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Chapter 2

Improving Informational Bases of Performance Measurement with Grey Relation Analysis

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Abstract

Performance measurement (PM) needs objective empirical data with causal relevance in order to steer and control financial performance generation. In business practice, there is often a lack of such objective data. A surrogate might be collected subjectively based on data generated by questioning corporate experts. Such an involvement of subjects can rapidly lead to an immense extent of data that (partially) imply incomplete information. To handle this imperfection of data, the Grey systems theory (GST) and especially its element, the Grey relation analysis (GRA), seem to be methodologies able to improve informational bases for PM purposes. Therefore, GRA is able to reveal those performance indicators that considerably influence the corporate financial performance, the key performance indicators. GRA is able to supply valid results with only four data points of a time series. Hence, the GST provides an improvement of the PM framework in situations of incomplete information, which is demonstrated in the following.

Keywords: small samples, performance measurement, performance indicator selection, causal ambition

1. Introduction

In business practice, empirical data with causal relevance for financial performance generation are required for steering and controlling demands. Often there is a shortage of such data. Therefore, a severe problem has to be solved by the management. From the development and implementation of measurement and management systems, for example, performance management and measurement, a provision of causal-oriented data as a quantitative basis for

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steering and controlling purposes can be expected. PM as the quantitative database of management control operates as an information supply system for the performance management. The current relevance of the topic is shown by Rigby and Bilodeau [1] who expose the balanced scorecard (BSC) as one of the most popular management tools for strategically oriented performance management. A comprehensive BSC also requires the identification of causal interdependencies between indicators that drive the corporate's financial performance. But in business practice, often a shortage of especially objective data exists. To derive causal hypotheses on financial performance generation, subjectively based data can be collected and used in the framework of a PM design as a surrogate. Afterwards, these data can be intersubjectivated groupwise and objectivated by statistical validation.

Generating subjectively based data by interviews or questionnaires often leads to an excess of such data implying problems of handling. In this case, appropriate performance indicators have to be selected which contribute to the success of an organization. Identifying and ensuring an effective PM demands a focus on the cause-and-effect relations between these performance indicators. Their estimation and validation induce methodical questions how to cope with imperfect information. This challenge *inter alia* demands analytical decision support. Besides the known disciplines and methods to handle imperfect information, like stochastics, Fuzzy Mathematics or DEMATEL (as a technique of groupwise intersubjectivation), this chapter provides a partial view on Grey systems theory (GST) as a conception to improve poor data situations for PM and to operate already with a few data.

As organizations often do not have sufficient objective databases for PM purposes, they must refer to subjective data usually filtered out of tacit knowledge stemming from employee interviews. These finally lead to a large number of performance indicators determined by the means and relations of the fixed corporate strategy and its usage of identified cause-and-effect relations which is indispensable for causally ambitioned performance control. This is the framework that demands an evaluation and reduction of the obtained variety of indicators to main key performance indicators (KPIs).

For instance, 50 performance indicators are denominated as candidates by a company's employees with expert status. Hypostatizing the causal interdependencies of these would leads to a challenge without any operations research (OR) support. In addition, how could an organization obtain quick but also valid information for the selection of the KPIs, without multicriteria decision support, if the Statistics require a sample size implying longstanding data collection?

Do there exist methods to transform subjectively based data into intersubjectivated ones reaching closer to quasi-objective data and therefore allowing more detailed conclusions for the PM context?

Such methodology is made available by the GST that has been developed to handle situations with incomplete information that cannot be coped by other support disciplines. Thus, performance indicators can be selected by aid of the Grey relation analysis (GRA) based on subjective information. GRA analyses the geometric relationships of compared discrete objectives as well as of subjective indicators and is able to operate with a sequence length of minimally four data points. In situations with databases being too small for statistical analyses, processes of intersubjectivation or validation become possible. With GRA, PM would be enabled to prepare an order of the KPI priorities resulting from the geometrical similarity of the performance indicators' time series to the sequence of the top strategic financial performance ratio. In addition, it is also possible to display the interdependencies between the residual indicators in a network or in a causally ambitioned map by GRA to steer and control the performance generation in the PM system context.

2. Performance management and performance measurement

To focus the whole company on a long-term financial success, it is necessary to reflect and if required to recombine the objectives of the corporate strategy on every single company level, in each business unit and in the cognitive systems of the employees. Thus, the integration and therefore the implementation of the corporate strategy ensures the value creation in an organization. This value creation is also known as the generation of financial performance. The term "performance" is much discussed and underlies no standardized definition. It only becomes clear by an individual corporate-specific description [2]. The special task of the PM is to provide an information supply system for the management by finding the causal relationships that are related to financial performance. The causes of financial performance are not only financially dimensioned. The challenge of a thriving business is to include nonfinancial performance measures often anchored in the intuitive implicit knowledge of the employees. The ability to respond to altered circumstances presupposes an update of critical success factors [3, 4]. An entire focus of an organization on a backward-looking financial performance indicator system as it was usual in traditional Management Accounting with its reference to the decomposed structure of financial ratios (e.g. DuPont scheme) is inconceivable in today's dynamic business and Management Science. Instead, a new operational framework is necessary. Such a scope should include all relevant aspects of the corporate performance [4, 5]. This superior framework is tailored as a management and control system and is also known as the Performance Management of the organization. To provide an adequate information basis for the Performance Management, a measurement of the KPIs is necessary [6]. Therefore, the PM addresses three central functions: measurability of financial and especially nonfinancial indicators, identification and selection of the most important indicators that drive financial performance and lead to value generation. Thus, an additional transparency for the different members of the organization is provided. For this, a sound knowledge of employees about the process of financial performance generation is necessary [7].

Hence, the interaction of Performance Management and PM shows that these two internal corporate systems cannot be separated. The PM may be viewed double-edged: First, as a feedback-oriented system that supplies Performance Management with norms and information on current processes by data measured in the past and presence. Thus, a base to derive counteractions exists. Furthermore, a feedforward tool is made available, which informs about failings of the conceptual framework so that a new causal model will have to be developed, validated, and implemented [4]. Without any knowledge about the interaction between those systems, the organization misses the opportunity to control and dominate the performance-generating process [2, 8].

The performance-generation process has multidimensional aspects incorporated by the responsibility of multiple causes that lead to an unidimensional financial effect specified by the owners of an organization [4, 9]. Consequently, the interaction of the multidimensional PM and the Performance Management conduce to the improvement of the corporate performance. For quantifying the financial and nonfinancial measures, the PM serves support for a performance recording. Often a shortage of available, objective empirical data for the representation of performance indicators occurs, which has to be handled by the management control. In case of missing objective data, it is indispensable that the PM manages this problem by collecting subjectively based data on the basis of surveys or interviews which enable a quasi-objectivation of these measures [10, 11]. Even if organizations should have historical objective data, subjectively based data should not be ignored. Many times, historical data have been collected in varying frequencies and ranges. In this case, an usage within a PM seems to be inappropriate [12].

Revelations of the interdependencies between the KPIs that are essential for the value creation or rather the performance improvement can only be determined by sufficiently articulated knowledge. At this, it is necessary to differentiate between the explicit knowledge on the one hand which is simple to communicate and can be made available to all individuals that want to use it. On the other hand, there is the intuitive implicit knowledge that makes important performance-related causal relationships available [13, 14]. The implicit knowledge is characterized by four conditions: difficult to imitate, hardly to replace, only transmittable to a limited extent (not by the normal use of language), and scarce existence [13]. The tacit knowledge is, however, very difficult to create because it has been sharpened over years in extensive activities and experience of individuals. To evoke this dormant, subject-bound, intuitive knowledge, Abernethy et al. [10] propose to interview or rather execute subjective questionnaires so that the employees give partly insights into their tacit knowledge. This results in a variety of subjectively based data which first need to be reduced to a manageable level and can be intersubjectivated to work with. Here, the task of the PM should be based on an adequate—even optimal—complexity reduction [15]. Thus, the immense amount of subjective data has to be channelled, properly. Besides the PM has to concentrate on the essential factors with the aid of intersubjectivated data. All this is taking place to avoid that the PM System is more confusing than helpful.

2.1. Strategic alignment of performance indicators

The PM should not only be understood according to the phase of validating the established hypotheses at the beginning of the PM process but rather by Bourne et al. [16] as a tool to identify appropriate indicators covering structure and processes of an organization in a dynamically changing environment. To focus on inadequate measures would constitute a resource-wasting framework. Hence, the organizational, multidimensional PM System requires a selection of such KPIs endogenously linked to the corporate strategy and thus able to improve the performance [17]. Various studies [18, 19] detected that systems that are constructed as too complex have a negative influence on the performance. Too complex systems lead to an overload of information and consequently cause an increase of administrative costs [20]. Therefore, the amount of KPIs has to be limited to a level cognitively manageable by the members of the organization [17, 21].

On account of a lack of objective data, organizations may refer to subjective estimations stemming from samples being too small or too fragmented to apply statistical methods (**Figure 1**). Small or fragmented data sizes lead to incomplete information. This problem is to be solved by the GST. Fuzzy Mathematics, which focus on experience data of an individual, are characterized by a clear content (intension) but by unclear (not determined) quantitative boundaries of an expression—for example "very strong"—(extension of information). GST is more suitable with concepts of multiple meanings (e.g., performance), is additionally able to handle fuzziness situations and disposes of a clearly defined extension [22]. Thus, the above-mentioned problem of poor and incomplete information is almost impossible to solve with Fuzzy Mathematics or Statistics. The incomplete nature of the information needs to be managed in the PM context. A subjective query that was collected over a small number of periods can be considered as an incomplete information, if the experts of the organization deliver only a few estimations of the extent of an indicator [23]. Reducing the volume of performance indicators needs subjectively-based and thus poor information [24]. The organizational challenge is to solve this problem by providing valid results for PM also in case of small samples in situations of incomplete information. This would be possible by reference to support models for comprehending and decoding the problems of the system [25, 26].

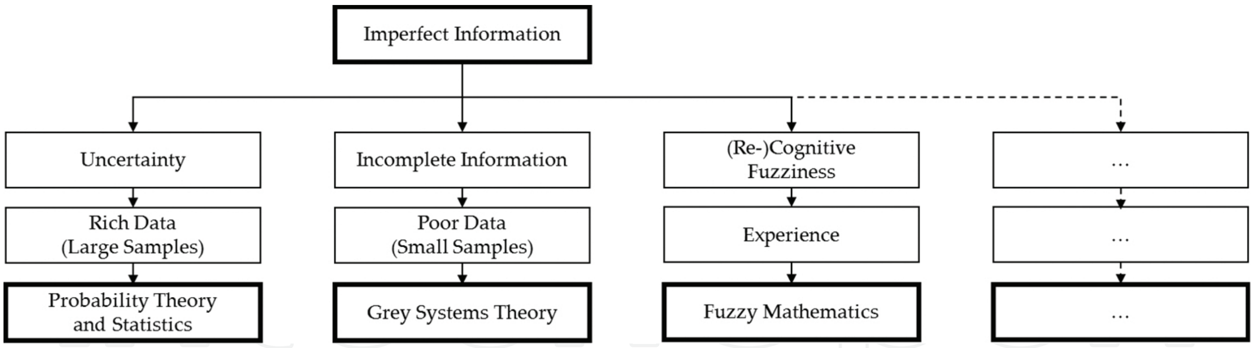

Figure 1. Imperfect information, situations and instruments.

In the PM context, it is important that a strategy is formulated as simple as possible [27]. If the extension of the strategy is then reduced to a manageable minimum, the organization possesses a list of factors most important for performance generation [28]. But this does not deliver a sufficient condition to control an organization successfully. Instead, it is essential to know how the factors are interrelated to actuate the right "lever" for an increase in financial performance [29]. Therefore, a causally ambitioned network of interdependencies of the KPIs seems to be useful [30].

2.2. Causal mapping

The performance of an organization can be interpreted as a result of past actions of the managers. To explain this performance, a causally ambitioned model with all relevant relations between the considered indicators is indispensable. Thus, the process leading to performance can be visualized. Such an illustration (e.g., a map) delivers – especially if structured—a blueprint for implementing the corporate strategy [31].

A map generally provides the visualization of a reference framework. In the 1970s, the political scientist Axelrod [32] spread the methodology of cognitive maps that should illustrate simplified social studies. A cognitive map provides an optical representation of the structures people perceive in their environment [9]. Cognitive maps serve management with a tool for evaluating alternative business situations in order to meet better an uncertain, dynamic corporate environment and to simplify complex issues [33]. Here, the organization should, however, focus on a visualization of tacit knowledge [10].

A simple list of the most important corporate strategy factors would point out the indicators the organization has to focus on. As an enumeration, such a list, however, would not represent the interdependencies within the system. To control as well as to monitor the performance generation, it is necessary to understand the causal relations between the KPIs [34, 35]. Therefore, it is fundamental to keep in view the cost–benefit ratio: a too detailed map costs a large amount of time [10], a graphical apposition of ovals does quantify dependencies in the system [32]. GRA as an OR management support is simple in usage and provides meaningful results already after a few periods. Additionally, it even enables a visualization of the outcome within a relational network [36].

In contrast to parametric approaches like the correlation analysis, nonparametric mapping approaches are much more able to represent the multidimensionality of the performance generation. By avoiding assumptions, nonparametric approaches focus on mapped causal relationships among the measures based on their perceived environment [11]. Organizations tend to skip a statistical validation of their causal model. The reasons for this are the perceived obviousness of the model, the time exposure or rather the high validation costs [20, 37, 38]. The changing dynamic and competitive environment requires an adjustment of an organization's causal model to adapt the strategy continuously. In order to meet this condition sufficiently, an ongoing customization of an organization's cause-and-effect network is not manageable with regard to time and costs that appear by longstanding serial questionnaires [39].

A sole focus on subjectively based data can lead to systematic judgment errors by incorrect estimations of individuals. Thus, such data are to be considered as incomplete because of small or fragmented sample sizes [39]. In addition, subjectively based data in the PM context can imply errors in the described network of relations because of the occurrence of new environmental circumstances. On account of these changes, a resulting illustration of interdependencies can be inadequate to reality. Therefore, it is indispensable to improve these data with quantifying methods and consequently intersubjectivate them. So, there is a necessity of research in new mathematical applications with regard to measurement and especially to PM which is yet limited to the fundamental methodologies of sociology (survival analysis), psychology (various psychometric methods) and economics (econometrics) [11]. In such social economic systems with poor information, it is challenging to look for solutions in Statistics because of the system's dynamic characteristics. In this case of incomplete and fast-changing information, the application of GRA may be advisable [40].

3. Applying Grey systems in performance management

The GST first appeared in 1981 by Deng [41]. According to that, a Grey system (GS) has the structure of a black box, which contains a system of both known and unknown variables. The unknown represents a "black", totally incomplete information and the known a "white", absolutely complete information. Hence, a (Grey) incomplete information can be understood as an information that is partially known as well as to some extent unknown [42]. Inconsiderably, whether it is the message format, the coordination mechanism or just the behaviour within a system: As soon as a lack of information within this system is disseminated, it is referred to as a GS [36]. In practice, as already mentioned in the previous chapter, it is difficult to concretely obtain all information about an examined object [40]. Systems with a lack of information can be found everywhere: for example, the biological limitations of the human senses, the constraints of important economic conditions or the unavailability of technical resources. The GS as a system of incomplete information is also known as an "indeterminate system" of which the fundamental characteristics are small samples and/or interruptions of time series [42].

On the account of the small size of the samples problems within information systems with incomplete information cannot be solved with statistical methods [42]. With increasing sample size, the statistical power of a validation method grows [43]. Thus, sample sizes are preferable, in which the standard error is as low as possible. Various studies [44–46] consider large numbers of data points as necessary for the application of statistical support of time series as well as cross-sectional analysis in PM. For instance, according to McDonald and Ho [45], an organization needs to obtain quarterly data for a moderate time series analysis for almost six years in order to make a statement about possible causal relations by structural equation modelling. In social and economic systems, which are driven by the highest degree of dynamism and continuous changes, such problem solving demands for overextend the conditions of typical situations of business practice. Some variables in the system underlie a faster change of their environment conditions than the measurement lasts at all, so that the analytical results are irrelevant and therefore superfluous [41]. The resulting situation of incomplete information can be supported by GST [23].

The enormous volumes of data arising from subjective questionnaires about the performance indicators (k_i) need reduction. **Table 1** shows the result of such a decimation to those indicators which are most essentially interlinked with the financial performance generation. For this, benchmarking of the most representative indicators is crucial [47]. The expression x_{it} represents an opinion aggregated from the individual members of an expert group in period

t to performance indicator k_i. Here, GST disposes of a major advantage because of the ability to provide valid results already from a number of data points with $t \geq 4$. Thus, the GST is able to work with incomplete information in terms of decimating the indicators to the KPIs [36].

Period t						
Performance indicator (k_i)	Q_1	Q_2	Q_3	Q_4	…	Q_t
k_1	x_{11}	x_{12}	…	…	…	x_{1t}
k_2	…	x_{22}				…
k_3	…					…
k_4	…					…
…	…					…
k_i	x_{i1}	…	…	…	…	x_{it}

Table 1. Subjective questionnaire.

3.1. Buffer operator in Grey systems theory

The GST could be the way out for problems of incomplete and therefore inadequate data. The challenge for PM is especially the collection of performance relevant data often derived from the answers to subjective questionnaires within organizations. From time to time, this requires a certain number of subjective data as shown in **Table 1**. Nevertheless, in practice, it may occur that experts cannot answer their quarterly surveys (e.g., vacation, illness or simple absence). Therefore, the GST is providing a buffer operator, which makes it possible to complete missing information in fragmented queries, without this leading to informational distortion or loss. If two adjacent entries of a data sequence are described by $x(n-1)$ and $x(k)$, then, $x(k-1)$ represents an old information, and $x(k)$ operates as a part of a newer information. If there is a gap between entries within a data sequence, a lack of information because of the insufficient completion of an expert's questionnaire occurs (e.g., $X = (x(1), x(2)\ x(3), x(5))$. A new value $x(4)$ can be created as follows:

$$x^*(k) = \alpha \cdot x(k) + (1-\alpha) \cdot x(k-1), \alpha \in [0,1]. \tag{1}$$

The value of α represents the weighting of the informational content with regard to its currency. If $\alpha > 0.5$, the researcher attaches more importance to the newer information than to the older one and vice versa [23]. For simplification, no preference with respect to the timeliness of information should be assumed in the following, so that old and new information should be weighted equally ($\alpha = 0.5$).

In cases of a blank first entry $x(1)$ or a missing last entry $x(n)$ of a sequence X—for example, measured customer contentment—the gap cannot be filled by the method of adjacent neighbour generation, but rather by methods called stepwise ratio generator

$\sigma(k) = \frac{x(k)}{x(k-1)}; k = 2, 3, ..., n$ or the smooth ratio generator $\rho(k) = \frac{x(k)}{\sum_{i=1}^{k-1} x(i)}; k = 2, 3, \ldots, n$. If the first value is missing, the method operates with the adjacent values within the sequence right of the missing one: $x(1) = \frac{x(2)}{\sigma(3)}$ or $x(1) = \frac{x^2(2)}{x(3) - x(2)}$. If only the last sequence value shows an empty entry, the two previous sequence data help to create an adequate "substitute": $x(n) = x(n-1)\sigma(n-1)$ or $x(n) = x(n-1)\big(1 + \rho(n-1)\big)$ [23].

3.2. Grey relation analysis

The challenge of GRA is to clarify which factors influence the PM system in a desirable extent, to strengthen and to focus those subsequently. In the past, this has been discussed in scientific articles and essays about system theory. However, this methodology still attends rare attention in the context of Performance Management [23, 48–50]. This model was chosen, as it tries to work as an ideal PM support with its consideration of both financially and nonfinancially dimensioned factors by analysing the system's factors that display sufficient influence on the top strategic financial ratio but appear as incomplete [51]. By means of the Performance Management as well as by the efficient and effective KPIs identified by the PM, the entire organization could be aligned to its strategy and vision [52]. Therefore, GRA attempts to discover the sequences of the KPIs by determining the geometrically most similar sequences to the top strategic financial performance ratio to uncover the system's most descriptive factors [23]. Therefore, an organization has to determine a reference sequence, which optimally represents the strategy of the organization and thus the behaviour of the entire system [53]. The strategy and hence the ultimate performance generation should be illustrated by the KPIs. Here, Paquette and Kida [27] showed in their study that it is important to reduce the extension of the strategy to a minimum. So, in order to reflect the strategy by a reference sequence, it is advisable to refer to a single factor and not to a variety of multiple sequences. Kasperskaya and Tayles [34] propose that both types of indicators (financial and nonfinancial) within a well-functioning PM system should be used, but, however, the financial measures dominate in practice. Kaplan and Norton [52] also consider that a financial measure should be attributed the most weight in a strategy-focused organization, so that it can monitor and control their operational and strategic budgeting. Thus, a financial measure should also be used as a reference sequence in the selection of the strategy-related KPIs in a PM System.

The GRA is a part of the GST mentioned earlier and is based on all of its assumptions and conditions [47]. In this context, a Grey relation proposes the valuation between two autonomous systems or two indicators within a system over a determined time series. It is precisely this point where the examination method GRA can be used. The elements are examined for homogeneous or heterogeneous temporal behaviour which means the development of the considered indicator in terms of time. If the elements display a very similar, homogeneous development concerning the time series, a high relational degree is assumed and vice versa. First, a reference sequence $X_0 = (x_0(1), x_0(2), ..., x_0(n))$ is defined. Afterwards it is possible, to compare the geometrical similarity of the reference sequence with another system's element and its sequence $X_i = (x_i(1), x_i(2), ..., x_i(n))$. If $\gamma(x_0(k), x_i(k))$ is the image of the real numbers at point k as well as $x_0(k)$ and $x_i(k)$ display x_0 and x_i at point k, and $\gamma(X_0, X_i)$ reflects all data points of every sequence (i = 1, 2, …, n) with k = 1, 2, …, m, then the Grey relation coefficient follows the formula [36, 53]:

$$\gamma(x_0(k), x_i(k)) = \frac{\min_i \min_k | x_0(k) - x_i(k) | + \xi \max_i \max_k |x_0(k) - x_i(k)}{| x_0(k) - x_i(k) | + \xi \max_i \max_k | x_0(k) - x_i(k) |}. \tag{2}$$

The value $\xi \in [0, 1]$ describes the differentiation coefficient that aids to adjust the various relation coefficients. Lin et al. [54] suggest for ξ a value of 0.5 to attain a stable and appropriate distinction.

Then, the Grey relational degree $\gamma(X_0, X_i)$ could be calculated as follows [36, 47, 53]:

$$\gamma(X_0, X_i) = \frac{1}{n} \sum_{k=1}^{n} \gamma(x_0(k), x_i(k)). \tag{3}$$

That leads to $0 < \gamma(X_0, X_i) < 1$, so that a value of 0 can be interpreted as a blank and a value of 1 suggests a complete and perfect relation of the two compared sequences [47].

Though, the Grey relational degree by Deng functions as a historical basis of the GRA in this case, it is not applied in the further process because of its dependence of the sequence order in the calculation $(\gamma(X_0, X_i) \neq \gamma(X_i, X_0))$, and therefore, its rank reversal problems. As a result, the more general Grey incidence analysis is focused which is based on the approaches of symmetry and thus protected against the problems of Deng's Grey relational degree. The relative and the absolute degree of incidence are to be attributed to the more general approach of the Grey incidence analysis. Nevertheless the Grey relational degree and the Grey incidence are used synonymously [53].

First, the absolute degree of incidence is considered. Assuming X_I is an economic factor of the regarded system and k represents the ordinal number of this factor. Then $X_i = (x_i(1), x_i(2), ..., x_i(n))$ represents the series of the index and thus the temporal behaviour of an economic factor. Equivalently, this could be transferred to the PM context, so that various cash flows of several months, confidence of the employees in management or contentment of customers with a corporate's products are constituted as performance indicators [24]. These sequences may take various forms. If the sequence of an indicator is given by $X_i = (x_i(1), x_i(2), ..., x_i(n))$, then $X_i - x_i(1)$, or rather:

$$\left(x_i(1) - x_i(1),\ x_i(2) - x_i(1), \ldots,\ x_i(n) - x_i(1)\right) \tag{4}$$

illustrates a fluctuating image and therefore a development of the indicator behaviour [23]. The area under the curve can therefore be quantified as follows:

$$s_i = \int_1^n (X_i - (x_i(1))\mathrm{dt}. \tag{5}$$

As a result, the sequences can occur by decreasing (A), increasing (B) and vibrating (C) temporal behaviour. To be able to compare sequences with each other, a zero-starting point operator is applied [23]:

$$X_i D = x_i(1)d, x_i(2)\mathrm{d}, \ldots, x_i(n)d \ \text{ and } \ x_i(k)d = x_i(k) - x_i(1) \ \text{ with } \ k = 1, 2, \ldots, n. \tag{6}$$

Consequently, the comparison of two sequences appears possible, so that also statements about the area beyond the curves can be made (**Figure 2**) [23].

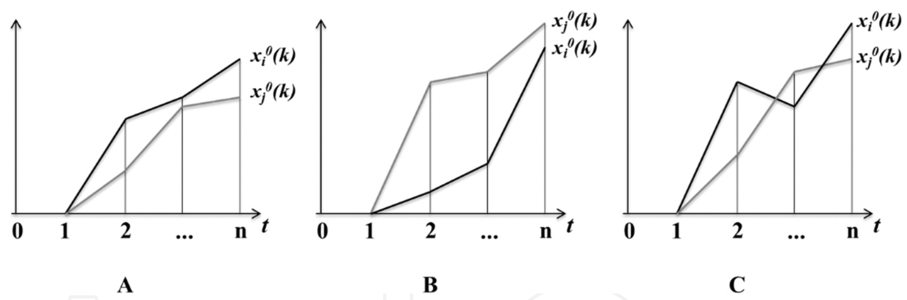

Figure 2. Relationship between two sequences. (A = x_i^0 is located above x_j^0; B = x_i^0 is located underneath x_j^0; C = x_i^0 and x_j^0 alternate positions).

Now, the area s_i between X_i^0 and abscissa can be calculated by the following equation [56]:

$$|s_i| = \left| \sum_{k=2}^{n-1} x_i^0(k) + \frac{1}{2} x_i^0(n) \right|. \tag{7}$$

Here, however, rather the area between the two curves, X_i^0 and X_j^0 is of interest, which can be described by the following equation [55]:

$$|s_{ij}| = |s_i - s_j| = \left| \sum_{k=2}^{n-1} \left(x_i^0(k) - x_j^0(k) \right) + \frac{1}{2} \left(x_i^0(n) - x_j^0(n) \right) \right| \tag{8}$$

Assuming the length of both sequences is the same (otherwise the sequences could be adjusted, as described in Subchapter 3.1), then the absolute degree of incidence of the sequences X_i and X_j can be determined by [23]:

$$\varepsilon_{ij} = \frac{1 + |s_i| + |s_j|}{1 + |s_i| + |s_j| + |s_i - s_j|}. \tag{9}$$

In the PM, the challenge is to associate both financial and nonfinancial measures [34]. However, in case of this endeavour, problems of differently scaled indicators can emerge. Likert scale estimations by experts of employee satisfaction, for example, can be set in relation. But this would be no normalization as demanded by the concept of the absolute degree of incidence [56]. On the contrary to this, the concept of the relative degree of incidence provides a quantitative description of the rate of change of two sequences to their initial values, thus enabling a sufficient normalization. The closer these rates of changes of the two sequences are, the greater is the relative degree of incidence r_{ij} between them. Assuming that X_i and X_j are two sequences of an equal length with initial values that are different to zero, then there is no connection or linkage between the absolute and the relative degree of incidence, so that the absolute degree ε_{ij} can be relatively large, whereas its relative counterpart r_{ij} can be extremely small and vice versa [23]. Using the relative degree of incidence, an equal length of the sequences is assumed, this means an identical number of data points for the two sequences X_0 and X_i, where $X_0 = \left(x_0(1),\ x_0(2),\ \ldots, x_0(k)\right)$ constitutes the reference sequence. Afterwards, to be able to compare the possibly differently scaled indicators and so their sequences, the values of each sequence are divided by their initial value:

$$X_0' = \left(x_0'(1),\ x_0'(2), \ldots, x_0'(k)\right) = \frac{x_0(1)}{x_0(1)}, \frac{x_0(2)}{x_0(1)}, \ldots, \frac{x_0(k)}{x_0(1)}, \tag{10}$$

$$X_i' = \left(x_i'(1), x_i'(2), \ldots, x_i'(k)\right) = \frac{x_i(1)}{x_i(1)}, \frac{x_i(2)}{x_i(1)}, \ldots, \frac{x_i(k)}{x_i(1)}. \tag{11}$$

Subsequently, the zero-starting point is determined analogously to Eq. (5), so there is the possibility to calculate the areas $|s_i|$ and $\left|s_{ij}\right|$ as well as the relative degree of incidence r_{ij} [57]:

$$|s_i'| = \left| \sum_{k=2}^{n-1} x_i'^0(k) + \frac{1}{2} x_i'^0(n) \right|, \tag{12}$$

$$|s_{ij}'| = \left| s_i' - s_j' \right| = \left| \sum_{k=2}^{n-1} \left(x_i'^0(k) - x_j'^0(k) \right) + \frac{1}{2} \left(x_i'^0(n) - x_j'^0(n) \right) \right|, \tag{13}$$

$$r_{ij} = \frac{1 + \left|s_i'\right| + \left|s_j'\right|}{1 + \left|s_i'\right| + \left|s_j'\right| + \left|s_i' - s_j'\right|}. \tag{14}$$

Using these formulas, it is possible to calculate the respective relative degree of incidence between the variety of performance indicators and the reference sequence, to disclose for example the ten most "important" sequences/indicators for the reference sequence, the KPIs. To get an overview of the dependencies within those 10 KPIs, also the relative degrees of incidence between the KPIs can be calculated so that an interdependency network emerges [55]. Since there is only the possibility of building a network of interdependencies between the KPIs by GRA, the cause-and-effect-relationships lack a detailed explanation. This network, however, is likely to be understood as a construct of the holistic organizational strategy which is determined by "highly correlated" KPIs. If then the strategy changes or rather is adjusted to altered circumstances, the indicators act to the same extent, so that their cause-and-effect relationships are inconsiderable [58]. Nevertheless, the KPIs in their combination must be selected providing sufficiently the strategy and therefore its means and relations.

4. Example of application

The following example of a PM relevant application shall illustrate the possibility of simplifying the indicator selection in the PM with GRA in case of poor data situations. Therefore, the estimations of 50 performance indicators, the possible KPIs, by five organizational experts over four quarters serve as initial data for the example. For the reference sequence, to reflect the corporate strategy as simple as possible, the cash flows over the four quarters are used. The 50 performance indicators show a pre-selected pool of indicators elicited, for example by interviews [10]. They can range from employee satisfaction over customer contentment to process quality, for instance. Then, the experts are encouraged to estimate the respective extent of the indicator k_{it} in the considered period with regard to the Saaty scale (with 1 = very weak extent to 9 = very strong extent) [59]. After the other four experts have analogously estimated, the respective indicators in each period, an aggregated group matrix is created by the mean value of the experts' estimations (**Table 2**). The corresponding cash flows of the considered periods should fictitiously serve as a compliant financial target indicator of the corporation and thus as the reference sequence of the application example.

According to the equal length of all sequences, the values of **Table 3** can be normalized in a certain way by Eq. (10) in order to make the differently scaled sequences comparable (**Table 3**).

The indicators 1–50 do not require to consist of subjective data. For example, customer satisfaction, as a performance indicator, could be represented by an objective measure such as the amount of product returns, if existing. Subsequently, the sequences of **Table 3** need to be moved to an initial value of zero with the zero-starting point operator of Eq. (6) (**Table 4**).

Aggregated experts' estimations	**Period t**	Q_1	Q_2	Q_3	Q_4
Reference sequence j: cash flow		1,000,000	1,500,000	1,750,000	1,250,000
Performance indicator (k_i)					
k_1		4.0000	4.4000	2.6000	4.6000
k_2		5.4000	6.6000	4.8000	2.8000
k_3		5.0000	4.0000	3.4000	5.2000
k_4		7.0000	5.4000	4.8000	3.0000
…		…	…	…	…
k_{50}		5.2000	5.6000	5.4000	4.4000

Table 2. Aggregated experts' estimations.

Normalized aggregated estimations	**Period t**	Q_1	Q_2	Q_3	Q_4
Reference sequence j: cash flow		1.0000	1.5000	1.7500	1.2500
Performance indicator (k_i)					
k_1		1.0000	1.1000	0.6500	1.1500
k_2		1.0000	1.2222	0.8889	0.5185
k_3		1.0000	0.8000	0.6800	1.0400
k_4		1.0000	0.7714	0.6857	0.4286
…		…	…	…	…
k_{50}		1.0000	1.0769	1.0385	0.8462

Table 3. Normalized aggregated estimations.

Then, it is possible to calculate the area between the abscissa and the respective sequence $|s_i'|$ by Eq. (12). The geometrical nearness between a considered sequence and the cash flow reference sequence $|s'_{ij}|$ can be determined by Eq. (13) and consequently also the relative degree of incidence r_{ij} with the help of Eq. (14).

Thus, it is possible to provide a ranking of the geometrically most similar sequences with regard to the cash flow reference sequence (**Table 5**). In this example, the number of KPIs is limited to a count of ten as proposed by Markóczy and Goldberg as the optimal number to work with in PM [60].

GRA not only provides a ranking of the most important indicators of complex systems, it also offers the possibility to reveal the dependencies between the considered indicators by a network map. For this purpose, the relative degrees of incidence between the ten KPIs are determined by Eq. (13) (**Table 6**).

Images with zero-starting point	**Period t**	Q_1	Q_2	Q_3	Q_4	$\lvert s_i \rvert$	r_{ij}
Reference sequence j: cash flow		0.0000	0.5000	0.7500	0.2500	1.6250	1.0000
Performance indicator (k_i)							
k_1		0.0000	0.1000	−0.3500	0.1500	0.0250	0.3846
k_2		0.0000	0.2222	−0.1111	−0.4815	0.0611	0.6207
k_3		0.0000	−0.2000	−0.3200	0.0400	0.4600	0.6969
k_4		0.0000	−0.2286	−0.3143	−0.5714	1.4000	0.5590
…		…	…	…	…	…	
k_{50}		0.0000	0.0769	0.0385	−0.1538	0.1154	0.4056

Table 4. Images with zero-starting point.

Key performance indicator	**Relative degree of incidence (r_{ij})**	**Ranking**
k_{15}	0.9219	1
k_{10}	0.9167	2
k_{14}	0.9129	3
k_{13}	0.8958	4
k_{23}	0.8857	5
k_{21}	0.8847	6
k_{31}	0.8552	7
k_{43}	0.7780	8
k_{24}	0.7719	9
k_{12}	0.7572	10

Table 5. Relative degrees of incidence of the performance indicators and their ranking.

KPI	k_{15}	k_{10}	k_{14}	k_{13}	k_{23}	k_{21}	k_{31}	k_{43}	k_{24}	k_{12}
k_{15}	1.0000	0.4995	0.5629	0.9219	0.8400	0.9422	0.7285	0.9904	0.5635	0.5948
k_{10}		1.0000	0.8161	0.4793	0.5520	0.5153	0.6138	0.5020	0.8148	0.7572
k_{14}			1.0000	0.5373	0.6305	0.5830	0.7123	0.5660	0.9980	0.9129
k_{13}				1.0000	0.7842	0.8725	0.6862	0.9137	0.5378	0.5663
k_{23}					1.0000	0.8857	0.8458	0.8469	0.6312	0.6708
k_{21}						1.0000	0.7626	0.9508	0.5837	0.6174
k_{31}							1.0000	0.7337	0.7133	0.7642
k_{43}								1.0000	0.5666	0.5983
k_{24}									1.0000	0.9145
k_{12}										1.0000

Table 6. Network of KPI dependencies.

Table 6 shows the relative degrees of incidence between the KPIs, which can be interpreted as reciprocal as these degrees can be understood as a kind of "Grey Correlation" [42]. However, similar to the DEMATEL approach, it is important to limit the dependencies to the really "essential" and "significant" ones. Therefore, the shaded fields are not considered subsequently so that only those dependencies which exceed the threshold, the average of the matrix (mean value = 0.74161862), should remain for further analytical procedure.

5. Results and conclusion

The GST shows considerable advantages, particularly in a complex system as the PM. At the present time, it is indispensable to involve the dynamic environment in management control. For this purpose, it is necessary to continuously focus the corporate strategy and objectives in order to create a long-term financial success. The problems that especially occur as a consequence of incomplete information and small sample sizes can be a huge hurdle. The PM requires a permanent update which cannot be enabled by mere application of the existing statistical methods. The PM represents a highly dynamical system with ever-changing environmental conditions. This prohibits an appropriate data measurement with analysis by common statistical methods. Data alter before statistic samples can provide any analytic results. Therefore, it is important to seek methods with minimum data size demands. According to that, the GST with its applications can be useful with its low requirements in sample sizes. Specifically, GRA offers important advantages for the selection of KPIs in poor data situations with the additional possibility of a visual representation of the revealed KPIs within a network of interdependencies.

In conclusion, GRA provides the feasibility to support the performance generation process and to assist PM as a tool-selecting performance indicators in case of incomplete information with small sample sizes. Besides, GRA is able to visualize the performance generation in a map that facilitates steering and control of the organization in the framework of Performance Management [35]. The ability to include financial and non-financial measures provides further advantages for GRA. So, it definitely appears suitable as an OR tool for management control, in particular in PM.

GRA as one of the submethods of the GST will help to improve the informational bases of PM by its possibilities of flexible usage. Therefore, GRA should serve as a feedback as well as a feedforward-oriented PM support. Initially, it provides intersubjectivated data for the performance management, which then disposes of improved informational bases for counteraction measures. After structural breaks of the system, in which PM is implemented, GRA is supposed to inform about such defects and should operate as a feedforward-oriented support for deriving, validating and implementing a new causal model.

The rising number of OR-publications on GST issues demonstrates the enhancing importance of this theory for the analysis of complex systems. However, there are only a small number of articles in the PM literature referring to GST [49]. GST with its wide range of applications is nevertheless an appropriate OR method to support PM. Because of its relevance specifically in poor data situations with incomplete information, PM literature should increasingly focus GST as an important support instrument.

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