Business Analytics and Performance Management: A Small Data Example Combining TD-ABC and BSC for Simulation and Optimization

Steen Nielsen¹

Cluster for Operations Research and Logistics, Department of Economics and Business
Economics, Aarhus University, Denmark

May 20, 2017

Abstract

The purpose of this paper is twofold: first, it discuss the potentials of combining performance management with the concept and methodology of business analytics. The inspiration for this stems from the intensified discussions and use of business analytics and performance in organizations by both academics and professionals. Second, the paper demonstrates and evaluates the idea of business analytics on a numerical example combining the balanced scorecard and TD-ABC. Four different scenarios are analysed by means of spreadsheet Monte Carlo simulation and optimization to show how such a combination can be made and assess the consequences. The paper shows that in order to be able to fulfil future jobs descriptions; accountants must not only have specific quantitative skills but also creativity and imagination. In addition, the results of the simulation scenarios show the complicated nature of decision making and the careful considerations needed before actually making a decision. For practical implications, the paper establishes some basic ideas for integrating the business analytics methodology for selecting and evaluating accounting problems and it therefore paves the way for analytics performance management approaches.

Keywords: Management accounting, business analytics, simulation, balanced scorecard, optimization, Time-Driven ABC, decision making.

1 Introduction

In a commentary in Accounting Horizons (2012), Moser asks if accounting research is stagnant. His answer to this question is a qualified 'yes'. There are several reasons for this answer. One of them is that researchers within the field of accounting rarely collaborate with researchers who use different methods or with researchers outside the field of accounting. Researchers tend to work with researchers who use the same research methods. The result is that our research does not have much impact on society and on practice because no one outside the accounting research society cares about our results even though real management accounting has evolved considerably over time (Zimmerman, 2001; Hopwood, 2007; Birnberg, 2009; Kaplan, 2011).

Over the years, the concept of change in management accounting research has been studied from many different angles using different theories, for example functionalist, behavioural relations, institutional theories, actor network theories, interpretive and critical perspectives together with many different methodologies such as field studies, case methods, archival studies, and experimental studies (Berry *et al.*, 2009). Still a source of frustration is that only few research results are used in the practical world (Merchant, 2012) in spite of the fact that management accounting is an applied and practical field

¹ e-mail: sni@econ.au.dk

that constantly faces new challenges from the business world (Kasanen *et al.*, 1993; Otley, 2001; IMA, 2008a; CIMA, 2009b; Kaplan, 1998, 2012; Merchant, 2012). For research to merely contribute new theories is not good enough; instead the researchers should try to advance the body of knowledge, i.e. to develop predictive theories that specify both the behaviour and the context required for achieving the specified outcome (Ahrens and Chapman, 2007). McAfee and Brynjolfsson (2012) also argue that *'all these can be done in areas that so far have been dominated by intuition rather than by data and rigor'*.

The movement toward the increased use of 'analytics' (i.e. business analytics and the use of data) in business and organizations therefore represents an interesting new venue from which management accounting and management control can benefit. Several surveys have shown the importance of analytics for now and for the future (e.g. Accenture, 2013; Gartner, 2012; McKinsey, 2011; and SAS-Institute, 2014). Surveys conducted within the management accounting area also show the increased importance for management accountants of having the right analytical skills (Collier *et al.*, 2007; ACCA, 2009; CIMA, 2008, 2012; IFAC, 2011) to interpret large sets of interrelated data, and the importance of being familiar with new accounting tools (CIMA, 2009b; Collier *et al.*, 2007). A Gartner Survey (2013) made the importance of analytics explicitly clear: *'BI (ed. business intelligence), analytics and performance management are the top areas for CFOs' IT interest'*.

Studying the backgrounds of the top 100 global companies' CFOs, McKinsey (2013) found four different profiles for a CFO; the finance expert (or numbers guru), the generalist, the performance leader, and the growth champion. They all view the benefits of analytics from different perspectives. Not only is the CFO's role more important now than it was a few years ago, but issues such as risk management, internal and external communication together with e.g. leadership, creativity and innovation are important in order to be able to interact and explain outcomes and results (ACCA, 2009; CIMA, 2012). Specifically, team building seems to be an important skill that supports business analytics (IFAC, 2011). This is also documented in a survey made by Ernst and Young (2008) related to the changing role of the financial controller, where focus is on team building and management.

Even though the concept of big data or 'big data analytics' is often related to un-structured data (e.g. data from the internet such as data used by Amazon, Facebook, Twitter and YouTube) there are also a number of interfaces to a company's performance area such as different dashboards (Eckerson, 2011; Giles, 2012 in The Economist). The three-fold challenge of big data is therefore: deciding which data to use, deploying analytics, and using its insights to transform operations (McKinsey, 2013). But using structured small-data (i.e. spreadsheet data in rows and columns on e.g. customer payments) is also relevant (Davenport and Kim, 2013).

Only few examples exist discussing BA (Business Analytics) and management accounting (one example is Schläpke *et al.*, 2013).

Three themes of research have led us to propose an analytics approach for management accounting research:

- Holistic models dominate performance management research. Research has shown the need for holistic models based on strategy such as the balanced scorecards, the pyramid model, different business models, strategy model and the use of different tools for real business problems and analysis (Berry *et al.*, 2009; Ferreira and Otley, 2009; Kaplan and Norton, 1996; Simons, 1995; Flamholtz and Hua, 2003; Malmi and Granlund, 2009).
- Management accounting should solve problems that relates to the real world (Ahrens and Chapman, 2007; Hopwood, 2002; Kaplan, 1998, 2011; Kasanen *et al.*, 1993; Merchant, 2012). Birnberg (2009, p. 3) makes this very clear by saying: *'At a time when practice is in need of assistance, our current focus has led to research that is primarily intended to enhance current*

models rather than assist in solving the problems of practice'. This would make management accounting and performance management an instrument for competitive advantage for real business. As said by Kurt Lewin (see Argyris and Schon, 1996, p.44): *'there is nothing more practical than a good theory*'.

- Management accountants need to handle huge amounts of data from many different sources to be able to make decisions. Specifically, they have to go into the black box and use 'big/small data' as input for decisions in the future, for example, to make predictions including consequences for uncertainty and risk in decisions. This will lead to new and holistic quantitative research methodologies that can handle aspects from raw data and allow the management accountant to draw upon all relevant tools that can improve decisions (Dechow and Mouritsen, 2005; Langfield-Smith, 2007; Chenhall, 2005; Zimmerman, 2001). Birnberg (2009) also suggests that the practical problems faced by management accountants be solved by transgressing the boundaries of management accounting and interacting with non-accountants.

In light of the above reflection, the purpose of this paper is to address these challenges by introducing the approach of 'business analytics' into performance measurement and management. Specific emphasis will be placed on how developments in related fields and disciplines interact i.e., how technological innovations and new methodologies affect upon each other. This paper seeks to answer two specific research questions: *a)* how can the management accounting community benefit from the growing interest in business analytics and; *b)* if more research within the field of modern performance management should be devoted to analytics, how could this be done?

To answer these two research questions we analyse the driving forces and elements in business analytics (from both literature studies and surveys) and combine these elements with the models and decisions in management accounting. Based on our findings we see a need for increasing the focus on business analytics for decision making.

Then, we combine BSC and TD-ABC in a holistic stochastic model and use this as a numerical example to show the challenges that the accountants face when decisions are to be made based on the outcome of such a model. Finally, we discuss the demand for accountants' analytical skills, which we expect to soar in the future.

Our discussion shows that a number of opportunities exist for expanding – not only empirical management accounting research – but also to stimulate and expand the academic and professional areas for the individual student and accountant.

In the future, business analytics will pervade most traditional accounting topics and decisions such as e.g., product mix, make-or-buy, profitability, assignment of costs, and pricing at the operational as well as at the strategic level by a large number of data and techniques.

Topics such as dynamic and stochastic performance, optimization, value creation, fact based decisions, and reporting through visualization are concepts and tools that the accountant has to be acquainted with in order to be able to live up to companies expectations and to add value to the company. To work within these areas the accountant must also possess specific soft skills such as the creativity and imagination required for building data-driven model, e.g., simple performance measurement models, activity-based costing, target costing, and the balanced scorecard.

Management accounting researchers often discuss the gap between theory and practical research, but this study shows that the gap can be closed by combining three areas of research that are usually seen as separate, i.e., accounting models and concepts, business analytics, and management science methods.

Finally, our numerical example demonstrates that a decision maker has a number of considerations regarding trade-offs before (s)he can make her/his best choice – here simplified by the trade-offs between different ways of reducing variation for specific production measures.

The paper is structured as follows. Section 2 explores the concept of analytics going through the different stages of BA from framing the problem to the communication of the results. Section 3 discusses the challenges and possibilities for combining business analytics and management accounting research referred to as ‘analytics performance management’. Section 4 shows a numerical example of integrating BSC and TD-ABC in a BA setup including running four scenarios. Section 5 finishes the paper with a conclusion, implications and ideas for future research.

2 Driving forces of business analytics

Business analytics is ‘*the use of data, information technology, statistical analysis, quantitative methods, and mathematical or computer- based models to help managers gain improved insight about their operations, and make better, fact-based decisions*’ (Davenport and Harris, 2007). Business analytics focuses on developing new insights and understanding of business performance based on data and through hard and soft tools. In contrast, Business Intelligence provides historical, metric-driven decision making and answers questions such as how many units did we sell, what did customers buy and for how much. BI is characterized by the creation of simple rules and alerts and the distribution of known facts to systems and people (Desai *et al.*, 2004; Garcia, 2011).

Often BA separates into three main levels (Davenport and Kim, 2013; Evans and Lindner, 2012).

Descriptive analytics means converting past and current data into usable information in the form of reports (e.g. costs, sales, and revenue), charts, PivotTables, and graphs. The idea is to identify patterns by using statistical measures (e.g. the mean, correlation, range, and standard deviation) to make informed decisions (Evans and Lindner, 2012). Visualizing tools are important here and cover different types of charts, scorecards, frequency distributions, clustering, Pareto analysis, decision trees or as pointed out by SAS-Institute: ‘a picture is worth a thousand words’ (Choy, SAS-Institute, 2012). Examples of descriptive analytics could be data about how many resources and cost did we spend on capacity, how did our sales prices develop last month, how much did we sell to customer x, y, and z? Or which factory/department has the lowest/highest productivity?

Predictive analytics means to go beyond merely descriptive characteristics of data, by using data from the past and current to be able to make relevant predictions for future behaviour of customers, costs, sales, and competitors’ reaction. Predictive analytics tell us about past performance and makes it possible to come up with relevant forecasts for the future by examining historical data in detail, detecting patterns or relationships and then extrapolating these relations forward in time (Evans and Lindner, 2012). Evaluating the predictive power of a model refers to a model’s ability to generate accurate predictions of new observations from possible future values (cross-sectional) or by time-series data (Shmueli and Koppius, 2011). Items such as, cause-and-effect relationships, the balancing of financial and non-financial measures, what are internal and external measures, and what data is highly relevant reliable and timely for decision makers, belong to the most important assumptions and questions (IFAC, 2011). Even though forecast is not easy, and that the only certainty is that the forecast will be wrong, ‘it is far better to foreseen even without certainty than to not foresee at all’ as Henri Poincaré (father of the chaos theory) stated in 1903.

For example, the executives at Carterpillar (a global manufacture of construction and mining) knew that its business was closely tied to shifts in gross domestic product (GDP), asked its economist to find a

leading indicator of performance related to GDP. They found that Carterpillar's sales to users predicted shifts in the economy and business cycle – with a lead time of six to nine months - in relation to U.S. GDP. Although the company underestimated the depth of the recession in 2007, it used the information to trim operations and came out of the recession in a much better position than its rivals. This shows how predictive analytics based on an important single external measure can be used on the linkage between a general economic indicator and the internal KPIs (Fortune Magazine, May 23, 2011, p. 141).

Predictive tools used may be classified as: predictive logic and data-driven modelling, what-if analysis, (stochastic) simulation, mathematical relations and functions, scenario analysis with goal seeker functions or sensitivity analysis. Examples of predictive questions could be: how much do we expect to sell next quarter to customer x, y and z if a new supplier starts its production in two months? How can we expect net profit to develop next year if the financial crisis continues? Or how much can we expect to improve in productivity over the next two years given a status quo situation for our branch? Explanatory statistical models used in descriptive analytics do not imply predictive power because these models are built for testing causal hypotheses that specify how and why certain empirical phenomena occur (Shmueli and Koppius, 2011).

Prescriptive analytics implies using experimental design and optimization to identify the best possible alternative given different scenarios, criteria and objectives, by using e.g. linear optimization, integer optimization, heuristics, nonlinear or non-smooth optimization tools (Davenport and Kim, 2013; Evans and Lindner, 2012). Many problems simply involve too many choices or alternatives for a human decision-maker to effectively consider (bounded rationality). Prescriptive analytics uses optimization to identify the best – and most likely – alternatives to minimize or maximize some objective. Examples of prescriptive questions could be: which customers should we choose to maximize revenue given our revised strategy? Which products should be produced to maximize net profit within the next quarter if we can choose among different machinery with different levels of technology? Which distribution channels should we choose to minimize costs if a new distributor has emerged? Or what is the probability of getting a net profit below zero (or any other positive or negative value) if we optimize our BSC or our TD-ABC model subject to specific capacity constraints?

To be able to handle both internal but also external data, companies normally use different data mining principles. Data mining is the extraction of hidden predictive information from large databases (Ramamohan *et al.*, 2012). Data mining is a rapidly growing field of BA that focuses on better understanding characteristics and patterns among variables by a variety of statistical and analytical tools and a better understanding of the underlying theory (Evans and Lindner, 2012).

Figure 1 shows the synergy of the relationships that define business analytics.

Figure 1: Roadmap to proactive decisions
Ref. Davenport and Harris (2007)

Both predictive and prescriptive analytics are used for generation of new theory, developing new measures, comparing competing theories, improving existing theories, assessing the relevance of theories, or assessing the predictability of empirical phenomena (Shmulie and Koppius, 2011).

Several contributions have outlined how analytics will influence future areas such as supply-chain-management (Liberatore and Luo, 2010), create value, (Kiron and Shockley, 2011) or improve decision-making (Romanenko and Artamonov, 2014).

Kobielus (2010) defines advanced analytics as:

Any solution that supports the identification of meaningful patterns and correlations among variables in complex, structured and unstructured, historical, and potential future data sets for the purposes of predicting future events and assessing the attractiveness of various courses of action. Advanced analytics typically incorporate such functionality as data mining, descriptive modelling, econometrics, forecasting, operations research, optimization, predictive modelling, simulation, statistics, and text analytics.

Since the beginning of the millennium a number of surveys about the importance and benefits of analytics (and performance) have been conducted (Davenport *et al.*, 2002; Morris *et al.*, 2003; Harris and Davenport, 2006; LaValle *et al.*, 2010). The survey conducted by Davenport generally confirms that analytics approaches are correlated with higher performance. According to a Gartner (2012) survey, organizations get \$10.66 of value for every \$1 invested in analytics; adoption rates for analytics will go from 25%-35% today and will continue to accelerate adoption beyond 2020. This will influence the content of the job for CIO (Chief Information Officer), for the CFO (Chief Financial Officer) and for the CMO (Chief Marketing Officer) according to Gartner (2012).

Davenport and Harris (2007) also document a large number of case studies and companies who have gained benefits by using analytics such as Procter & Gamble, Barclays Bank, Boston Red Sox, and Harrah's Entertainment. Even though these companies may be characterized as relatively big companies, they used relatively simple models. Capital One, for example, was able to identify and serve market segments before its peers. The key to this ability was the company's closed loop of testing, learning and acting on new opportunities (Davenport and Harris, 2007, p. 42). In a later article (Davenport and Kim, 2013) discuss in more details how the decision maker can go through different stages; from recognition of the problem to presenting the outcome in different layouts.

3 Management accounting in a business analytics setup

The IBM Institute for Business Value together with the Saïd Business School at the University of Oxford conducted a study, the 2012 Big Data @ Work Study, which surveyed 1144 business and IT professionals in 95 countries including interviews with more than two dozen academics. The study shows that 63 percent – nearly two thirds – of the respondents report that the use of information and analytics (including big data) does create a competitive advantage for their organizations.

This compares to 37 percent of the respondents in IBM's 2010 New Intelligent Enterprise Global Executive Study and Research Collaboration – a 70 percent increase in just two years. The 2010 survey also revealed that the top performing companies are 15 times more likely to apply analytics to strategic decisions than their underperforming peers. Data is the key item for this. Bad data, on the contrary, will put even the smartest decision maker at a disadvantage. It is the responsibility of senior management to align the company's two critical assets: people and data.

Often different accounting models are combined (known as accounting packages, see e.g., Kaplan, 2006; Cokins and Pirello, 2007; Gurowkan and Lawson, 2007; Malmi and Brown, 2008; Nielsen *et al.*, 2008; CIMA, 2009b) and further developed. This will complicate the design and use in combination with BA even more.

Using analytical techniques and statistical analysis for management accounting decision problems is, however, not new at all. In earlier time, however, the utilization of these techniques were concerned about selecting a specific OR-technique for the purpose of demonstrating it for a limited - but often specific management accounting or control problem in - isolation (see e.g., Multiple Regression Analysis of Cost Behaviour, Benston, 1966; Multiple Regression Model for Cost Control, Jensen, 1967; Stochastic CVP analysis, Liao, 1975; Cost Variance Investigation by the Use of Markov Processes, Dittman and Prakash, 1978; Relevant Costs, Congestion and Stochasticity in Production Environments, Banker *et al.*, 1988; Comparison of Accounting Systems by the use of Heuristics in Selecting Economic Optima, or Dickhaut *et al.*, 1983)².

Without going into research details and discussions of different paradigms - much of this type of research may in fact be called 'data-driven' – although other words such as inductive reasoning or explorative research have been used throughout the years (see, e.g. Abnor and Bjerke, 2009; Dane, 1990; Burrell and Morgan, 1979).

A citation from CIMA Conference in London 2015 (Big Data and Business Analytics) also says: *'Analytics will play a vital role in the future of finance, so CFOs, finance managers, management accountants and other finance professionals will benefit'*.

Kaplan and Norton, (2008, p. 6) mention specific scenario planning, dynamic simulation and war gaming as ways to test the robustness of companies' strategies.

In an interview with Paul Sharman in Strategic Finance, March 2008, Kaplan has also pointed to the importance of BA by saying:

Management accounting analytics is no longer constrained by limited or complex access to companies' databases. But to excel at analytics, management accountants will require extensive training in modeling, multivariate statistics, and econometrics.

²Two pioneers within statistical determination of costs are the work of Joel Dean's article from 1936, and Johnston's book Statistical Cost Analysis from 1960. Both of these show how different statistical analyses for costs and output can be used. However, also Solomon's book from 1951: 'Studies in Cost Analysis' has come up with ideas within industrial accounting. In the second edition from 1968, Solomon came up with thirty-four articles, including areas such as 'Operational Research and Accounting (Stafford Beer) and 'Multiple Regression Analysis of Cost Behaviour' (George J. Benston), topics that today probably would be characterized as a predictive analytics part of 'Business Analytics' framework.

Inspired among others by Schläpke *et al.* (2013), the SAS-Institute (Haxholdt Presentation, 2007), Liberatore & Luo (2010), and Năstase and Stoica (2010), a APM (Analytics Performance Management) framework will be the combination of three different areas; accounting models and concepts, content of business analytics, and different management science methods, as shown in figure 2.

Figure 2: Intersection area of three separate research areas

‘Analytics’ means the discovery, communication and visualization of meaningful patterns in data conducted simultaneously by the application of statistics, computer programming and operations research. Analytics also includes the word ‘dynamic’ to keep pace with the changes in order to provide relevant performance information.

This taxonomy incorporates elements and disciplines within each area. To show the differences between a ‘traditional view’ and a view based on BA for teaching, two simple examples are given below:

- *Example 1: In a product costing setup, e.g. by the use of a time driven ABC model, we teach the students how to define activities, cost drivers, and how to assign costs and create a profitability analysis. But normally, we do not include the discussion of how we get the data, how to make some preliminary statistical analysis (e.g. by the use of factor analysis, correlation, and multiple regression) for testing which cost drivers to use and what the effect of variation in a cost driver means for our model (e.g. by using confidence intervals). Neither do we normally include the effect of uncertainty for cost drivers (e.g. could be triangular distributed while process time for machine X could be normal distributed). Nor do we change a few decision variables in order to optimize the TD-ABC model as a whole and see the effect on net profit.*
- *Example 2: For a performance management system such as the balanced scorecard, we teach how many KPIs a company could or should use, how to define the KPIs, the relation to different perspectives, and why and how the KPI should be related to the firm’s strategy. But normally, we do not teach for example, the sensitivity or changes in causality from the customer perspective to the financial perspective, nor which KPIs will have the greatest impact on our future growth and profitability, or when we can expect our present strategy to peak under the present circumstances. Therefore, we cannot demonstrate for the students the use and the effect of the type of data on different KPIs, for example, on the financial*

perspective (e.g. by using different time-lags situations) or which KPI is the most important one for our financial result under different scenarios. Therefore, the students will never experience the interaction and learning (which is some of the most important aspects in BSC) between different types of KPIs, or the effect of different ranges of uncertainty.

A combination of these two examples will be demonstrated and discussed in the next section. Both of these examples are cross-functional, they demand the use of statistical analysis, and they demand data from both internal and external sources. Analytics can illuminate these high-level questions only if the decision-maker can see across departments, processes and perspectives. In the traditional way of teaching, it is simply not possible to make the relevant tests and discuss strategic learning feedbacks. Making the strategy the object function will not only demand the discussion of WHAT and HOW, but also the WHY which is of great importance for the decision-maker (Davenport, 2006; 2009; Blocher, 2009; Ferreria and Otley, 2009).

Traditional management accounting decisions such as price settings, profitability analysis, costs planning, determination of capacity costs, choosing the right distribution channel for a particular customer and their trade-offs (from vendor to customer) are in fact also cross-departmentally related items, where data are both cross-sectional and often time-series based.

Or as LaValle *et al.* (2011) express it:

Knowing what happened and why it happened is no longer adequate. Organizations need to know what is happening now, what is likely to happen next and what actions should be taken to get the optimal results.

However, it is important to be aware that predictive analytics and explanatory statistical modelling are fundamentally disparate (Shmueli and Koppius, 2011).

4 A numerical example – integrating BSC and TD-ABC

Perhaps the best way to introduce and demonstrate the nature and spirit of using analytics performance management is to apply the concept to a numerical example. We use a spreadsheet-based Monte Carlo simulation and optimization model (also referred to as Spreadsheet Analytics). Often, both BSC and TD-ABC are treated as deterministic even though it is well known that the cost estimates and cost drivers are uncertain or stochastic by nature (Davenport and Kim, 2013; Otley, 2012; Gribbin *et al.*, 1996).

We base our simulation and optimization example presented here in a paraphrased version of Nielsen and Nielsen (2008). Using an Excel 2010 add-in named @RISK 7.0 (Palisade Corporation 2016) give us an easy and accessible way of demonstrating the idea of business analytics within management accounting³.

The example combines BSC with a TD-ABC including the use of different probability distributions and assumptions about associations between input and output KPIs. Because the TD-ABC provides a bottom-up view of processes and the BSC provides a top-down approach, the combination strengthens the insight into the supply and demand of resources and creates a form of equilibrium where the company strategy and its forces are balanced in the absence of other factors (Kaplan 2006; Lim, 2001)⁴. Even though

³Other examples are e.g. Crystal-Ball (Oracle), BestFit (Decisioneering), or Analytical Solver Platform (Frontline Solvers). These simulation tools contain up to approximately 40 different and known probability distributions that can be used for input variables. Many distributions are of the PERT-type (Program Evaluation and Review Technique) also used in projects (see, e.g. Gribbin *et al.*, 1996).

⁴In a BSC online Net Conference in 2007 for Palladium / Balanced Scorecard Collaborative, MacGillivray discusses the topic 'Executing an Analytics Based Strategy' through adopting algorithmic decision-making techniques and using sophisticated software. Scientific management is no longer merely a skill that creates competitive advantages; it is now a basic prerequisite for company management as such (MacGillivray, 2007).

a company should go through all stages in real life (see Appendix), we will focus on the last stage called prescriptive analytics as shown in figure 3.

Figure 3: The Analytics Balanced Scorecard

The prescriptive stage is similar to what is often called a 4th or 5th generation of BSC where relevant causality is determined and where the main idea of the double loop learning process is used (Argyris, 1991, Argyris and Schön, 1978). The main focus of the double loop learning process is to help organizations learn from their actions such that they can advance from being defensive and reactive to being proactive. Learning is fundamental to the balanced scorecard framework (Kaplan and Norton, 2008). Wiersma (2009) also find that managers use the BSC for decision-making and for decision-rationalizing.

If TD-ABC is integrated within BSC, then a relevant number of leading and lagging indicators from ABC must be defined within the perspectives. Whether these indicators are named leading or lagging depend solely on their purpose and their relative use in a specific design or decision circumstances⁵. However, most indicators can be used directly as inputs to the BSC (e.g. metrics from the time-equations or the choice of cost drivers). Lagging financial measures are metrics used for profit, costs, and profitability (e.g. Net Profit, EVATM, Total Cost to Serve, or RoCE)⁶.

It is also important to realize that even the most advanced computer models and designs cannot predict the future and even if they could, we would probably not dare to act on the prediction alone (De Geus, 1992).

But the right computer models can help us ‘make up our minds and learn from it’ and help us test our understanding of the world such that we get an insight into possible problems and consequences of

⁵Granger discusses three types of indicators in his book ‘Forecasting in Business and Economics’ (1980, chap. 7.2); leading, coincident, and lagging, where a coincident indicator is an indicator that shows the current state of a metric. This metric should be used to give a full view of where the company has been and how it is expected to change in the future. The way in which the three types of indicators interact depends on the formulation and the purpose of the model (Granger, 1980). In System Dynamics, however, stock and flow (or Level and Rate) diagrams are used as a way of presenting the structure of a system where stocks are characterized as the state of the system upon which decisions and actions are based (Sterman, 2000). Contrary to econometrics, System Dynamics can cope with elements such as accumulation processes, inter-dependence, feedback, and threshold effects (Nielsen and Nielsen, 2008).

⁶It is important to realize that the model only includes the results of the specific variables defined as KPIs or metrics relevant for the strategy. Several other incidents and registrations (e.g. cash flows, dividends, and write-downs) still exist, but may not necessarily be part of the model (but are part of the yearly public financial accounts).

our plans before they are implemented (De Geus, 1992). Organizational learning is a way to help companies react faster to external changes. But being faster doesn't necessarily mean being smarter. What firms need are way to recognize when their problems are of the own making (Senge, 1990).

Because the BSC model is a complex real-world system that consists of a high number of variables (KPIs) and their associations it cannot be evaluated by analytically methods alone (such as algebra or calculus) (Law and Kelton, 1991). Therefore, simulation (or a heuristic procedure, used e.g. by Leitch *et al.*, 2005) is often the only type of investigation possible under some projected set of operations conditions, e.g. maximizing profit, RoCE or EVA™ or minimizing costs. Kaplan and Norton (2008c) have also referred to the idea of such an interactive model with different trade-offs as a "Closed-Loop Management System" designed to create close links between the strategy and different tools such as ABC, Six Sigma, and lean, in order to monitor and learn about the way the BSC model performs.

The spreadsheet model is designed to run for 60 months or 5 years (a strategy is often defined for a period of 3-5 years) and includes a number of input variables that relate to both BSC and to TD-ABC. Because the idea of a stochastic simulation is to provide stable predictions of performance and of the variance of performance (Conway, 1963; Nelson, 2004) the number of simulation iterations is set to 1,000 (an alternative would be to use @Risk's auto-convergence feature).

A stochastic model is a tool for estimating probability distributions of potential outcomes by allowing for random variation in one or more inputs over time which would be the case for many KPIs in the BSC model (vs. single point estimation). If real data existed, we could fit the underlying distribution for each input variable and use it as an input in our budget and planning model for the next period.

We assume that prior information exists for some BSC indicators, referring to the probability distribution of the corresponding input variable. Table 1 displays the probability distributions used for the BSC and TD-ABC input variables in this example. We also assume that all constants and target values of the variables are perceived as known.

Because of its possible impact on the outcome of the model, each probability distribution must be carefully chosen in a real life model and must reflect the assumptions made for that distribution as well the expectations about the data (see e.g., Law and Kelton, 1991).

We have chosen different distributions to illustrate the variety of applications of this model. For example, it is often possible to fit normal-like historical data to a Beta distribution with different values for a_1 and a_2 parameters and artificially low/high minimum and maximum parameters. As the Beta distribution can be controlled by these four parameters, this can lead to a very accurate fit from a mathematical viewpoint, which is most relevant from a practitioner's standpoint (Gribbin *et al.*, 1996).

BSC KPIs:	Input Parameters	Probability Distribution and Input Values
Training score	31	Beta ($a_1=3$; $a_2=5$; min 0; max 100)
Order placement	25 %	Normal (mean 25 %; std. 0.1)
Material cost per product	325	Uniform (min 240; max 450)
Employee expenses	3.200	Triang (min 2,800; max 3,600)
Product sale price	3.200	Uniform (min 2,800; max 3,600)
TD-ABC Cost rates (\$/min):		
Procurement	4,50	Beta ($a_1=4$; $a_2=4$; min 3; max 6)
Production	6,50	Beta ($a_1=4$; $a_2=4$; min 6.2; max 7)
Sales	3,00	Beta ($a_1=5$; $a_2=7$; min 2; max 5)
Administration	2,20	Beta ($a_1=3$; $a_2=6$; min 3; max 5)

Table 1: Distribution's Parameters for BSC and TD-ABC

Just to give two examples of the input probability distributions figure 4 shows the probability distributions for the Order Placement and the Cost Rate for Administration, where Administration is skewed to right (positive skewness).

Figure 4: Probability distributions for Order Placement and Administration

The characteristics of the model follow three features:

- 22 KPIs (variables) are assigned to the four BSC perspectives and 27 system constants including the TD-ABC parameters (both rates and time units);
- all variables of the model are connected to each other by different basic arithmetical operations including a few building tools in Excel itself such as min, max, if-statements); and
- 27 equations with a number of KPIs and their relations.

It is important to realize that all mathematical and statistical calculations and techniques use data as input (Hair et al., 1998). Therefore, numbers by themselves do not constitute information, which is why information technology is not really information-oriented by default but data-oriented. Only the human mind can provide purpose and hence relevance to data (Emblemsvåg, 2005). Finally, information must be turned into knowledge for the decision maker, defined as ‘*information combined with experience, context, interpretation and reflection*’ (Davenport et al., 1998).

Besides, the model also includes five ‘stocks’ that interact with a number of different KPIs. The concepts of time-lags (also called delays) and non-linearity are taken into account and can be controlled in the model. Below, we will use four scenarios showing different problems and options.

Base-run scenario

The base-run scenario is based on existing assumptions as shown in table 1 for the integrated BSC and TD-ABC model. For all four scenarios, we will only focus on two outputs or forecast values: total TD-ABC costs and RoCE (Return on Capital Employed) p.a. Figure 5 illustrates the consequences and results (i.e. as Probability Density Graphs) for the base-run.

Figure 5: Output for TD-ABC costs and RoCE p.a. for base-run simulation

We note that the TD-ABC cost output includes additional information that can be used by the decision maker to change or improve the result (e.g. Mean, Std. Dev., Skewness, and Kurtosis). If we look at the distribution for RoCE p.a., the decision maker can easily estimate the probability of getting RoCE p.a. below zero (or any other positive or negative value), for instance. As shown in figure 5, with the “left slider” set at \$0.00, the estimated probability of losing money (in the sense that the RoCE p.a. is \$0.00 or less) is about 31%. Similarly, the “right slider” shows us that the estimated probability of achieving a RoCE p.a. that exceeds zero is about 69%.

There is several other facilities that could be used here e.g., the best distribution fit for the forecasted value of RoCE p.a. in year 5. It shows up that @Risk estimates this to be an Extreme Value Minimum distribution (not shown here). Such an information could then be used as input for the planning periods, e.g., by setting a target value or trying out other scenarios.

Second scenario – modelling a simple optimization problem

Instead of just focusing on the existing circumstances and assumptions, a decision maker can include ranges for a number of variables or KPIs in order to find the best mix of these KPIs such that he can maximize a forecast, in this example the mean of RoCE p.a. in year 5. In this case, an ‘educated guess’ is neither sufficient nor trustable and therefore the decision maker has to design a valid model with all the necessary assumptions. Problems involving large amounts of variables, non-linear functions, lookup tables, if-then statements, or stochastic (random) elements as in this example will be very difficult (if not impossible) to solve analytically. In such cases, the decision maker should opt for a tool and a software system that can handle simulation and optimization simultaneously and any size and any complexity.

This scenario is based on selecting and expanding some of the existing single point variables to see the consequences for RoCE p.a. in year 5 to get insight into which KPIs may or may not be the most relevant to focus now and in the future. To give the model a relevant number of ranges for these variables, the following additional information is used as Adjustable Cell Ranges, which is a mix of BSC parameters and time units in the TD-ABC model.

BSC Parameter:	Lower	Static Value	Upper	Continuous/Discrete
Unused capacity staff	20%	50%	60%	C
Working days/month	18	25	30	D
TD-ABC Time Units (in min.):				
Procurement	22	25	27	C
Production	43	45	48	C
Sales	5	8	13	C
Administration	6	7	11	C

Table 2: Decision variables for BSC and TD-ABC

The decision maker now wants to maximize the mean of RoCE p.a. in year 5, using the same assumptions as in the previous example. The progress graph and the output result are shown in figures 6 and 7 (the number of trials is set to 75 and the number of simulations to 500).

Figure 6: The progress graph for RoCE p.a. over a period of 5 years

As can be seen from figure 7, @Risk has found an optimal stochastic combination after about 45 iterations (including values for decision variables not shown here).

Figure 7: Output for TD-ABC costs and RoCE p.a. for the optimization situation

Comparing to the base-run scenario we can see that the total TD-ABC costs have changed from 46,684 to 43,130 (or a reduction by about 8%), and that the mean for RoCE p.a. in year 5 has improved from 4.46% to 6.56% in this scenario, which is a considerable improvement of 44%⁷. The insight or learning give the decision maker new options for improving – depending on additional costs and consequences.

Third scenario – reducing the standard deviation for a forecast variable

In the third scenario we wish to improve one of the forecast variables in the model. There are several ways of doing so. In this case, we just add a simple constraint on RoCE p.a. in year 5 by saying that we will only accept a standard deviation that does not exceed 21.5 %, instead of 22.5 % as it is now (see right hand side of figure 8). Such a small adjustment (about 5%) or improvement could be part of a Six Sigma project (Arnheiter and Maleyeff, 2005).

Similarly, simple metrics from Six Sigma combined with TD-ABC can easily be incorporated in the BSC , e.g., by using PPM, a yield standard deviation, or the skewness (Summers, 2011). In addition, the

⁷Even though this difference seems insignificant, the idea is just to illustrate the effect of a relatively simple and small change in a single input variable. It is easy to change other input variables and to get a much larger effect (e.g. by changing some of the cost parameters).

mere addition of a few lean metrics may open up for new possibilities for measuring performance and adding value (Maskell and Kennedy, 2007). Six Sigma seeks to improve the output of a process by identifying and removing the causes of defects and by minimizing the variability in manufacturing processes. All other assumptions made in scenario two remain unaltered. The results for total TD-ABC costs and RoCE p.a. in year 5 are shown in figure 8.

Figure 8: Output for TD-ABC costs and RoCE p.a. for a revised optimization situation

As can be seen from figure 8, a reduction of the standard deviation on RoCE p.a. by about 5% has also reduced the mean outcome for RoCE p.a. from 6.56% to 4.13%. Even though these changes may seem relatively small, they may in fact imply large amounts of money (see e.g., the example of Sears documented by Rucci *et al.*, 1998. Sears' model documented that a 4% improvement in customer satisfaction translates into more than \$200 million in additional revenues in a period of 12 months).

We also see that the probability of losing money is about 30% and has thus increased compared to scenario two. A relevant question in such circumstances could be: '*which inputs improves RoCE p.a. in year 5 the most*'? If we can answer that question, we can gain valuable insights into what controls the output of our decision. With this information we can determine where best to spend our time and money (Schriber, 2009).

This is shown in figure 9 as a Tornado Graph based on Regression Coefficients values for RoCE p.a. after 5 years together with the Progress Graph for the optimization.

Figure 9: The revised progress graphs for RoCE p.a. and regression coefficients

We first note that an optimization is reached between 48 and 50 trials after going through a number of minor steps. Second, some inputs are relatively unimportant (e.g. training score and sales) and can perhaps even be replaced by their expected values, whereas the decision process can be quite sensitive to assumptions made about some other inputs (e.g. Order Placement and Product Sales Price on the positive side), which should then continue to be random inputs.

Fourth scenario – a reduction in the standard deviation for Order Placement

Having seen the result from scenario three (and specific the information from the Tornado Graph shown in figure 10), it would be interesting to re-run the same scenario, but now with a reduction in the standard deviation of the Order Placement which has shown to have the largest impact on RoCE p.a. in year 5. So, instead of using a standard deviation of 10% (see table 1) we set this to 5%. The result for RoCE p.a. in year 5 is shown in figure 10.

Figure 10: TD-ABC costs and RoCE p.a. after reducing the standard deviation for Order Placement

The output clearly shows a large impact on the mean of RoCE p.a. in year 5 – from 4.2% in scenario three to 14.4% here – and a reduction in the standard deviation (from 21.5% to 12.7%). However, the reduction in the standard deviation has also had an effect on the mean of total TD-ABC costs, from 44,389 in scenario three to 47,111 here - or about 6% increase. However, the probability of getting a RoCE p.a. in year 5 below zero has now decreased considerably, from 27% to 11.6% in the present scenario. So in this situation, the decision maker is better off reducing the standard deviation (which normally also costs money), as both the RoCE p.a. improves and the probability of getting a value below zero falls, even though the total TD-ABC costs increase. It is important to understand such problem or dilemmas if the analysis is to be used for prediction analysis (Davenport and Kim, 2013, see also Schmueli and Koppius, 2013, for the difference between explanatory statistical models and predictive analytics).

Another interesting trade-off could be to test whether a company should increase the satisfaction of employees (e.g. by increasing the budget for education and training, i.e. an internal KPI) or if a company should increase the customer loyalty (e.g. by increasing the organization's loyalty programs. i.e. an external KPI). The first choice may be characterized as a short run option whereas the second may be a long term option. But the model design gives the decision maker almost endless possibilities of testing

such trade-offs⁸. Afterwards, the decision maker must be able to check the model assumptions by feedbacks and double loop learning (Argyris and Schön, 1978; Kaplan and Norton, 2007).

We always have to address the fundamental question of whether the data can be seen as valid and sufficiently accurate. If this is not the case, decisions based on the flawed data could be disastrous (Kershaw and Kershaw, 2001).

Even though risk and uncertainty are already to some extent implicitly included in the model above (by the use of different probability distributions), it would be necessary explicitly to discuss the consequences for the outcome in a more structured way if a concept such as 'risk management' is to be included (Kaplan and Norton, 2008). The decision maker has to define his own level of risk aversion (Demski, 1994). Normally, a decision maker is seeking to reduce risk (e.g. by improving skewness or reducing the standard deviation). The idea is not to avoid risk (which is impossible), but to identify it and to have a plan for it (Collier *et al.*, 2007).

5 Conclusion and implications

The purpose of this paper was to discuss and offer some new ideas for combining performance measurement research with business analytics. We began the discussion by synthesizing the implications of the business analytics movement, classifying different types of analytics and the three stage model developed by Davenport and Kim (2013), envisioning the roles and responsibilities that analytics professionals have in organizations. By using the three stage model of analytics we have suggested the use of analytics for performance measurement and management in order to close an important gap between theory and practice pointed out by many accounting researchers.

What we have advocated is not a revolution, but rather an evolution or adjustment of existing empirical research. Inspired by trends in other business areas such as logistics and finance, we argue that management accounting research should exploit the opportunities that the analytics movement offers and start developing theories and suggestions for fact-based decisions with a high external validity, i.e., research that will make our effort relevant for practice.

A simple numerical example has clearly demonstrated how the decision maker can use business analytics for improving and choosing among several future options. Even though we have focused on one example from the field of prescriptive analysis, specifically in the solving stage, we have demonstrated the complexity but also the opportunities faced by the management accountants in the future. Which action to take must be based on insight, degree of risk, and the level of decision conservatism, e.g., going from about 30th-percentile to 12th –percentile level if we want to focus on the probability to get a RoCE p.a. below zero as shown in the different scenarios.

The decision field for management accountants is an obvious candidate for business analytics, a fact that has been sporadically mentioned in a few management accounting articles (but a lot in whitepapers from consulting companies). Classical topics such as pricing, costing, planning, reporting and performance measurement are important decisions areas where different topics and techniques from analytics can be used to improve decision making and, therefore, to increase the external validity of our research. But we also have to focus on giving management accounting students and professionals the right skills in order

⁸ Often this is described in a PESTEL analysis where time-series methods (e.g. linear and non-linear methods, exponential smoothing, and ARIMA methods) can be used. External data bases (e.g. Bloomberg Business or the article of Bryant *et al.*, 2004) can also be used, not only for getting information about specific variables and metrics, but also as a starting point for building 'generic' BSC models, for example within a business sector. Such models are already being used in the classrooms for creating what is called 'data-driven' models, for example in finance, but could also be used within management accounting and control.

to convince the companies that they should add value to the business; if not, other groups of professionals will take over (statisticians/econometricians, data scientists or other highly quantitatively educated people).

In today's highly connected business environment, the pace of change is rapid and the pressure to keep up is quite overwhelming. Today, practical business is about the ability to change course fluidly and to react to movements in all areas of the business. Faster cycles of scrutiny on performance against expectations are increasingly demanded across all levels; from tactical to operational to the strategic level.

Yesterday's single and simple modelling approaches with single point estimates will be replaced by holistic (stochastic) model approaches which enable the decision maker to test even small changes to see the effect for the whole company and the effect for the financial result. However, the decision maker can never come up with exact consequences from a model - but as the famous statistician, George E. P. Box (1987) once said, 'All models are wrong but some are useful'.

Not only do we think that our discussion may have impact on research as discussed above, but we also believe that it will have impact on business practice too. For example, predictive analytics could be useful for generating new theory, comparing competing theories, improving existing theories, assessing the relevance of theories, or assessing the predictability of empirical phenomena (Schmueli and Koppius, 2011). The idea is to produce new and interesting solutions for accounting decisions on the problem in question which may already have been discussed in qualitative terms in the company or in the literature. For practice, such fact-based discussions and solutions would also be of high interest.

Finally, a review of a number of surveys concerning accountants and skills also emphasizes the need for not only hard skills which of course is central, but also for soft skills related directly to analytics such as creativity and imagination (Leonhardi, 2011; Davenport *et al.*, 2010). Of particular interest is what is now called 'visualization research', which means the process of representing data graphically and the interaction with these representations in order to gain insight into the data structure and correlations of groups of data. Modern visualization research addresses the problem of converting data into compelling, revealing, and interactive graphics that suit users' and decision makers' needs.

Therefore, management accountants are facing not only big challenges, but also a great opportunity to be part of improving the decision environment for management accountants in the 21st century.

Appendix: Combinations of TD-ABC and BSC in the different stages of BA

<i>Model and elements</i>	<i>Design stage (definitions)</i>	<i>Descriptive analytics (what happened)</i>	<i>Predictive analytics (what will happen next)</i>	<i>Prescriptive analytics (why something happened)</i>
Integrating TD-ABC with the Balanced Scorecard	Focus on designing, selecting and mapping KPIs and perspectives (i.e. financial and non-financial KPIs within BSC and TD-ABC elements), defining leading and lagging KPIs, building causal performance maps (from internal or external sources), defining loops and feedback structures.	Focus on historical data and measures and KPIs, (e.g. labour, capacity, overheads, TD-ABC costs, revenue) at different levels for activities, and cost drivers, identifying value and non-value activities (e.g. by different types of cost drivers) or comparing to benchmarks and targets and costs for unused capacity.	Focus on rolling/dynamic forecasts for different KPIs (e.g. by changing relevant input variables) such as raw material prices, customers' preferences and satisfaction, including risk analysis. It is important to distinguish between internal and external data and variables that are a result of the model.	Focus on the experimental design, i.e. optimization/minimization of different KPIs (e.g. revenue, profit/ costs) subject to different requirements and constraints for different decision variables such as capacity in the internal perspective, or number of employees or training days in employee perspective), overheads or targets for different KPIs in different perspectives or changes in the time-equation for TD-ABC.
Examples of techniques that can be used	Using cognitive mapping of perspectives, team building for perspectives, computerized discovery of causal links (and time lags) between KPIs, ethnographic analysis of interview data, interactive mapping by expert participants, CLD (Closed Loop Diagrams) for stock and flows, explorative factor analysis, path analysis and SEM (Structural Equation Modelling) for finding relevant KPIs.	Using descriptive statistics measures (e.g. mean, mode, median kurtosis, skewness, standard deviations), different fitting tools (e.g. batch fitting for data), bootstrapping (i.e. statistics for small data sets), decision trees, correlations and regression, construction of Pivot tables, frequencies, or cross-tabulation.	Using logic/data-driven modelling, trend lines estimation, exponential smoothing, ARIMA (AutoRegressive Integrated Moving Average) models, dynamic and rolling forecasts (i.e. linear and non-linear regression), fuzzy expert systems, data mining, stochastic and risk simulation methods. But also scenario analysis and the Delphi method based on a panel of experts can be used for building relevant forecast models.	Using optimization (linear and non-linear), heuristics, stochastic simulation, integer optimization, System Dynamics (including levels, stocks and feedback loops). The output can be visualized in different ways, e.g. by using Efficient Frontier analysis and advanced visualization techniques. Data and reports for different levels of KPIs in one perspective can be studied and changed for the next test scenario to see the effect on the financial perspective.

Literature

- Abnor, I. and Bjerke, B. (2009), *Methodology for Creating Business Knowledge*, 3rd Edition, Sage Publications.
- ACCA (2009), *The CFO's New Environment*, A Report Prepared by CFO Research Services in Collaboration with ACCA, UK.
- Accenture (2013), *Analytics in Action: Breakthroughs and Barriers on the Journey to ROI*.
- Ahrens, T. A. and Chapman, C. S. (2007), "Management accounting as practice Accounting", *Organizations and Society*, vol. 32, pp. 1–27.
- Argyris, C., and Schön, D. (1978), *Organizational Learning*, Reading: MA: Addison-Wesley.
- Argyris, C. (1991), "Teaching Smart People to Learn", *Harvard Business Review*, May/June, 99-109.
- Argyris, C. and D. A. Schon. (1996), *Organizational Learning II Reading*, MA: Addison-Wesley.
- Arnheiter, E. D., and Maleyeff, J., (2005), "The Integration of Lean Management and Six Sigma", *The TQM Magazine*, Vol. 17, No 1, pp. 5-18.
- Banker R.D., S. M. Datar, and Kekre, S. (1988), "Relevant Costs, Congestion and Stochasticity in Production Environments", *Journal of Accounting and Economics*, pp 171-197.
- Benston, G. J. (1966), "Multiple Regression Analysis of Cost Behavior", *The Accounting Review*, pp. 657-672.
- Berry, A. J., Coad, A. F., Harris, E. P., Otley, D. T., and Stringer, C. (2009), "Emerging Themes in Management Control: A Review of Recent Literature", *The British Accounting Review*, 41, pp. 2-20.
- Birnberg, J. G. (2009), "The case for post-modern management accounting: Thinking outside the box", *Journal of Management Accounting Research* 21: 3–18.
- Blocher, E. J. (2009), "Teaching Cost Management: A Strategic Emphasis", *Issues in Accounting Education*, Vol. 24, no. 1, pp. 1-12.
- Bryant, L., d. A. Jones, and S. K. Widener (2004), "Managing Value Creation within the Firm: An Examination of Multiple Performance Measures", *Journal of Management Accounting Research*, 16, 107-131??.
- Burrell, G. and Morgan, G. (1979), *Sociological Paradigms and Organizational Analysis, Elements of Sociology of Corporate Life*, Pearson Education.
- Chenhall, R.H. (2005), "Integrative strategic performance measurement systems, strategic alignment of manufacturing, learning and strategic outcomes: an exploratory study", *Accounting, Organizations and Society*, Vol. 30 No. 5, pp. 395-422.
- CIMA (2008), *Improving Decision Making in Organizations Un-Locking Business Intelligence*.
- CIMA (2009a), *Insight – the e-magazine for management accountants What is CIMA's definition of management accounting?*, UK.
- CIMA (2009b), *Management Accounting Tools for Today and Tomorrow*, UK.
- CIMA (2012), *Professional Identity of Management Accountants: Leadership in Changing Environments, Volume 8 / Issue* , UK.
- Cokins, G. & Pirello, (2007), *PUTTING IT ALL TOGETHER - A unified Approach to Performance Management*, SAS-Institute.
- Collier, P.M., Berry, A. J., and Burke, G. T. (2007), *Risk and Management Accounting: Best Practice Guidelinnes for Enterprise-wide Internal Control Procedures*, CIMA Publication, UK.
- Conway, R. W. (1963), "Some tactical problems in digital simulation", *Management Science*, 10 pp. 47-61.
- Dane, F.C. (1990), *Research Methods*, Brooks/Cole Publishing Company, USA.
- Davenport, T. H., Harris, J. G., and Cantrell, S. (2002), *The Return of Enterprise Solutions: The Director's Cut*, Accenture, Institute for high Performance Institute.
- Davenport, T. H. (2006), "Competing on Analytics". *Harvard Business Review*, January.
- Davenport, T. H. (2009), *The Rise of Analytical Performance Management*, SAS-Institute.
- Davenport, T.H., Delong, D.W. and Beers, M.D. (1998), "Successful knowledge management projects", *Sloan Management Review*, Vol. 39 No. 2, pp. 43-57.
- Davenport, T. H. and Harris J. G. (2007), "The Dark side of Analytics", *Harvard Business Review*.
- Davenport, T. H. and Harris, J. G. (2007), *Competing on Analytics: The New Science of Winning*. Harvard Business School Press.
- Davenport, T. H., and Kim, J. (2013), *Keeping Up with the Quants*, Harvard Business Review Press, USA.

- Davenport, T. H., Harris, J. G. and Morison, R. (2010), *Analytics at Work Smarter Decisions Better Results*, Harvard Business Press, USA.
- Dechow, N. and Mouritsen, J. (2005), "Enterprise resource planning systems, management control and the quest for integration". 30 *Accounting, Organizations and Society*, pp. 691–733.
- De Geus, A. P. (1992), "Modelling to Predict or to Learn", *European Journal of Operational Research*, 59, 1-5.
- Demski, J. S. (1994), *"Managerial Uses of Accounting Information"*, Boston, Kluwer.
- Desai, M.S., Desai, K.J. and Ojode, L. (2004), "A Global Information Technology Model: Business Applications in Developing Economies (case studies)", *Information Management & Computer Security*, vol. 12, no. 5: 401 – 410.
- Dickhaut J. W. and Lere, J. C. (1983), "Comparison of Accounting Systems and Heuristics in Selecting Economic Optima", *Journal of Accounting Research*, Vol. 21. No. 2, pp. 495-513.
- Dittman, D. A., and Prakash, P. (1978), "Cost Variance Investigation: Markovian Control of Markov Processes", *Journal of Accounting Research*, 16, No. 1, pp. 14-25.
- Eckerson, W. (2011), *Big Data Analytics: Profiling the use of Analytical Platforms in User Organizations*, Business Applications and Architecture Group, Tech Target.
- Emblemsvåg, J. (2005), "Business Analytics: Getting behind the Numbers", *International Journal of Productivity and Performance Management*, 54, No 1, pp. 47-58.
- Ernst & Young (2008), *The Changing Role of the Financial Controller*, UK
- Evans, J. R., Lindner, C. H. (2012), "Business Analytics: The Next Frontier for Decision Sciences", *Decision Line*, 43 (2), pp. 4-6.
- Ferreira, A. and Otley, D. (2009), "The Design and Use of Performance Management Systems: An Extended Framework for Analysis", *Management Accounting Research*, 20, pp. 263-282.
- Flamholtz, E. and Hua, W. (2003), "Searching for Competitive Advantage in the Black Box", *European Management Journal*, Vol. 21, No. 2, pp. 222–236.
- Gartner, (2012), *Business Intelligence, Analytics and Performance Management Market Trends and Dynamics*.
- Gartner, (2013), *The CFO's Six Technology Imperatives Results of the 2013 Technology Issues For Financial Executives Survey*, Financial Executives Research Foundation, Inc., USA
- García, J., (2011), *Business Intelligence buyer's guide: BI for Everyone*, Summary Edition, TEC.
- Giles, Big Data lessons from the leaders: The Economist, 2012.
- Granger, C. W. J. (1980), *Forecasting in Business and Economics*, Academic Press, USA.
- Gribbin, D. W., Lau, A. H.-L., and Lau, H. S. (1996), *A Practical stochastic framework for ABC*, Working paper.
- Gurowka, J, and Lawson, R. A. (2007), "Selecting the Right Costing Tool for Your Business Needs", *The Journal of Corporate Accounting & Finance*, March/April, pp. 21-27.
- Hair, J.F. Jr., Anderson, R. E., Tatham, R. L., and Black, W. C. (1998), *Multivariate Data Analysis*, Prentice Hall, USA
- Harris, J. G. and Davenport, T. H. (2006), *New Growth from Enterprise Systems: Achieving High Performance through Distinctive Capabilities*, Accenture, Institute for High Performance.
- Hopwood, A. G. (2002), "If only there were simple solutions, but there aren't: some reflections on Zimmerman's critique of empirical management accounting research", *European Accounting Review*, 11:4, 777-785.
- Hopwood, A.G., (2007), "Whither accounting research?", *The Accounting Review* 82 (5), pp. 1365–1373.
- IFAC (2011), *Predictive Business Analytics: Improving Business Performance with Forward-Looking Measures*,
- IMA (2008a) *Definition of Management Accounting*, Institute of Management Accountants, Montvale, NJ, USA
- IMA (2008b), "Meet Bob Kaplan", *Strategic Finance*, March 19-21.
- Jensen R. E. A (1967), "Multiple Regression Model for Cost Control – Assumptions and Limitations", *The Accounting Review*, April, pp. 265-273.
- Kaplan, R. S. (2006), "The Competitive Advance of Management Accounting", *Journal of Management Accounting Research*, 18, pp. 127-135.
- Kaplan, R. S. (1998), "Innovation Action Research: Creating New Management Theory and Practices", *Journal of Management Accounting Research*, 10, pp. 89-117.
- Kaplan, R. S. (2008), "Linking Strategy to Operations", *Journal of Accountancy*, October, pp. 80-84.
- Kaplan, R. S. (2011), "Accounting scholarship that advances professional knowledge and practice", *The Accounting Review* 86 (2): pp. 367–383.

- Kaplan, R. S. (2012), "The Balanced Scorecard: Comments on Balanced Scorecard Commentaries", *Journal of Accounting & Organizational Change*, 8(4): 539-545.
- Kaplan, R. S. & Norton, D. P. (2008), *The Execution Premium Linking Strategy to Operations for Competitive Advantage*, Harvard Business Press.
- Kaplan, R. S. and Norton, D. P. (1996), *The Balanced Scorecard – Translating Strategy into Action*, Harvard Business School Press, Boston, USA.
- Kasanen, E., Lukka, K., and Siitonen, A. (1993), "The Constructive Approach in Management Accounting Research", *Journal of Management Accounting Research*, Fall 1993, pp. 243-264.
- Kershaw, R., and Kershaw, S. (2001), "Developing a balanced scorecard to implement strategy at St. Elsewhere Hospital", *Management Accounting Quarterly* 2(2), 28-35.
- Kiron D., and Shockley, R. (2011), "Creating Business Value with Analytics", *MITSloan Management Review*, Fall, pp. 56-64.
- Kobielus, J., (2010), *The Forrester Wave: Predictive Analytics and Data Mining Solutions*, Forrester Research, Inc. USA.
- Langfield-Smith, K. (2007). "A review of quantitative research in management control systems and strategy". In: Chapman, C.S., Hopwood, A., Shields, M.D. (Eds.), *Handbook of Management Accounting Research*. Elsevier, Oxford, pp. 753–784.
- LaValle, S., Hopkins, M. S., Lesser, E., Schokley, R., and Kruschwitz, N. (2010), "Analytics: The new Path to Value: How the Smartest Organizations are Embedding Analytics to Transform Insights into Action", *MITSloan Magazin Review*, Fall.
- Law, A.M. and Kelton, W.D. (1991), *Simulation Modeling & Analysis*, McGraw-Hill Int. Edition, Singapore.
- Leitch, R. A., Philipoom, P. R., and Fry, T. D. (2005), "Opportunity Costing Decision Heuristics for Product Acceptance Decisions", *Journal of Management Accounting Research*, 17, pp. 95-117.
- Leonhardi, D. (2011), "Soft Skills: The Killer app' for Analytics", *Analytics Magazine Org*, November /December, pp. 34-37.
- Liao, M. (1975). "Model Sampling: A Stochastic Cost Volume-Profit Analysis", *The Accounting Review*, pp. 780-790.
- Liberatore, M.J., Luo, W., (2010). "The analytics movement: Implications for operations research", Vol. 40, No. 4, July–August, p. 313–324
- Lim A. (2001), *The Importance of Activity-Based Costing/Management to the Balanced Scorecard* Andrew Lim, director, Balanced Scorecard Solutions Pte Ltd.
- Malmi, T., and Brown, D. A. (2008), "Management control systems as a package—Opportunities, challenges and research directions", *Management Accounting Research*, vol. 19 pp. 287–300
- Malmi, T. and Granlund, M. (2009), "In Search of Management Accounting Theory", *European Accounting Review*, 18: 3, pp. 597-620.
- McAfee, A., and Brynjolfsson, E. (2012), "Big Data: The Management Revolution." *Harvard Business Review*, 90, pp. 60–68.
- Maskell B. H. and Kennedy, F. A. (2007), "Why do we need lean accounting and how does it work?", *The Journal of Corporate Accounting & Finance*, pp. 59-73.
- McKinsey (2011), *Competing through data: Three experts offer their game plans*, USA.
- McKinsey (2013), *Today's CFO: Which profile best suits your company?*, USA
- Merchant, K. A. (2012), "Making Management Accounting Research more Useful", *Pacific Accounting Review*, 24, No. 3, pp. 334-356.
- Morris, H., Graham, S., Andersen, P., Moser, K., Blumstein, R., Vesset, D., Martinez, N., and Carr M. (2003), *The Financial Impact of Business Analytics*, Teradata software/technology.
- Moser, D. V. (2012), "Is Accounting Research Stagnant?", *Accounting Horizons*, 26, no. 4, pp. 845-850.
- Nelson, B. L. (2004), "Stochastic Simulation Research in Management Science", *Management Science*, 50, No. 7, pp. 855-868.
- Nielsen, S., Jakobsen, M. and Melander, P. (2008), "The Knowledge, Attitude, Priority of Usage, and Benefits Associated with Management Accounting Practices: A Survey of Danish Companies", *Int. J. Accounting, Auditing and Performance Evaluation*.
- Nielsen, S. and Nielsen, E. H. (2008), "System Dynamics Modelling for a Balanced Scorecard Computing the Influence of Skills, Customers, and Work in Process on the Return on Capital Employed", *Management Research News*, Vol. 31 No. 3, pp. 169-188.
- Năstase, P., Stoica, D., (2010), "A new business dimension- business analytics", *Accounting and Management Information Systems*, Vol. 9, No.4, p. 603-618.

- Otley, D. (2012), "Performance Management under Conditions of Uncertainty: Some Valedictory Reflections", *Performance Management*, 24, No. 3, pp. 247-261.
- Otley, D. (2001), "Extending the Boundaries of Management Accounting Research: Developing Systems for Performance Management", *British Accounting Review*, 33(3): pp. 243–261.
- Romanenko, A., and Artamonov, A. (2014). *Inform's January Org.*, pp. 34-44.
- Ramamohan Y., Vasantharao, K., Chakravarti, C.K. , Ratnam, A.S.K. (2012), "A study of Data Mining Tools in Knowledge Discovery Process", *International Journal of Soft Computing and Engineering* (IJSCE) ISSN: 2231-2307, Volume 2, Issue 3, July.
- Rucci, A. J., Kirn, S. P., and Quinn R. T. (1998), "The Employee-Customer Profit Chain at Sears", *Harvard Business Review*, January/ February, pp. 82-97.
- SAS-Institute, Kiron, D., Prentice, P. K., and Ferguson, R. B. (2014), "The Analytics Mandate", *MITSloan Management Review Report*.
- Schmueli, G. and Koppius, O. (2011), "Predictive analytics in information systems research", *MIS Quarterly*, 35, pp. 553-572.
- Schläfke, M., Silvi, R., and Möller, K. (2013), "A Framework for Business Analytics in Performance Management", *International Journal of Productivity and Performance Management*, 62, No. 1, pp. 110-122.
- Schriber, T. J. (2009), "Simulation for the Masses: Spreadsheet-based Monte Carlo Simulation", *Proceedings of the 2009 Winter Simulation Conference*.
- Senge, P. (1990), *The Fifth Discipline: The Art & Practice of the Learning Organization*, Currency Doubleday, New York.
- Simons, R. (1995), *Levers of Control, How Managers Use Innovative Control Systems to Drive Strategic Renewal*, Harvard Business School Press, Boston, MA.
- Shmueli, G., and Koppius, O. R. (2011), "Predictive Analytics in Information Systems Research", *MIS Quarterly*, Vol. 35 No. 3 pp. 553-572.
- Sterman, John D. (2000), *Business Dynamics: System Thinking and Modelling for a Complex World*, McGraw-Hill.
- Summers, D. C. S. (2011), *Lean Six Sigma*, Prentice Hall, Pearson, USA.
- Wiersma, E. (2009), "For Which Purposes do Managers use Balanced Scorecards? An Empirical Study", *Management Accounting Research*, 20, 239-251.
- Zimmerman, J. (2001), "Conjectures regarding empirical management accounting research", *Journal of accounting and Economics* 32 (1–3), pp. 411–427.
- Zimmerman, J. L. (2011), *Accounting for Decision Making and Control*, 7/e,

Other references:

- BetterManagement Today: Competing on Analytics segment. On-Demand Webcast
<http://www.bettermanagement.com/seminars/today.aspx?l=14136>
- University of Maryland – Smith School of Business- Course on Competing on Analytics in Europe
<http://www.rhsmith.umd.edu/global/courses/2007-08/FranceGermany2008.html>
- SAS INSTITUTE INC. WORLD HEADQUARTERS SAS CAMPUS DRIVE CARY, NC 27513 TEL:
 919 677 8000 FAX: 919 677 4444 academicprogram@sas.com www.sas.com/academic
- Ivey School of Business course on Competing on Analytics by Peter Bell http://www.ivey.uwo.ca/faculty/Peter_Bell.html