Balanced Scorecard Simulator – A Tool for Stochastic Business Figures

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Abstract. Long term business success is highly dependent on how fast the business reacts on the changes in the market situation. Those who want to be successful need relevant, in-time and accurate information. *Balanced Scorecard Simulator* is a management tool that can be used efficiently in the processes of planning, decision and controlling. Based on the Balanced Scorecard concept the program combines imprecise data of business figures with forward and backward computation. It is also possible to find out whether or not the data are consistent with the BSC model. The visualization of the simulation results is done by a Kiviat diagram. The aim of the design is a software tool based on a BSC model and MCMC methods but is easy to handle.

1 Introduction

Hard competitive conditions continuously challenge enterprizes to improve the quality of information on which entrepreneurial decisions are based. For this reason management tools that support these processes play an important role. The Balanced Scorecard (BSC) is today a well-known and widely used concept from Kaplan and Norton (1996). It was successfully integrated in the management processes of many companies, because it introduces the performance from different economic and business perspectives and helps to understand and recognize the factors on which company prosperousness depends. BSC figures are regularly computed from retrospective information and are used to be compared with a corporate goal, to analyze the differences and to set new targets. The *Balanced Scorecard Simulator* is an easy-to-use management tool which supports the Markov Chain Monte Carlo (MCMC) simulation of Balanced Scorecard indicators. It also improves the forecast quality of business figures. The quality of the simulation results can be achieved through modeling stochastic indicators on the one hand and of their functional dependencies designed as an equation system on the other hand. It detects contradictions primarily in data which should fulfill a system of equations. The goal is to

obtain realistic characteristic quantities which cannot be measured with hundred per cent precision (Friedag and Schmidt (2004)). Consequently, with the *Balanced Scorecard Simulator* complete and precise information about indicators which is based on non-contradictory data can be achieved and erroneous decisions avoided. The performance measurement system in the simulator is based on the Balanced Scorecard of Kaplan and Norton (1996). Some tools which are based on imprecise business figures already exist, for a possiblistic approach cf. Müller et al. (2003) and for a probabilistic approach cf. Schmid (1979) and Lenz and Rödel (1991). However the *Balanced Scorecard Simulator* is an absolutely novel approach that not only brings financial and non-financial indicators together in an equation system but also uses MCMC techniques as an appropriate instrument for the simulation.

2 Model

The MCMC simulation is based on a stochastic model of the selected BSC indicators, cf. Fig. 1.

The model is characterized by the following three features:

- 24 indicators (variables) and three system constants are assigned to the four BSC perspectives (employee and innovation, internal business process, customer and financial perspective). The indicators were selected following the procedures applied in an earlier case study (Todova and Ünsal (2005)).
- All variables of the model are connected to each other by the four basic arithmetical operations;
- 15 equations with up to three variables exist. Obviously, each equation can be uniquely solved for each existing variable ("separation principle").

3 Prior information

It is assumed that for some BSC indicators there exists prior information which refers to the respective probability distribution $\pi(x)$ of the corresponding variable x. Five classic types of distribution are considered:

- Normal distribution: $\pi(x) \sim N\left(\mu, \sigma^2\right)$
- Uniform distribution: $\pi(x) \sim U(a, b)$
- Triangular distribution: $\pi(x) \sim Tr(a, b, c)$
- Exponential distribution: $\pi(x) \sim Exp(\lambda)$
- Cauchy distribution: $\pi(x) \sim Ca(a, b)$

These distributions are implemented in the *Balanced Scorecard Simulator* because they are the most commonly used distributions. But other distributions can easily be implemented. At present, the specification of a distribution from
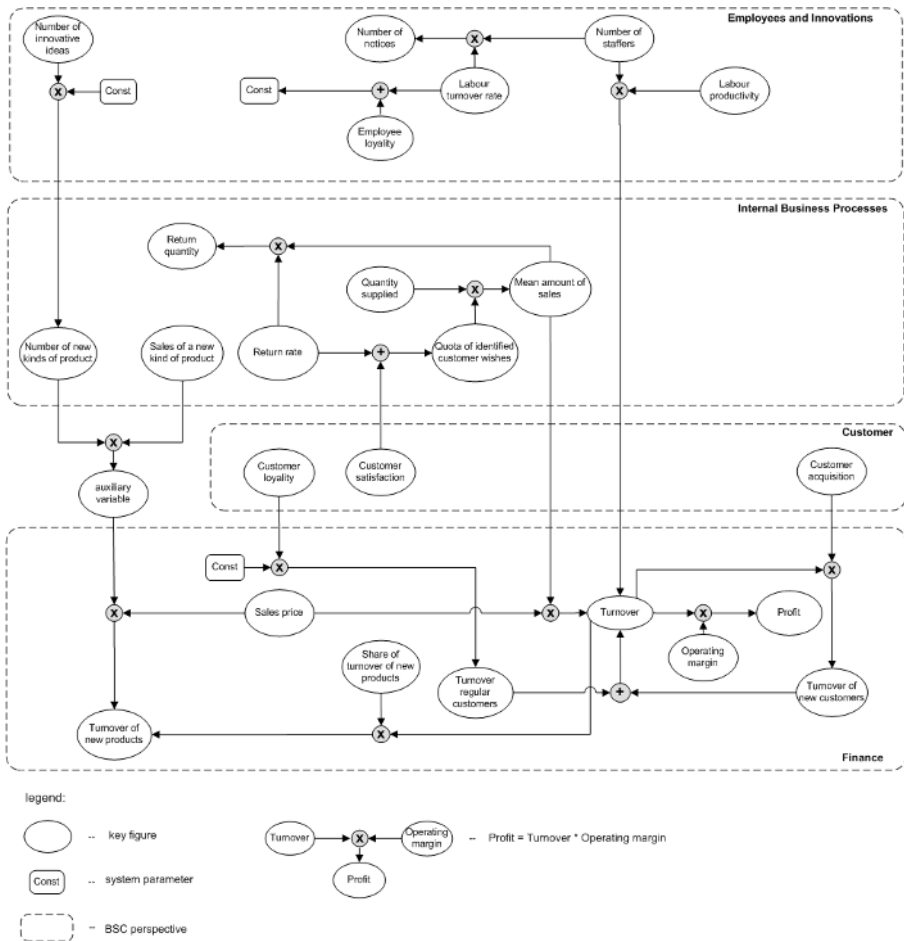
Fig. 1. Balanced scorecard model graph

data and the parameter estimation is not included in the software. All constants and target values of the variables are consequently regarded as known.

4 Simulation

The process of simulation is carried out in two steps. In the first step a sample is drawn from every known distribution of an indicator. An imputation of unknown variables is based on the whole equation system. The fusion of several samples for a variable that exists in more than one equation is carried out in the projection step. The results are tabulated as well as visualized in a Kiviat diagram.

4.1 Metropolis Hastings algorithm

The simulation of the BSC indicators is carried out using the Metropolis Hastings procedure. The Metropolis Hastings (MH) algorithm is a kind of Markov Chain Monte Carlo (MCMC) method. The MH procedure is suitable for the generation of random numbers of any arbitrary probability density function. The resulting sample is denoted by $x = \{x_1, \ldots, x_T\}$. The MH algorithm which is used in the *Balanced Scorecard Simulator* is described by the algorithm 1 (Köppen and Lenz (2005)).

Algorithm 1 MH Algorithm

Input: $\pi()$ – target function
    $q(\cdot, \cdot)$ – proposal distribution, transition kernel
    T – sample size (number of iterations)
Output: $x = \{x_1, \ldots, x_T\}$ – sample
 1: t = 0
 2: initialize x_t
 3: **repeat**
 4:     increment t
 5:     generate $y \sim q(x_{t-1}, \cdot)$
 6:     generate $u \sim U(0, 1)$
 7:     calculate $\alpha(x_{t-1}, y) \leftarrow min\left\{1, \frac{\pi(y)}{\pi(x_{t-1})} \frac{q(x_{t-1}, y)}{q(y, x_{t-1})}\right\}$
 8:     **if** $\alpha(x_{t-1}, y) \geq u$ **then**
 9:         $x_t \leftarrow y$
10:     **else**
11:         $x_t \leftarrow x_{t-1}$
12:     **end if**
13: **until** $t = T$

The random numbers are not drawn directly from the target function $\pi()$, but from a proposal distribution $q()$ instead, where it is easier to draw samples from. The proposal distribution $q(x, y)$ is selected from a set of methods that exist for variants of the MH procedure. The Independence Chain Method used in the *Balanced Scorecard Simulator* allows to draw candidates from an independent proposal distribution $q(x, y) = q(\cdot)$. Consequently, the value x_{t-1} does not influence the candidate y drawn at time t. Therefore the acceptance probability for the candidate y in the above algorithm is modified as follows, cf. Liu (2001):

$$\alpha(x_{t-1}, y) = min\left\{1, \frac{\pi(y)}{\pi(x_{t-1})} \frac{q(x_{t-1})}{q(y)}\right\} \tag{1}$$

The proposal distribution is defined at the start of the simulation and depends on the distribution type of the target function. The density of the normal distribution $N\left(\mu_N, \delta_N^2\right)$ serves as a proposal distribution for almost all target

functions. The parameters of the proposal distribution are denoted as $\mu_N = E_\pi[X]$ and $\delta_N^2 = Var_\pi[X]$. $E_\pi[X]$ represents the expected value and $Var_\pi[X]$ represents the variance. In the case of a Cauchy distribution $q(\cdot,\cdot)$ becomes a Cauchy density as a proposal function with the same location parameter but a 110% scaling parameter in comparison with the given Cauchy function.

4.2 Projection step

Multiple samples $x, \hat{x}_1, \ldots, \hat{x}_k$ referring to a selected indicator are computed in a simulation run, where k depends on the number of equations where the indicator occurs. The samples they have to be merged and a projection step is necessary at the end of the simulation to obtain an estimator from these samples. First of all the product space is spanned:

$$dom\hat{X} = domX \times dom\hat{X}_1 \times \ldots \times dom\hat{X}_k \qquad (2)$$

As the indicators have to fulfill each single equation, a projection on the subspace $X - \hat{X}_1 - \ldots - \hat{X}_k = 0$ is performed. The projection is carried out in step 9 of algorithm 2.

Algorithm 2 Projection step

Input: $\left(X, \hat{X}_1, \ldots, \hat{X}_k\right)$ for each indicator

Output: $\hat{f}_{\hat{X}}$, $E\left[\hat{X}\right]$, $Var\left[\hat{X}\right]$

1: $\underline{q_{max}} \leftarrow max\left\{\underline{q_1}, \ldots, \underline{q_k}, \underline{q}\right\}$ { Determine the maximum of all lower 1% quantiles $\underline{q_i}$ of all samples $X, \hat{X}_1, \ldots, \hat{X}_k$}
2: $\overline{q_{min}} \leftarrow min\left\{\overline{q_1}, \ldots, \overline{q_k}, \overline{q}\right\}$ { determine the minimum of all upper 99% quantiles $\overline{q_i}$ of all samples $X, \hat{X}_1, \ldots, \hat{X}_k$}
3: **for all** Variables **do**
4:    **if** $\underline{q_{max}} > \overline{q_{min}}$ **then**
5:      $I_q \leftarrow \emptyset$, mark system as inconsistent
6:    **else**
7:      $I_q \leftarrow \left[\underline{q_{max}}, \overline{q_{min}}\right]$
8:    **end if**
9:    Calculate $f\hat{X}(x) \leftarrow c \cdot f_X(x) \cdot f_{\hat{X}_1}(x) \cdot \ldots \cdot f_{\hat{X}_k}(x)$ $\forall x \in I_q, c \in \Re_+$
10:   Calculate $E\left[\hat{X}\right] \leftarrow \sum\limits_{j=1}^{k} x_j \cdot \hat{f}_{\hat{X}}(x_j)$
11:   Calculate $Var\left[\hat{X}\right] \leftarrow \sum\limits_{j=1}^{k} \left(x_j - E\left[\hat{X}\right]\right)^2 \cdot \hat{f}_{\hat{X}}(x_j)$
12: **end for**

The lower ($\underline{q}$) and upper ($\overline{q}$) quantiles and the median are determined for the graphic visualization of the results, cf. Fig. 1.

5 The software

The BSC model was implemented as the *Balanced Scorecard Simulator*. The simulator connects several applications with an Excel GUI and VBA to input prior information. The simulation is coded by the statistical programming language R which communicates with Excel via the R-Excel server. The simulation results are presented as a predetermined Excel table and as a Kiviat diagram. The Kiviat diagram maps all simulated indicators with the target values as entered by the user. Additionally, it is possible to examine the sensitivity of the indicators dependent on the given prior information, before running the simulation. An automatic storage of intermediate results allows for an analysis of inconsistencies in the BSC system. Furthermore, the performance measurement system can be extended by a further indicator if this indicator is assigned to one of the four perspectives of the given BSC.

6 Simulation example

In this section we illustrate the *Balanced Scorecard Simulator* by an example. In our example full prior information is provided for all 24 characteristics, cf. Tab. 2, columns 2 and 3. The simulation is primarily used to identify inconsistencies of the BSC data. In addition, a new indicator is established, namely "costs" related to the financial perspective, which is defined as $costs = turnover - profit$. The indicator *turnover regular customers of the previous period* is constant and set to 1900.

The CPU operating time of a test run with a number of iterations $T = 100.000$ is approx. 5 min. The data set does not contradict the given model. The columns $\hat{\mu}$, $\hat{\sigma}$ and planned target values in Tab. 2 show the result of the simulation. An analysis of the computed expected values and standard deviations for every indicator provides evidence that the imprecision (error intervals) of the simulated quantities are reduced. The observed values are adjusted in the way that a shift is proportional to the prior variance of a variable.

The results of simulation are visualized in a Kiviat diagram, cf. Fig. 1. This chart type is suitable for the representation of multiple indicators. If a system of equations is classified as inconsistent, only the number and the names of the incorrect indicators are reported by a result notification. This makes it easier for the user to identify the causes of inconsistency in the data.

7 Summary

The adaptation and modeling respectively of key figures as random variables in a BSC enhances the information content and brings the BSC closer to reality, (cf. Müller et al. (2003)). Randomness happens due to a kind of 'natural'

Table 1. Prior information of the BSC characteristic quantities

BSC indicator	distribution	target value	$\hat{\mu}$	$\hat{\sigma}$	planned target value
Number of innovative ideas	$N(18, 2^2)$	18	18.00	1.86	20.00
Employee loyalty	$U(0.97, 0.99)$	0.99	0.99	0.0004	0.99
Number of notices	$U(1, 3)$	2	2.06	0.24	2.05
Number of staffers	$N(205, 5^2)$	205	201.14	3.76	203.70
Labour turnover rate	$N(0.01, 0.001^2)$	0.01	0.01	0.0006	0.01
Labour productivity	$N(20, 2^2)$	20	19.94	0.42	20.00
Number of new kinds of product	$U(3, 5)$	4.5	4.47	0.86	5.00
Sale set of a new kind of product	$U(45, 50)$	50	47.49	1.43	50.00
Returns quantity	$N(89, 5^2)$	90	89.75	4.40	100.00
Return rate	$N(0.19, 0.02^2)$	0.2	0.17	0.01	0.20
Quantity supplied	$N(550, 10^2)$	556	548.73	9.30	625.00
Mean amount of sales	$N(440, 10^2)$	445	439.45	9.41	500.00
Quota of identified customer wishes	$N(0.8, 0.01^2)$	0.8	0.80	0.01	0.80
Customer loyalty	$N(2, 0.01^2)$	2	2.00	0.01	2.04
Customer satisfaction	$U(0.6, 0.7)$	0.6	0.65	0.03	0.60
Customer acquisition	$N(0.05, 0.01^2)$	0.05	0.05	0.0003	0.05
Turnover of new products	$U(1990, 2010)$	2000	1999.40	5.67	2037.04
Sales price	$N(8, 2^2)$	9	8.50	0.57	8.15
Share of turnover of new products	$N(0.45, 0.001^2)$	0.5	0.45	0.00	0.50
Turnover regular customers	$N(3800, 50^2)$	3800	3795.20	44.36	3874.07
Turnover of new customers	$N(199, 10^2)$	200	198.78	6.09	200.00
Turnover	$N(4000, 25^2)$	4000	3994.38	20.54	4074.07
Operating margin	$N(0.25, 0.02^2)$	0.27	0.25	0.01	0.27
Profit	$N(1000, 25^2)$	1100	999.25	22.09	1100
Costs	unknown	unknown	3013.77	129.07	2974.07

longitudinal derivation of indicators, errors in observations and measurements of actual data of BSC indicators or evaluation tolerance in target data.

The software *Balanced Scorecard Simulator* is an equally useful management tool for planning, decision making and controlling, i.e. it allows the computation of consistent target values, it produces coherent, analytical data and supports the controller to detect incoherencies in the values of the BSC.

Planned future investigations in the field of simulation of stochastic business figures concern the following topics:

- Simulation of arbitrary performance measurement systems or an individual adjustment of the indicators and perspectives in a business-specific BSC;
- Performance improvement of the simulation method, efficient estimation of distributions and parameters and sampling from multi-dimensional distributions;
- Improvement in the debit quantity regulation in the *Balanced Scorecard Simulator.*

Further improvements of the software can be achieved by implementing multivariate density estimation of real data of a company's data warehouse. Due to the fact, that the Metropolis Hastings algorithm is used for sampling, this does not influences the simulation.
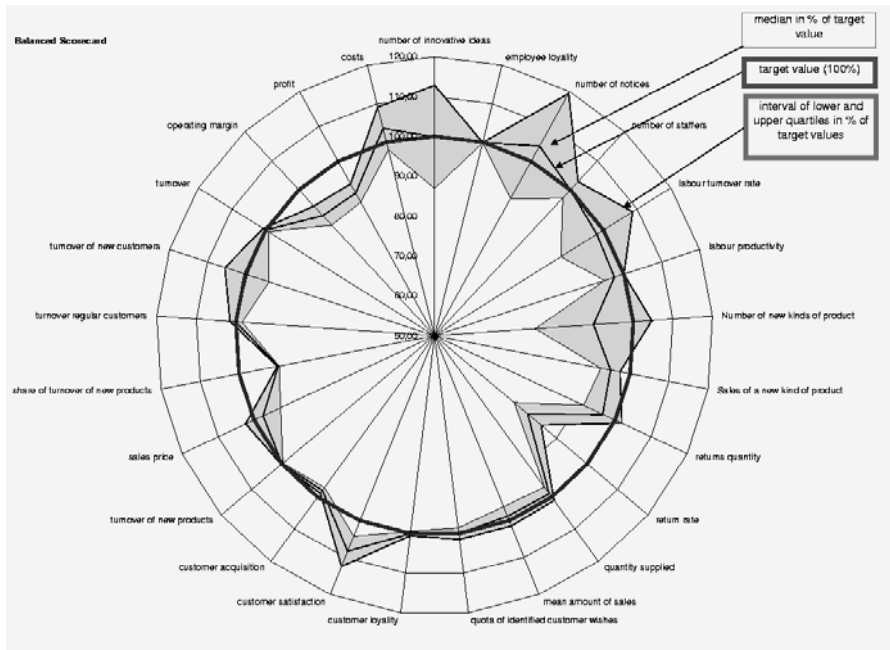
Fig. 2. Simulation results of BSC characteristic quantities in Kiviat diagram form

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