (performance indicator - PI) the uncertainties of each PM will affect the uncertainty of the PI.

The formula to calculate a PI or weights of different PMs, may not be general over time (for example if the range of products changes beyond its initial state).

An assumption underlying most performance measurement studies is that the structure of the system and the dependence relations between parts are known. These limitations constitute an important source of uncertainty that is visible when one tries to select the models (strategy maps) that represent the input/output relation of PMs.

An additional source of uncertainty comes from the imperfect knowledge about the interdependency relationships among the parameters and variables. These relationships are conditioned by the system's environment and may generate contradictory information, ambiguity or randomness fuzziness.

Examples of UC_A:

- There are 2 similar products assessed to infer about its field performance. The average performance (PI) of the products will be the average of their individual performances. Now let us assume Product 1 and 2 are assessed each in 3 critical variables and there is a new product more complex that is assessed in 6 critical variables. The aggregated PI may not represent this situation.
- The method of calculation of one PM is based on another but the defined formula was not the result of a generalised consensus between stakeholders.

UNCERTAINTY QUALITATIVE ASSESSMENT

As referred previously, quantitative methods usually require more resources and data than qualitative ones.

The first step to characterise uncertainty would be to identify what Uncertainty Components are associated with each PM.

The second would be to classify the uncertainty level of each Uncertainty Component. Given that, even in structured systems (such as automotive manufacturing plants) risk assessment and FMEAs use, typically, a Likert scale with 10 item. The authors propose a scale with only 3 levels (the minimum would be 2 levels) but similar solutions with other levels are also feasible.

For example, a scale for UC_A component could be:

No Uncertainty – There is a recognized formula that derives from theory and is not scientifically questioned.

Some uncertainty – An agreed formula is accepted by all stakeholders.

High uncertainty – The formula was defined without consensus and may be changed.

After building similar scales to each uncertainty component, a matrix could relate each PM with each uncertainty component. This matrix would be a tool to decide which uncertainty components would be further studied, and could provide evidence to change existing PMs. The uncertainty reduction of the PMS would provide less risk in decision making.

CONCLUSION AND FUTURE RESEARCH

This work provides a classification of uncertainty components that affect the quality of PMs. Can each uncertainty component be decomposed into a systematic and random part? This decomposition will allow the identification of causes that, if changed, could reduce uncertainty.

Case studies will be performed to ascertain the validity of these concepts.

The development of methods to propagate the uncertainty of the PMs throughout the PMS and through different hierarchic levels is being pursued by the authors in another research project.

This work will be extended to deal not only with the uncertainty in the PMS but also with the uncertainty of the decision criteria.

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