

TIME EVOLUTION ANALYSIS AND FORECAST OF KEY PERFORMANCE INDICATORS IN A BALANCED SCORECARD

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ABSTRACT

This paper offers a generic and rational construction of Balanced Scorecard. The construction involves implementing a time-managed approach to identify the evolution of the main contributors to the current company's strategy as well as their behavior in the future organizational performance. After the optimal structure of the model is generated employing financial and non-financial strategic indicators collected from the organization, the study puts forward a realistic analysis of the evolution in time of the performance metrics. This analysis is based on the Partial Least Square equations behind the Balanced Scorecard proposed methodology, statistically comparable to the Structural Equation Modeling. Using historical data in the final model, an accurate prediction of the performance indicators can be achieved in the Balanced Scorecard tool as the approach establishes a stable cause-and-effect sequence. Under certain statistical assumptions, this allows forecasting the effects of future strategic decisions. Although the paper proposes a generic methodology, applicable to any organization, both public or private, commercial or non-profit, this technique is applied, reinforced and validated with a practical example from a public-owned Swiss electricity company.

JEL: G39, M19, M40, L32

KEYWORDS: Balanced Scorecard, Key Performance Indicators, Performance Measurement, Structural Equation Modeling (SEM), Partial Least Squares (PLS), Principal Component Analysis (PCA), Public Organization, Energy Industry, Energetic Sector

INTRODUCTION

Numerous authors criticize older management systems that focus on financial indicators because of their shortfalls, retrospective emphasis and incapacity to indicate modern-day value-creating activities. Financial measures are usually regard as 'lagging indicators of performance', because they record the consequence of decisions not when decisions are taken, but rather as the financial effect of these decisions materialize, which can be long after the choice was made (Epstein and Manzoni, 1998). Other critics go much further by arguing that financial indicators do not increase customer satisfaction, quality, cycle time or employee motivation. Old management's approaches fail to notice the significance of the company's relationship with its environment, particularly with its customers. Therefore, the necessity is obvious for a series of performance criteria more oriented towards the organization's final goals (Butler et al., 1997).

A novel approach to strategic management was introduced by Robert Kaplan and David Norton in the early 1990s, named the Balanced Scorecard (BSC). Identifying some of the limitations and ambiguities of previous management systems, the BSC method offers comprehensive guidance regarding what organizations should focus on to "balance" the financial perspective with other crucial areas. The model facilitates companies to refine their vision and strategy and convert them into action, thereby supplying executives with a complete framework that translates the strategic goals of an organization into a consistent set of performance measures. These key measures are regrouped by strategic perspectives

comprising financial indicators and harmonizing them with operational measures that are the drivers of future financial performance, such as customer satisfaction, internal processes and the company's innovation and development activities (Kaplan and Norton, 1992).

One advantage of the BSC and one of the essential distinctions from other methodologies is the model has the ability to provide managers with a method of articulating a complex chain of cause-and-effect in the company. This pattern grants executives with a base to handle the drivers of wanted results and consequently, the cause-and-effect chain is crucial to the BSC. In fact, this is the heart of the model - connecting in a causal sequence the performance measures of the four strategic perspectives.

Kaplan and Norton (1996) presume the following underlying liaison: the measures of organizational learning and growth will affect the measures of internal business processes, which will influence the measures of the customer perspective, which, finally, will alter the financial measures. The metrics of organizational learning and growth are consequently the drivers of the performance measures of the internal business processes. The metrics of these processes are in sequence the drivers of the measures of the customer angle, while these performance indicators are the drivers of the financial ones. An optimal balanced scorecard should have a combination of result measures (lag indicators) and performance drivers (lead indicators). Each strategic field should have both lead and lag performance indicators, generating two directional cause-and-effect sequences: lead and lag performance indicators apply horizontally within the sections and vertically between sections. The causal paths from the metrics indicators on the scorecard should be connected to financial goals. This course of action entails that strategy is converted into a suite of hypotheses about cause and effect (Kaplan and Norton, 1996a; Kaplan and Norton, 1996b).

One of the drawbacks of the BSC lies in its construction. Despite the fact that the authors offer several fundamental elements and describe the milestones for building the BSC, the concepts are quite vague and can be difficult to apply in an organizational environment.

There are three main goals in this study. The first is to overcome the above limitations and advance several statements for a demonstrative construction of a BSC using the Partial Least Square (PLS) technique. The aim is to generate a realistic model applicable to any organization environment. The second objective is to validate the assumptions with a real example from a Swiss organization where performance indicators outline the strategic perspectives. A cause-and-effect structure will be generated and norms set as to which strategic perspectives are influencing the others. A main findings of this example is that the Kaplan and Norton's model of BSC is nothing more but a particular case of our conclusions. As the suggested approach establishes the most stable cause-and-effect sequence, the third and final objective is to accurately predict the future changes in performance indicators. Under certain statistic assumptions, this will naturally allow forecasting the effects of future strategic decisions.

The paper is organized as follows. In the next section, we present and underline the main BSC concepts from the specialized literature. We highlight the "idealistic" process of 4-axes construction followed by a logical structure allowing for the identification of the number of strategic perspectives and the performance indicators connected to each perspective. We put forward a tentative modeling of BSC that can be implemented in any organization environment. This is pursued by a real example of a Swiss establishment in the energy sector in which the PLS method is applied to build a coherent BSC. Using the structural equations behind the PLS Path Modeling, we better predict the future company trends and take enhanced corrective measures to quickly adapt in a challenging and complex organizational environment. The paper closes with some concluding comments.

LITERATURE REVIEW AND RESEARCH DEVELOPMENT

According to Kaplan and Norton, the BSC is a management model (not only a measurement tool) that allows organizations to identify their vision and strategy and translate into specific actions controlled through a coherent set of actions performance measures. It supplies responses across internal company processes as well as external results so that it constantly advances strategic performance and results. As mentioned by Fielden's (1999), worldwide organizations use BSC for translating vision and strategy into measurable objectives. Moreover, a recent study estimates that 60 percent of Fortune 1000 companies have worked with the BSC (Silk 1998). Adopters include top organizations such as KPMG, Peat Marwick, Allstate Insurance, and AT&T (Chow et al. 1997).

The BSC is set to handle the base of the company's efforts in defining and communicating the vital key interests to managers, employees, investors and even customers (Kaplan & Norton, 1993). With only four strategic perspectives, the BSC reduces information surplus by forcing executives to focus on the handful of measures that are most essential. Consequently, it enables organizations to outline financial outcomes while simultaneously monitoring the resources and obtaining the intangible assets they would need for future growth (Kaplan & Norton, 1996). The BSC offers managers with the ability to identify performance indicators that could forecast the wealth and health of an establishment. By translating strategy in quick and quantifiable actions, a BSC controls strategy in an organizational environmental and uncover hidden assets and information. Furthermore, by linking both internal and external people with these strategies, continuous learning and development can be attained (Pineno, 2002).

The BSC identifies cause-and-effect connections between the various constituents of a company (Kaplan & Norton, 1996). From a practical point of view, this is the core of the BSC, enclosing result metrics and performance drivers, connected together in a cause-and-effect relationship. In fact, the essence of the model is this hypothesis permitting measurements in non-financial areas to be used to predict future financial performance (Nørreklit, 2000).

However, the BSC also has several limitations with some of its key assumptions and relations underlined by numerous authors from the specialized literature. Nørreklit (2000) argues that there is not a causal but rather a logical connection between the strategic perspectives analyzed. Moreover, the author opposes that customer satisfaction automatically create superior financial outcomes. Indeed, series of actions produce high customer value ratio and this will eventually lead to good financial results, but this is not a matter of causality; it is commonsense since it is incorporated in the concepts. As a result, the BSC makes illogical assumptions, which may lead to the anticipation of incoherent measures, triggering sub-optimal performance. Additionally, the BSC is not a representative strategic management tool because it does not consider any rapport between organizational and environmental reality (e.g. competition). Consequently, a variance must be acknowledged between the strategy articulated in the undertaken actions and the presumed strategy (Nørreklit, 2000).

Kanji (2002) summaries more BSC weaknesses highlighting that the model is excessively abstract and not easy to use it as a measurement model. Furthermore, the links between criteria are not clearly defined and, lastly, the causal relationships are problematic (more like interdependence, rather than correlations). Finally, Malina & Selto (2001) claims that the BSC is very difficult to put into practice. The authors make reflections on some negative aspects of the BSC and assert important controversy and friction between the company and its distributors. They further concluded that the performance indicators employed in the model are biased or inaccurate, the communication about the BSC within a company is one-way and not participative (i.e. strictly top-down) and the benchmarks between organizations are inappropriate but used for evaluation.

Introduction to Structural Equation Modeling (SEM)

Within this environment of uncertainty and criticism, some authors (Shields, 1997; Shields & Shields, 1998) have called on management accounting researchers to make better use of Structural Equation Modeling (SEM). SEM is a statistical approach comprising a family of different techniques (Path Modeling, Partial Least Squares and latent variable SEM) that allows the simultaneous analysis of a series of structural equations. However, there seems to be some agreement that all SEM contain two features: first, the estimation of multiple interrelations between variables, and, second, the capacity to represent latent variables in these equations while accounting for assessed measurement error associated to the unsatisfactory measurement of variables. These techniques are specifically useful when a dependent variable in one equation becomes an independent variable in another equation (Hair et al., 1998).

An important concern is the need for a substantial sample size for the majority of SEM models. A suggested rule of thumb for latent variable SEM is a minimum sample volume of 100 (Medsker et al., 1994). Moreover, it has been recommended that a sample size of 200 may be needed to obtain valid fit measures and avoid generating erroneous conclusions (Marsh, Balla, & McDonald, 1988; James & James, 1989; Boomsma, 1982; Medsker et al., 1994). In spite of these issues, Smith and Langfield-Smith (2004) conclude that 11 of the 20 surveys (55%) had sample volumes beneath the acknowledged threshold of 200. Even if the endorsed sample size of 100 is deemed as the lowest level acceptable, three of the 20 papers (Magner, Welker, & Campbell, 1996, Chalos & Poon, 2000, Abernethy & Lillis, 2001) fall underneath this bound, denoting that the conclusions drawn from these studies could be inaccurate.

For this reason, management accounting researchers may be restrained from using covariance based methods because of the significant dataset requirements, and endorse the statement that this technique is suitable in areas where theory is relatively robust. Despite the fact that these limitations are true for latent variable SEM techniques, Partial Least Squares (PLS) modeling presents an appropriate alternative.

Partial Least Squares (PLS)

PLS regression is a recent technique that generalizes and merges features from both principal component analysis (PCA) and multiple regressions. It is particularly useful when predicting a series of dependent variables from a (very) large sequence of independent variables (i.e., predictors). It was used in the social sciences (specifically economics, Herman Wold 1966) but became popular first in chemometrics (i.e., computational chemistry) due in part to Herman's son, Svante (Geladi & Kowalski, 1986), and in sensory evaluation (Martens & Naes, 1989). Nevertheless, PLS regression is becoming an alternative in the social sciences as a multivariate method for non-experimental and experimental data alike (neuroimaging, see McIntosh, Bookstein, Haxby, & Grady, 1996). It was first pioneered as an algorithm similar to the power method (used for calculating eigenvectors) but was rapidly retained in statistical environment (Hervé, 2003). Offering strong forecast abilities (Hoskuldsson, 1988), the technique was successfully used in the Geology field (Tootle, Singh, Piechota & Farnham, 2007).

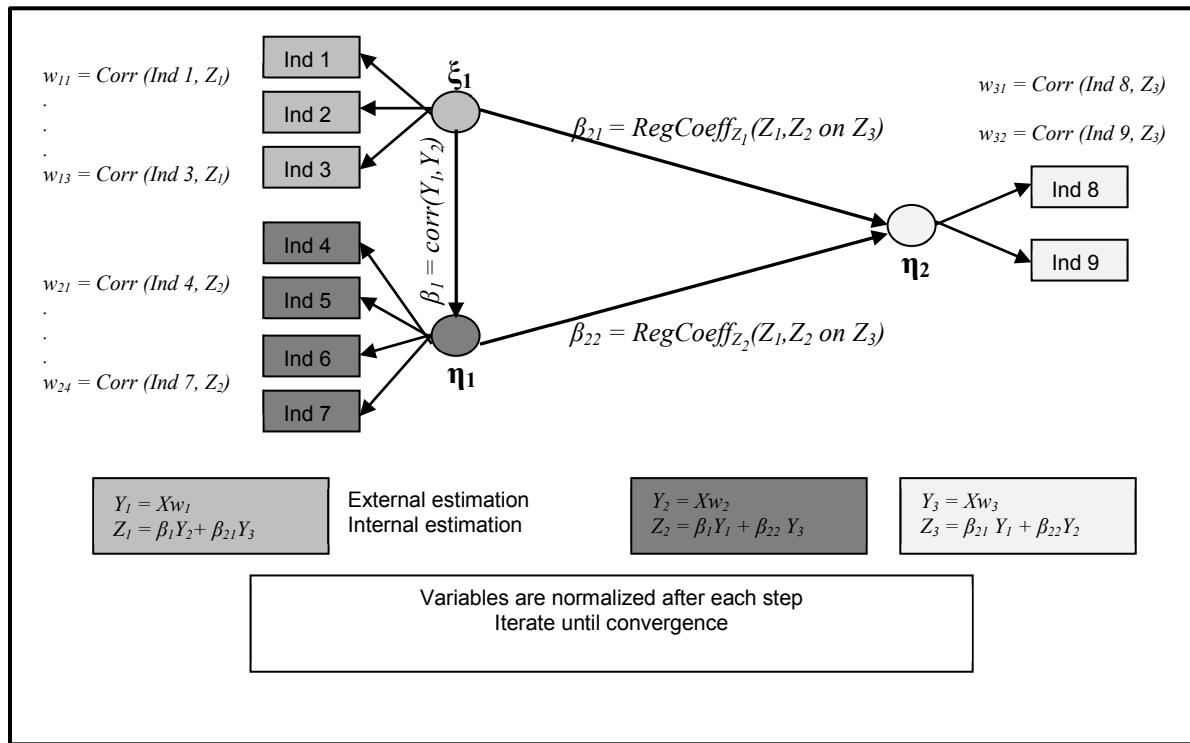
The usage of PLS, in spite of its intrinsic shortcomings (specifically that it is a limited-information method, aimed to maximize prediction, rather than fit), works out to be a way in which statistical modeling in management accounting research can progress without the need to obtain large samples, something which management accounting researchers have found challenging. Another advantage of PLS is the method's ability to accommodate non-normal data, generated by lower demanding assumptions behind the technique (Smith & Langfield-Smith, 2004).

However, there is some misinterpretation in the terminology used in the PLS field. Herman Wold first introduced the notion of Partial Least Squares in his research about principal component analysis (Wold, 1966) where the NILES (nonlinear iterative least squares) algorithm was developed. This algorithm (and

its extension to canonical correlation analysis and to specific situations with three or more latent variables) was later named NIPALS (nonlinear iterative partial least squares) (Wold, 1973; Wold, 1975).

The “PLS approach” concept is somewhat too large and combines PLS for path models on one side and PLS regression on the other. Following a suggestion by Martens (1989), this paper uses the term PLS for Structural Equation Modeling to designate the use of “PLS Path Modeling” as illustrated in Figure 1.

Figure 1: Example of PLS Path Modeling



Above figure describe the two key relations found in any PLS path model: a first one named the outer model, illustrating the connections between the latent variable and its manifest variables and a second one called the inner model defining the relationships among the latent variables themselves.

The outer model specifies the relation between the observed variables and the latent variables. Each latent variable ξ_j is implicitly explained by a set of observed variables x_{jh} . Each observed variable is connected to its latent variable by a simple regression:

$$x_{jh} = \pi_{jh0} + \pi_{jh} \xi_j + \varepsilon_{jh} \tag{1}$$

The Inner Model specifies the relation between the latent variables. The causality model leads to linear equations linking the latent variables:

$$\xi_j = \beta_{j0} + \sum_i \beta_{ji} \xi_i + v_j \tag{2}$$

The latent variables connected to ξ_j are segregated into two categories: the predecessors of ξ_j which are latent variables impacting ξ_j and the successors which are latent variables impacted by ξ_j . For any predecessor ξ_i of the latent variable ξ_j , the inner weight e_{ji} is equivalent to the regression coefficient of Y_i

in the multiple regression of Y_j on all the Y_i 's connected to the predecessors of ξ_j . If ξ_i is a successor of ξ_j then the inner weights e_{ji} is equivalent to the correlation between Y_i and Y_j (Tenenhaus & Vinzi, 2004).

The available software has been for many years LVPLS 1.8 developed by Lohmöller (1987, last existing version). Lohmöller extended the basic PLS algorithm in numerous aspects and published all his research results in 1989. More recently, Wynne Chin developed a user-friendly PLS Path Modeling software labeled PLS-Graph 3.0 (2001, for the last version) and Christian Ringle added more statistical tools for a comprehensive validation of the PLS model in his software entitled SmartPLS. Besides the user-friendly graphical interface to PLS Path Modeling, the algorithm has been further refined and improved with major capabilities, like cross-validation of the path model parameters using jack-knife and bootstrap.

Bootstrapping is the method of determining components of an estimator (for example its variance) by computing those aspects when sampling from an estimating distribution. One usual option for computing distribution is the observed distribution of the empirical variables. In the situation where a group of observed variables are assumed to be from an identically and independent distributed population, this can be solved by generating a number of resamples of the observations (and of same size of the observations), each of which is achieved by random sampling with replacement from the initial set of data. The advantage of bootstrapping compared to analytical techniques is its high straightforwardness - it is significantly easy to use the bootstrap in order to find estimates of standard errors and confidence intervals for complex estimators of the distribution, such as percentile points, proportions, correlation coefficients and odds ratios.

Nevertheless, even if newer and more complex PLS programs are available today (e.g. PLS-Graph or SmartPLS), a better analysis of the PLS Path Modeling allowed us to develop our own software from scratch. The goal was to combine all statistical techniques we are using in one single and reliable tool: compute the principal component analysis (PCA), estimate the path weighting scheme and, finally, generate bootstrap validation procedure and evaluate the best from all possible graphs.

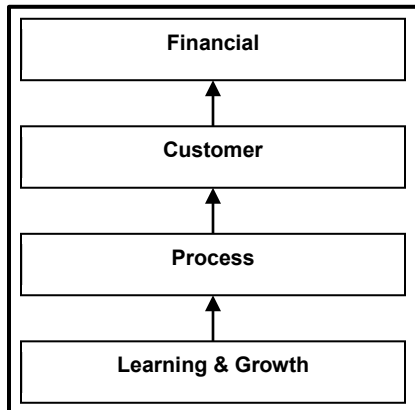
Ittner and Larekner affirmed in 1998 that "(...) decisions using multicriteria performance measurement systems should be computed using explicit, objective formula that prescribes the weights to be attached to each measure, or should be based on subjective evaluations where the weights to be attached to each measure is implicitly or explicitly chosen by the decision maker". This should always be taken into account when building, checking and validating assumptions of causality relations between performance indicators in the context of the BSC implementation. While this might seem difficult from a practical perspective, the PLS technique offers a suitable solution.

As shown in Figure 2, the initial statements of causality relations between the four strategic perspectives remain subjective in the Kaplan and Norton's BSC. The use of the PLS Path Modeling is recommended to establish, in a more objective way, the intensity of the relationships between the strategic perspectives (or the latent variables in PLS terminology) defined by their key performance indicators (or the observed variables in PLS language). Undoubtedly, whereas the choice of strategic perspectives and the hypotheses that link them remain subjective and biased in the case of Kaplan and Norton, the proposed model of structural equations aims "to provide a meaningful and parsimonious explanation for observed relationships within a set of measured variables" (MacCallum, 1995).

In a structural equations approach, the latent variables cannot be measured in a direct and precise way. Accordingly, these latent variables require measurable variables, which are described through performance indicators that can be directly observed and evaluated. The structural equations method is derived from the principal component analysis of the data (confirmatory or exploratory, in line with each specific case) to identify and validate the model of the causal relations which represent the focal point of

BSC. It is essential to stress that one of the intrinsic limitations in the use of structural equations in the BSC framework are the prerequisites for the data validation, which demands a significant quantity of observations in order to validate the final results. The collection of large series of data is not simple, especially in small and medium-sized companies. This is one reason why the PLS technique presents an important advantage in any case where large datasets are not available.

Figure 2: Generic Relationship Map in a BSC (Kaplan and Norton, 1996)



This figure illustrates the original cause-and-effect pattern in a BSC as defined by the Kaplan and Norton (1996), starting from the learning and growth perspective that will affect the measures of internal business processes which sequentially will influence the measures of the customer perspective which, finally, will affect the financial area.

DATA AND METHODOLOGY

Data Collection and Validation

The proposed approach presented in this paper, although universally appropriate to any type of organization, is portrayed using an example of a public-owned Swiss electricity institution. Based in western Switzerland, this governmental organization has active involvement in various electricity projects, especially those concerning to new sources of renewable energy. The core mission of the company is to establish a strong renewable electricity platform in western part of Switzerland.

Data were gathered with the help of the Corporate Strategy Head certifying high quality and reliable data. Data on 144 performance indicators were collected throughout the company over 2 years on a monthly basis. The critical part in the proposed methodology is the choice of the number of axes and of the corresponding measures. It is vital that the key measures describe to a certain extent the strategy of the organization. Undeniably, strategy performance indicators differ among corporations, especially among different sectors and areas (e.g. profit vs. non-profit, private vs. public, etc.). The initial cleaning of the database was completed with the business owners and under the guidance of the Corporate Strategy Head. Due to a relatively high number of duplicates and inconsistent data, only 64 key performance indicators were retained in the final database.

To find the number of strategic perspectives and filter all performance measures per each axis, the principal component analysis (PCA) was applied to the final database using PLS Assistant software. After the final selection and grouping of variables, the same software has been used for the PLS Path Modeling. The software is capable of evaluating the most stable PLS graph by employing the bootstrap technique to each possible arrangement and connection between the strategic perspectives (or latent variables in PLS terminology). Lastly, the data were validated using several measures frequently used in

the PLS specialized literature: AVE and Composite Reliability for the outer model validation and R-Square and Redundancy Index for the inner model validation.

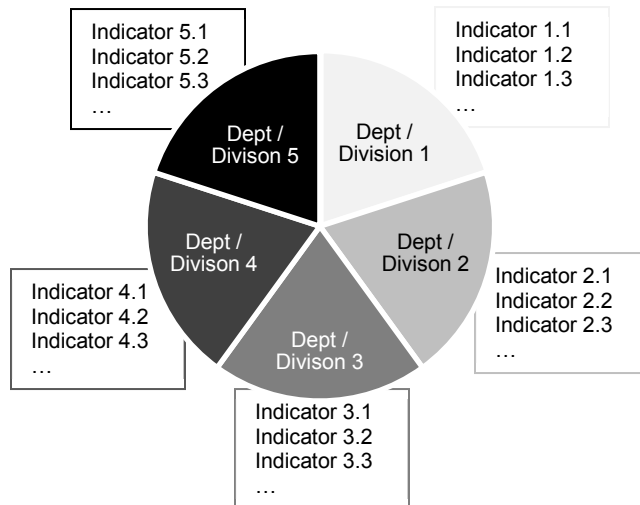
Detailed Methodology Exemplified with a Pragmatic Case

There are five consecutive steps proposed in this paper, at the end of which will allow the construction and implementation of a rational and optimal BSC: (1) collect historical data from the company, (2) sort out and prepare the final database, (3) determine and identify the numbers of strategic perspectives and performance indicators connected to former, (4) construct the cause-and-effect link between all strategic perspectives and, lastly, (5) operate this management tool for long-term planning.

At the end of the proposed five consecutive steps, and when fully implemented, the proposed BSC approach using PLS approach will allow the following: 1.) It identifies the vision and strategy emphasizing only the essential performance indicators. The accent is placed on the fact that financial measures must be “balanced” with non-financial ones, coming from other strategic perspectives, 2.) It retains only the key performance indicators strongly correlated to the objectives of the strategic perspectives, while seeking to identify the series of actions that ultimately create the success of the company, 3.) It will generate the cause-and-effect chain between the strategic analyzed by portraying the optimal diagram of the company’s strategy. 4.) It defines the organization’s crucial competences, vital to the development and the improvement of the processes relative to its success and 5) Using the structural equations behind the PLS Path modeling technique, the approach permits the forecast of required actions in order to achieve progress or in order to adjust and recalibrate after an imminent harmful impact.

As displayed in Figure 3, the first step is related to the collection of all historic key performance metrics throughout the company. This first step is fundamental greatly influences the following steps. Although this appears a simple task, it actually involves a massive time assembling the measures employed in the organization, especially building a valid historic database. Applying this step in our Swiss example resulted in a total of 144 variables summarizing their evolution over 24 periods on a monthly basis.

Figure 3: Identifying and Collecting Company’s Performance Indicators



Above figure shows an example of an organization with its various departments or divisions. After a careful analysis all performance measures will need to be identified and subtracted with the help of the main business owners.

Considering the significant number of indicators, the second step is associated with a final cleaning of the database (Table 1). As mentioned in the previous step, database preparation is essential as the collected

metrics could contain errors and might potentially pollute the findings. Accordingly, the variables should be characterized by (a) reliability and consistency, (b) same incidence in time, (c) ability to capture a fraction of the organizational strategy, (d) information singularity and (e) clarity and straightforwardness. This second step is realized through consistent analysis and intense top management discussions and will ensure that the retained variables are the essential drivers for the company. Following this step only 64 key performance indicators were retained.

Table 1: Example of Database Final Preparation and Cleaning

Strategic Performance Indicators Database					
Time Series	Ind 1.1	Ind 1.2	Ind 1.3	...	Ind Zz.Yy
Month 1	x	x	X		x
Month 2	x	x	X		x
Month 3	x	x	xxx		x
...		x	X		x
Month n		x	X		x

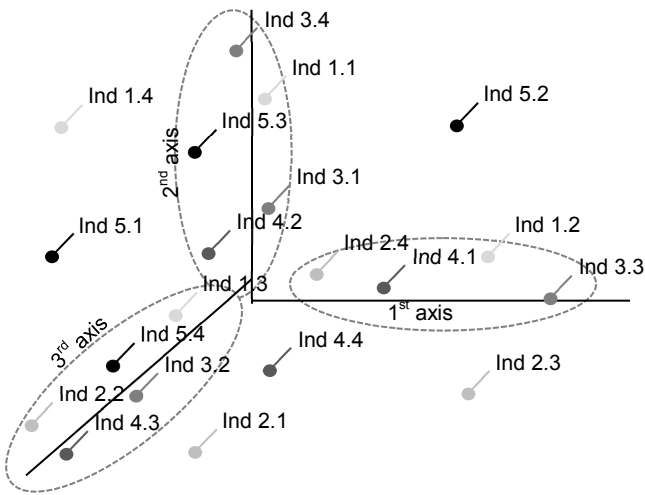
Missing variables
Unreliable variable

This table exemplifies the cleaning of the database, where one performance indicator contains several missing values and another one that have unreliable data (e.g. due to a change in the measurement or the re-definition of the variable). These kinds of indicators should either be corrected (if possible) or, otherwise, completely excluded from the final database.

Although this rational managerial selection has been engaged, the organization continues to have a large KPI database, which is quite difficult to manage in the BSC construction process. As showed in Figure 4, the third main step is to filter and assemble the variables within specific axes (or strategic perspectives) able to summarize a part of the company’s performance. There are three main achievements in performing this step. First is to generate the number of strategic axes encapsulating an suitable level of the total organization’s performance, second is to filter each axis and keep only the key measures that are highly correlated, disregarding any redundant and inappropriate information and, third is to tag these groups of indicators by examining the nature of information that gravitates each strategic perspective.

Several existing statistical techniques are available to accomplish the forth step. Factor analysis and principal component analysis (PCA) can be used. Although different, the two methods are frequently confused. Factor analysis becomes similar to PCA if the "errors" in the factor analysis model are assumed to have the same variance. Principal component analysis can be employed for dimensionality reduction in a dataset by conserving those characteristics of the data that affect most its variance and by maintaining lower-order principal components and ignoring higher-order ones. Such low-order components regularly summarize the "most important" features of the dataset. Factor analysis on the other hand, is a statistical method applied to designate variability among analyzed variables in terms of fewer unobserved variables named factors. Factor analysis helps in identifying "factors" that explain a diversity of results on distinct tests.

Figure 4: Filtering the Performance Indicators Per Strategic Perspectives



Above figure illustrates the three main achievements in performing this third step: 1) generate the number of strategic axes (example shows 3 perspectives), 2) filter and retain only the performance indicators that are highly correlated (illustrated by the circles seizing only the relevant variables) and 3) label the groups of indicators by analyzing the information that gravitates each strategic perspective (for the sake of clarity the perspective names have been kept as 1st, 2nd and 3rd axis).

The PCA suits better our study requirement, as it is fitting for a non-predefined experimental model, while factor analysis is better for models that have a standard beforehand. As the statistical method employed (e.g. PCA) is processing historical data, the results of the research will be dependent on the data available at the time of compendium. However, the intention of our study is not to develop the best indicators, which sometimes could be driven from subjectivity and personal preference, but to actually highlight the importance of the measures available.

Conducting this step in the Swiss company example over the 64 performance indicators, one can clearly notice that with five components, approximately 67% of the total organizational variance is explained (Table 2). This percentage can be explained as the influence of the axes on the total performance: the higher this percentage, the more explanation it provides on the company’s performance.

Table 2: Extract of Total Variance Explained

Component	% of Variance	Cumulative %
1	23.4	23.4
2	14.6	38.0
3	12.7	50.7
4	9.3	60.0
5	6.6	66.6
6	4.8	71.5

This table shows the extract of the first six components cumulating a total of 71.5% of the organization’s variance. However, with only five components (grey highlighted line) and a total variance explained of 66.6% it is assumed to be sufficient to extrapolate to the total variance of the company.

The same PCA also provides the influence of the variables (indicators) against each of these five axes with the help of the component matrix determining the correlation of all variables with each of these axes. Table 3 illustrates the correlation of the first 10 normalized variables with each axis. The nearer a

correlation is to zero, the less the corresponding variable affects the axis. Finally, the variables will be ordered and filtered with respect to the correlation is has upon the axes.

The first 10-15 performance measures per axis are preferred for selection. They are ordered in function of their correlation with the axis. These measures offer a picture of the clustered information. As the variables are ranked by correlation, their descriptive capacity decreases when advancing in the ordered list. This basic selection assembles the performance indicators specific to one area of the organization. To be precise, a simple mathematical grouping will classify the strategic areas specific to the company. The ranking and clustering of variables by axis allows us to label and define them strategically.

Table 3: Extract of the First 10 Indicators from Component Matrix (normalized)

VAR no.	VAR name	1 st axis	2 nd axis	3 rd axis	4 th axis	5 th axis
VAR001	Chiffre d'affaires net	0.835	0.031	-0.310	0.145	-0.273
VAR002	Chiffre d'affaires interne	-0.297	0.517	0.376	-0.185	-0.223
VAR003	Achats d'énergie	0.384	0.000	0.571	-0.472	0.345
VAR004	Résultat mouvements d'énergie (partiel)	0.932	0.132	0.064	-0.134	-0.133
VAR005	Autres produits d'exploitation	0.439	-0.622	0.227	0.232	-0.180
VAR006	Prestations activées	0.280	0.246	-0.611	0.187	0.397
VAR007	Prestations internes (produit)	0.170	-0.063	-0.673	-0.150	-0.188
VAR008	Produits d'exploitation	0.496	-0.583	0.026	0.229	-0.150
VAR009	Matériel & prestation	-0.455	0.629	-0.063	0.244	0.029
VAR010	Charges de personnel	-0.573	-0.101	0.350	-0.010	0.081

This table displays an extract of the first 10 performance indicators (out of the total 64 from the final database) with their respective correlation with each of the five components (or axis).

Even though statistically speaking the highest ranked measures are strongly correlated to the respective axis, one still needs to rigorously analysis the data and remove and/or replace those indicators that would not effectively support the definition of the perspective. While this procedure it is not mathematically corroborated, it is primarily intended to clear certain metrics that would violate the definition of the axis. The rejection or substitution of any performance measure must be well justified in support of the strategy defining the axes. In any economic environment (which by definition is uncertain), it is inappropriate to consider that all indicators correlated to the perspective in cause are also fully representative from a strategic point of view. Those performance indicators that do not describe the definition of the axis should not be selected in the final model as these might potentially corrupt the outcomes.

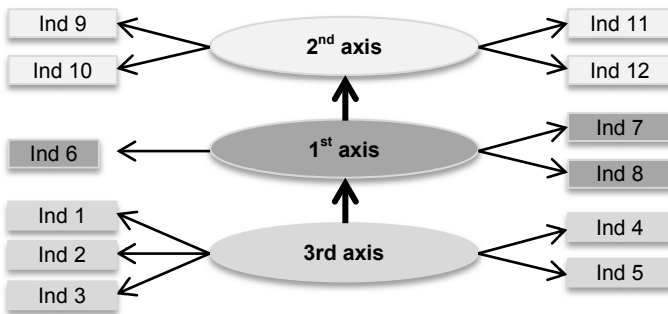
In order to maintain certain accuracy on the strategic perspectives, the final number of measures per axis should rarely exceed 10. This helps in better controlling and comprehending the final management tool. At the end of this third step, the organizational strategy from our chosen Swiss example was recognized to gravitate along five main perspectives: Finance Perspective, Internal Processes Perspective, Development and Growth Perspective, Support Perspective and, finally, the Quality Perspective each of them comprising 4 to 5 explanatory variables as explained in the next step.

Figure 5 illustrates the fourth major step in determining the current strategy of the organization is to apply a PLS Path Modeling regression on the final strategic perspectives. To determine the most sustainable cause-and-effect chain between the perspectives, all possible valid connections between these axes should be analyzed. The most stable PLS model from all possible combinations is the closest to the company's actuals strategy. The stability of the PLS model is determined with a bootstrap technique on each possible graph.

RESULTS AND MODEL VALIDATION

Applying the above fourth step to the specific Swiss example of this study, all possible valid connections between the five axes were analyzed, that is to say a total number of 52'720 possibilities. This step has been achieved using our educational software (PLS Assistant) that was developed and programmed from scratch based on PLS algorithms. Represented in Figure 6, the software is capable of selecting the most stable PLS graph from all valid arrangements. This diagram is the optimal structure of connections between the five strategic perspectives and turns out to be more representative than any other model, being the closest illustration of the actual organizational strategy.

Figure 5: Exemplification of a Cause-and-effect Chain Using PLS Path Modeling



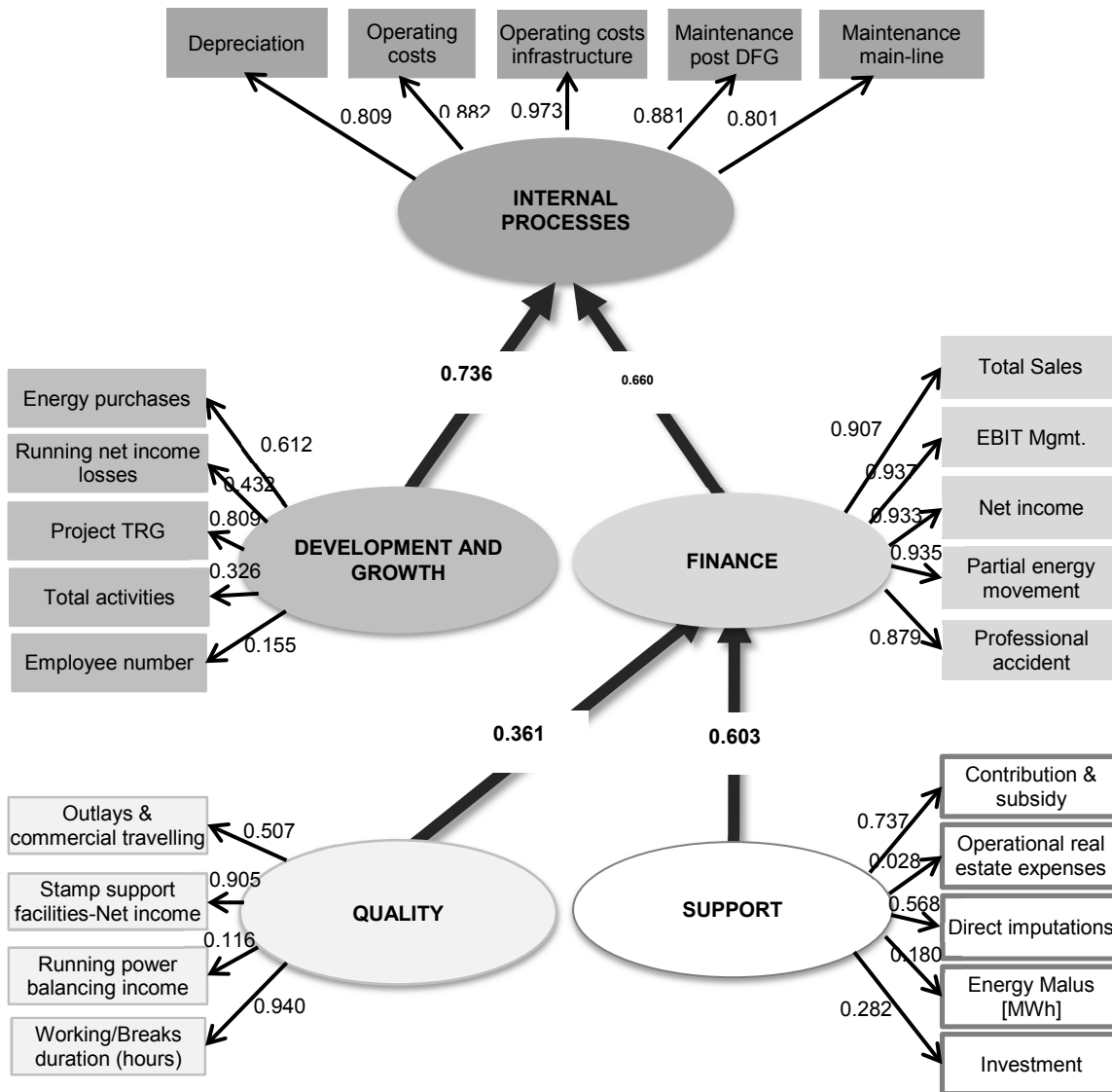
This figure illustrates three strategic perspectives together with their respective performance indicators linked in a cause-and-effect chain. The order of the axes is different to show that after the bootstrap technique is completed, the optimal model sequence might be different.

This assembly is the optimal structure of connection between the five axes and is more realistic than any other model - the closest to the actual organizational strategic vision. Contrary to Kaplan and Norton's BSC model, it was straightforward that this Swiss electricity company was not expected to have the angular stone characterized by the finance perspective. In fact, the company is an old and unhealthy institution lead by structural issues, with obsolete and inefficient equipment that erodes its competitive strength. The lead-management had to take some strategic decisions recently with the intention of restructuring their internal processes, by focusing on the financial and human aspects.

The finance perspective appears logically in this present strategy as a secondary, and hopefully temporary, objective. The financial indicators are strongly correlated with their axis, confirming their indirect contribution to improve internal processes. In a similar purpose, efforts are made in this Swiss institution to improve the quality of their services, but models tend to show in contrast that the support perspective has more impact on the financial axis. Lastly, the diagram emphasizes the emphasis on development & growth, support and quality in the present strategy.

When it comes to model validation from a statistical point of view (Table 4), the overall figures are assessing both measurement of the (outer) and structural (inner) model. As a general rule of thumb, to validate the outer model (measurement model), the Average Variance Explained (AVE) should be greater than 0.5 (Chin, 1998) and Composite reliability higher than 0.6 (Werts, Linn, and Jöreskog, 1974).

Figure 6: BSC's cause-and-effect Chain Using PLS Approach



The above illustration represents the optimal structure of connection between the four strategic perspective and is closest to the actual strategy of the organization. This final assembly was selected from all possible connections using the bootstrap technique, being the most stable PLS graph.

As for structural (inner) model validation, the best indicator is the R-square level. Values of 0.67, 0.33 and 0.19 are considered strong, moderate and respectively weak for the inner model valuation (Chin, 1998). The R-square have acceptable values for all perspectives being all in between the higher and medium thresholds.

As noted earlier, the inner and outer relations are founded on structural equations. Consequently, at the back of each PLS Path model are equations that explain the relationships between indicators and the corresponding axis (outer model equations) and between the axes or strategic perspectives themselves (inner model equations). The fifth major step is based on using these equations in order to study and predict the relations for the long term. From a practical viewpoint, there are significant benefits to doing this including that: 1.) examine the variance impact of one (or several) measures to the whole model; 2.) predict the strategic changes by looking at the relations between the strategic perspectives; 3.) visualize and manage both direct and indirect changes needed for an important change in the organization's

strategy; 4.) simulate the impact of resources allocation decisions on the future performance, thus complementing the traditional budget approach.

Table 4: PLS Model Validation Criteria

	AVE	Composite reliability	R-square	Redundancy index
DVLPMT & GROWTH	0.569	0.719		
FINANCE	0.842	0.864	0.658	0.402
INTERNAL PROCESSES	0.759	0.840	0.546	0.361
QUALITY	0.550	0.619		
SUPPORT	0.542	0.673		

The table is summarizing several validation criteria for the selected PLS graph. The AVE and Composite reliability are used for the measurement model validation (or the outer model, that is to say the relationships between the latent variables with its observed variables) and the R-Square and Redundancy index are employed to validate the structural model (or the inner model, thus the relations between the endogen and exigent latent variables)

Toward an Assisted Scenarios Simulation

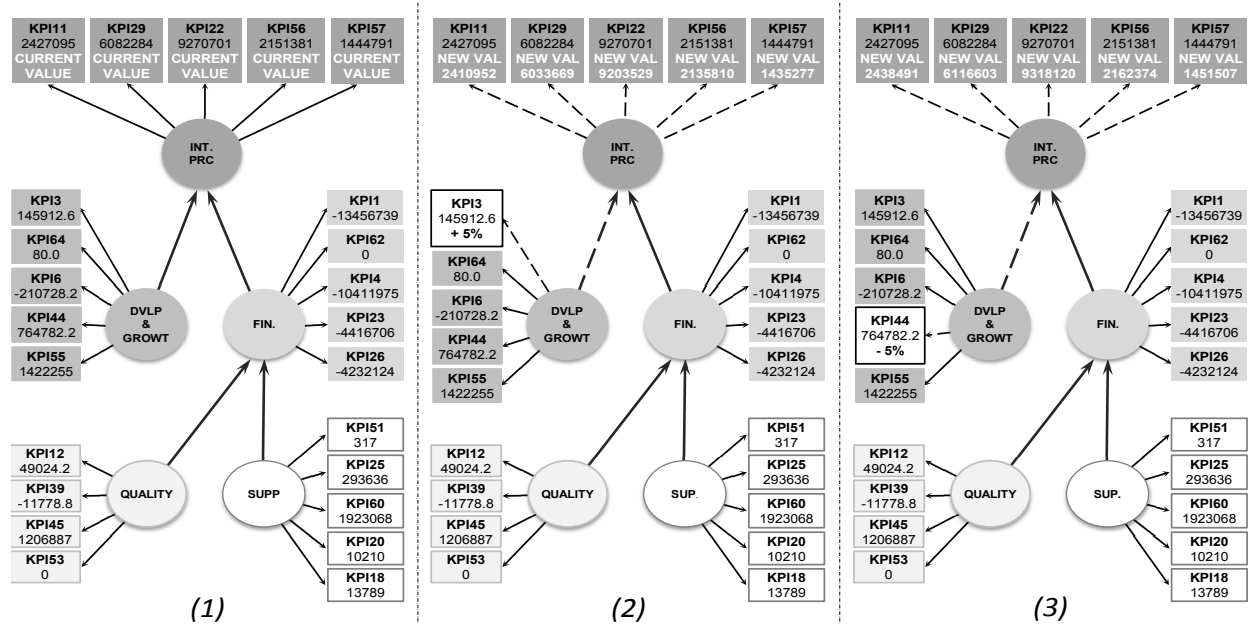
In any management-controlling field centered on strategic decisions, it is obviously appealing for the organizations to use Partial Least Square to simulate and measure impacts of strategic indicator variations over the rest of the model. With this kind of a tool, the manager can forecast the behavior of his current strategy, sorting the potential future of his organization into a couple of scenarios with the possibility to study the impact of each of them over the rest of the structure.

In estimating its coefficients, PLS uses algorithms having elements in common with both linear regression and LISREL. Similar to regression analysis, the PLS works with the variance of the individual data item derived from the means. When partialled out, the variance for the entire model via iterative analysis, PLS resembles LISREL. In fact, this latter characteristic allows the model to be categorized as a SEM technique (Gefen, Straub & Boudreau, 2000). Therefore, for many data analysis issues, estimates of the linear relationships between variables are adequate to describe the observed data, making them reasonable predictions for new observations. From this perspective, PLS is generally referred to as a “prediction oriented approach” (Sellin, 1995) statistically outperforming simple benchmark models (Cengiz & Herwartz, 2009).

Working with data provided by companies with many explanatory variables and comparatively little sample data is a statistically specific area where PLS proves to be useful in constructing prediction equations (Hoskuldsson, 1988). The model founded by bootstrapping comparison has good quality scores to to forecast variation of indicators. This variation should be rather small, otherwise the whole model weighing/loadings lose too much consistency to be faithfully used. In addition, as any statistical tool used, the prediction model should be considered more as trends rather than exactly future relevant values.

Using the PLS equations, a “simulation view” has been implemented in our PLS Assistant software in order for the manger to test the impact an indicator modification can have on the overall model (Figure 7). This exclusive feature of the PLS Assistant software allows managers to forecast different scenarios.

Figure 7: PLS Assistant 2.1 Simulation UI Presentations (1), Impact of different Scenarios Study (2&3)



Above graphs exemplifies a “simulation view” of future indicator changes if one measure is changed. Scenario 1 is the current BSC illustration as initially found after the PLS bootstrap techniques. In scenario 2 we increased KPI3 by 5%, whereas is scenario 3 we decreased KPI144 by 5%. Dotted lines illustrate the repercussions and new values for the performance indicators can be noticed in Internal Processes perspective.

Keeping notations values seen in Figure 1 and applying the forecast technique, the final equation is:

q_{ij} : Present value of the indicator

q'_{ij} : New value, simulated or chosen

$$q'_{31} = \left(\frac{q'_{21}}{q_{21}} - 1 \right) * \frac{w_{21}}{\sum_{k=1}^4 w_{2k}} * \frac{\beta_{22}}{\sum_{k=1}^2 \beta_{k2}} * \frac{w_{31}}{\sum_{k=1}^2 w_{3k}} * q_{31} \quad (3)$$

However, one should keep in mind that any company takes time to recalibrate from any change or crisis situation. Any change in the organization’s strategy should be completed in a pondered and controlled way. Furthermore, it should be noted that a public detained organization cannot be revolutionized or radically transformed as a private-owned company might be. The example used in this study refers to an electricity institution that has strong connections with the local public authorities, thus her status is borderline between these two concepts.

CONCLUDING COMMENTS

The research goal of this study was to develop and empirically validate a comprehensive framework that bridges a Balanced Scorecard model with a Structural Equation Modeling approach and endorses a modern understanding of aspects underlying the actual strategy, with the intent of better manage and control the corporate performance.

The fundamental step towards this objective was the development of a general frame of reference that harmonized previously contradictory theoretical assumptions associated with the Balanced Scorecard as well as with its ease of implementation. On this basis, the suggested framework is embracing several main concepts: 1.) tackles the issues of strategic vision of any company and converts the current strategy into an easy-to-use model for better integration, communication and long-term management, 2.)

highlights the key performance indicators that have the capability to capture the most relevant information from the organization, information that is strongly linked to the actual goals the company is aiming for, 3.) assembles distinctive strategic perspectives that summarizes organizational information in an appropriate way, in order to create a thorough illustration driving institutions on their road to success, 4.) establishes the relations between strategic perspectives in a cause-and-effect chain that underlines the interactions taking place at a strategic level, helping in emphasizing the organization's advantages and weaknesses and 5.) overcomes the static aspect of prior models disclosing the dynamic evolution over time by employing mathematical PLS equations, refining the planning and control of the main components within a company.

The main purpose of this paper was to examine the Kaplan and Norton BSC theory compared to a more pragmatic approach. Having established the strategic research framework, we empirically validate the proposed methodology by developing a strategic map in the context of a Swiss electricity organization. The results suggested that the BSC issues could be formalized in a more rigorous manner. It is thus possible to reconsider the notions advanced by Kaplan and Norton as showed in the analysis of this case.

The application of PLS Path Modeling converts the current strategy into a cause-and-effect model that can be monitored and controlled using a handful of main performance indicators. One might argue that by handling historical data, the model summarizes outdated information by illustrating a picture that cannot be exploited to predict future planning. While this concern is legitimate, the methodology is actually identifying the current strategy applied by the institution. Only by fully recognizing the actual situation one can plan for the period to come. The PLS regression is more suitable for maximizing prediction, thus the model is also capable of revealing the forecast strategy of the company. In addition, this approach permits the simulation of the resource allocation impact on the organization's overall performance. Finally, these managerial tools are applied in a moment of major need for strategic change in the company. The use of this approach acknowledges not only the recognition of the chain of causality between different strategic areas of the corporation's performance, but also reinforces the intuition with "a measure of the measures".

The necessary conditions for the proposed methodology are relatively constraining. It is essential to have an adequate number of indicators together with a consistent historical sample of data. Additionally, the real value of BSC lies more in the distribution and the understanding of the strategy at all levels within the organization. Therefore, this involves strong communication, interpretation and analytical skills.

We aimed to have high objectivity in our methodology. For both data collection and data analysis, some variables may have been biased by personal views. Our approach can be impartially applied. However, in practical terms a level of flexibility, that cannot be mathematically verified should be considered.

Even if the model founded with the current technique is robust, the PLS equation affiliated are no longer efficient if the scenario tested involve too much variations and thus loses its predictive strength. However, our tests with an alteration up to 50% show no radical change to the whole model robustness. Nevertheless, within the framework of our study, we limited the possible variation at only one indicator at a time and the variation did not exceed 5%. One should also note that the results found using the PLS simulation are trends and should not be treated as precise forecast values.

The Partial Least Square (PLS) technique will likely grow in usage in the coming period, as it is significantly less difficult to understand than the covariance-based methods when it comes to identifying a model and explaining results. However, PLS involves higher complexity for explaining loadings of the independent latent variables. Since the distributional characteristics of estimates are not recognized, the researcher cannot assess model significance with the exception of bootstrap induction. Additionally, being a new statistical technique, there are few commonly agreed thresholds for the model validity and

stability. Nevertheless, we used the small number of tools available for PLS Path Modeling approach, tools frequently employed in other PLS studies found in the specialized literature.

Based on the findings from our study, further research may have a higher degree of complexity and dynamism. The more insights are achieved into the “mechanics” underlying performance, the more individual models can be developed with the suggested method. It would be beneficial to apply our research framework to other industries or countries. The framework could be particularly valuable for analysis of other industries such as media, telecommunications and high tech. Increasingly, industries are characterized by a changing and challenging environment. It is time to change old and traditional tools with a more realistic approach to analyzing performance. A comparison of the results of such an analysis with the findings of this study could conduce to a higher validity and generalizability of the approach.

It is relevant to develop a more formal methodology to validate the organization's strategy in a rational way, while using a simplified model. Indeed the PLS method suffers from a deficiency of theoretical foundation. Similarly, Kaplan and Norton's approach was criticized in the specialized literature from this perspective as well. The difficulty with which future researchers will be challenged lies in the compromise between the pragmatism required by corporations and the need for the theoretical framework requested by researchers.

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