Fuzzy Modeling of Customized Solutions for Corporate Performance Assessment

Marius Pîslaru, Silvia Avasilcăi, and Lidia Elena Alexa

Abstract The social environment in which corporations operate is affected by their actions but equally corporations experience the pressures of society. The idea that the economic environment is currently in a transition phase from the knowledge-based economy and society to the innovation economy and society is strongly emphasized by the policy makers and experts' publications and reports underlining the pressure the companies are under in order to adjust to the environmental and economic changes and to become more competitive. The paper aims to develop and test, in a textile company from Iasi, a performance assessment model based on fuzzy modelling techniques. In order to assess corporate performance Balanced Scorecard approach was considered based on fuzzy technique. The corporate performance using lagging and leading indicators suggests that business performance should be evaluated not only by using financial indicators but also by simultaneously considering non-financial indicators. This way, it is possible to evaluate the business performance from a strategic perspective, taking into account not only past results but also leading indicators. The fuzzy it is suitable for industrial firms to monitor the performance indicators that can contribute to a sustainable competitive position.

Keywords Corporate performance assessment · Fuzzy modeling · Expert system design · Decision making

1 Introduction

The contemporary industrial environment, subject to both globalization and regionalization, generates continuous challenges for industrial companies and production systems within these, which must demonstrate on one hand reactivity to the external environment and, on the other hand, internal flexibility for developing and

M. Pîslaru (✉) · S. Avasilcăi · L. E. Alexa
Engineering and Management Department, "Gheorghe Asachi" Technical University of Iasi, Iasi, Romania
e-mail: mpislaru@tuiasi.ro; silvia.avasilcai@tuiasi.ro; lidia.alexa@tuiasi.ro

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M. Huseyin Bilgin et al. (eds.), *Eurasian Business Perspectives*, Eurasian Studies in Business and Economics 10/1, https://doi.org/10.1007/978-3-030-11872-3_17

maintaining a sustainable competitive position. Recent developments in the field of performance management and measurement are aligned to, and in the meantime are trying to respond to these contemporary challenges of the technological and socio-economic environment.

Both knowledge and innovation are essential elements for an industrial company in achieving and maintaining a sustainable competitive position. In this context, production systems are the interface between invention/innovation and socio-economic development, being the ones that translate innovation into finished products and brings them closer to the customer, thus contributing to continuous improving of the quality of life. The field of performance measurement has known an explosive development since 1992, when the Balanced Scorecard Model (Kaplan and Norton 1992, 1996, 2006a, b) was developed and promoted. The model triggered radical change in approaching organizational performance, being the catalyst for a multi-criteria approach of organizational performance. Up to that moment most approaches in the field were almost exclusively focused on the financial aspects of organizational performance. The BSC approach involves identifying key components of operations, setting goals for them and finding ways to measure progress towards their achievement (Leon-Soriano et al. 2010).

The Balanced Scorecard suggests to approach organizational performance by means of four “perspectives”: financial perspective, internal processes perspective, consumer perspective and innovation and growth perspective and it offers support to integrate physical and intangible assets into a comprehensive model (Rabbani et al. 2014) that creates a balance between financial and non-financial measures, internal and external stakeholders, long-term and short-term goals. Conceived initially as a tool for performance measurement, the extended use of this model made it to evolve into a strategic tool for organizational development (Avram and Avasilcăi 2014; Hoque 2014; Sorooshian et al. 2016).

Research in this field suggests that The Balanced Scorecard is used by 60% of the Fortune 1000 companies (Silk 1998). Other models used worldwide for performance measurement are “The Performance Pyramid” (Lynch and Cross 1995), the intangible asset scorecard (Sveiby 1997), ECOGRAI, the action-profit linkage model (Westbrook et al. 2000), the value added methods (EVA™—Economic Value Added, MVA™—Market Value Added), and more recently “The Performance Prism” (Neely 2002).

Although the BSC (Balanced Scorecard Model) conceptual framework has been widely accepted in the business community, the appropriate method of implementing the framework remains a challenge. For example, a broader set of non-financial attributes was incorporated into a company’s measurement system, using the analytic hierarchy process (AHP) and its variant, the analytic network process (ANP) in order to facilitate implementation of the BSC (Leung et al. 2006; Boj et al. 2014). A three-level feature weighting system based on BSC design was proposed to enhance case-based reasoning inference performance (Yuan and Chiu 2009). Although significant research has been carried out in the field of performance measurement, the complex problem of defining and modeling indicators, on one hand, and the problem of aggregating indicators into an efficient system that should contain and provide real-time information relevant for multi-criteria decisions are still subject to constructive debate.

Performance measurement is one of the world's top charts and is a major concern for organizations, especially industrial firms that are confronted with specific problems of production activities. The issue of performance parameters cannot yet be solved, especially with regard to aggregation of parameters in a flexible configuration that should provide, on one hand, real-time information for managerial decisions and, on the other hand, allow adjustment of performance parameters to environmental changes.

At the same time, the use of fuzzy logic for modeling economic phenomena is also a top research field in the world. Generally, using fuzzy logic in controlling industrial processes and especially in the field of performance, monitoring of production systems can provide the flexibility and reactivity necessary to achieve a high level of performance. The use of fuzzy techniques leads to solving a wide area of problems in the field of production systems, which would be a vital source of information for companies in terms of enhancing their performance and maintaining a sustainable competitive position.

The literature documents more and more initiatives for using fuzzy techniques for modelling economic phenomena and for industrial processes optimization. Still being a field less developed in the landscape of corporate performance assessment, such approach could be of real use for industrial companies in order to enhance their performances based on an integrated and flexible approach of using performance indicators (Yüksel and Dağdeviren 2010; Tseng 2010).

2 Fuzzy Model for Corporate Performance Assessment

Fuzzy logic represents a scientific tool which emulates human thinking allowing to model a system without comprehensive computation using both quantitative and qualitative data. The computations are made by words, and knowledge is defined by language rules (for example IF-THEN).

The success of fuzzy models in the sphere of management and different control systems is based on flexibility which is provided by the possibility of adding new linguistic variables, making it more elastic in design and implementation. This is one of the reasons why the modeling systems based on fuzzy reasoning became an increasingly common practice in the field of decision making especially in corporate performance assessment. The fuzzy modeling system proposed is based on three knowledge groups in order to point out the connections and principles that characterize different indicators and components of the corporate performance assessment, as well as their contribution to maintaining a sustainable competitive position. The inputs/outputs and the rules from every knowledge group are expressed through words or phrases combined with linguistic variables and fuzzy rules (Phillis and Andriantiatsaholiniaina 2001).

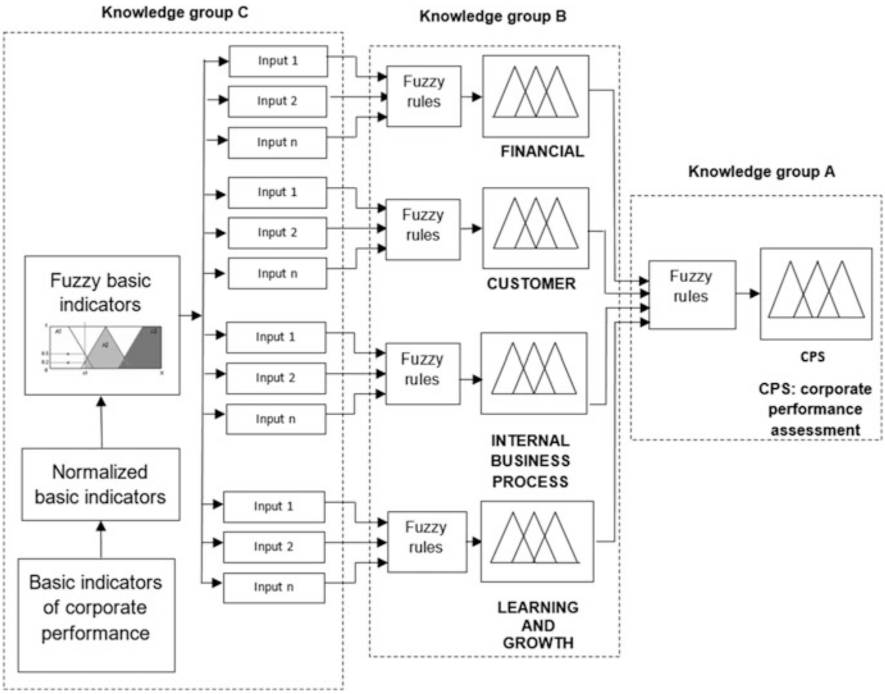

Fig. 1 Corporate performance assessment—fuzzy model. Source: Own model

The fuzzy model developed to support the sustainable competitive position of an industrial company is shown in Fig. 1. The fuzzy model is presented as an interconnected network of different knowledge groups whose goal is to point out a final characteristic of the system. The user provides input data for the first knowledge group named knowledge *group C* after a series of mathematical operations and fuzzy computations. For the other two knowledge groups, named B and A the aggregated input parameters are provided by other categories.

Based on the IF-THEN rules used by fuzzy logic reasoning, the input data from every knowledge group is combined in order to obtain a complex indicator, as an output data, which represent the input data passed to the next inference engine. Let's take into consideration, knowledge group B which uses the FINANCIAL resource indicator. This indicator is the combination result of the corresponding *Input 1*, *Input 2…Input n*, indicators. These ones are in turn the outputs of the knowledge group C. And so on, the FINANCIAL become as an input for knowledge group A, which based on the outputs of the other parameters namely, CUSTOMER, INTERNAL BUSINESS PROCESS and LEARNING and GROWTH computes the final output of the system, the CPS (corporate performance assessment) indicator.

Finally, the CPS is a very complex indicator which essentially is computed from a big number of basic indicators characterized by uncertainty and subjectivity. If we consider, for instance the parameters 'Customer satisfaction', 'Training and skill' and ‘New technologies’ it is very difficult to quantify these parameters on a common scale and to compute them in a mathematical manner in order to assess performance. This is why the fuzzy logic reasoning represents an optimal scientific tool capable to manage this type of subjective and uncertain situations. The system has the ability to allow the adjustment of indicators and features according to user needs and to tune the fuzzy rules embedded in any knowledge group, thus providing flexibility and accuracy to the system.

3 Corporate Performance Assessment Based on BSC Perspectives

This particular case study focusing on the use of fuzzy modelling in measuring corporate performance was conducted in a textile company in Iasi, Romania. The data was collected from interviews with managers from different departments of the company and were later processed and analyzed by the researchers. In practice, the model used in the performance assessment process of a company needs to be adjusted in accordance with the particular realities and requirements of the corporation.

The values of the indicators used in the model are usually provided by companies from internal data or are estimated using different techniques such as life cycle assessment, average emission factor models, etc. presented extensively in the literature. In this case, the performance indicators were defined based on the BSC perspectives suggested by Kaplan and Norton (1992) and were determined according to the literature (Kaplan and Norton 1996; Lee et al. 2008; Leung et al. 2006; Sohn et al. 2003; Ihsan and Dagdeviren 2010). As a result, four BSC perspectives (namely: *financial*, *customer, internal business process* and *learning and growth*) and 16 performance indicators based on these perspectives were included in the analysis (Table 1).

The basic indicators are filtered with the purpose to assign values in the interval [0, 1] called normalization. Let’s say that basic indicator c is the indicator value for the corporate whose performance we want to assess. In the interval $[a_i, A_i]$ is the target of indicator c, where b_i and B_i, represent the minimum respectively the maximum value. The normalized value z will be computed as in Eq. (1):

$$z = \begin{cases} \dfrac{x - b_i}{a_i - b_i}, & b_i \leq c \leq a_i \\ 1, & a_i \leq c \leq A_i \\ \dfrac{A_i - x}{B_i - A_i}, & A_i \leq c \leq B_i \end{cases} \tag{1}$$

Graphically this equation is presented in Fig. 2.

Normalized values, are calculated using linear interpolation between most desirable (target) and least desirable indicator values. In order to address information

Table 1 BSC perspectives and performance indicators

BSC perspectives	Performance indicators
FINANCIAL (40%)	Assets profitability
	Sale profitability
	Equity profitability
	Cash flow
CUSTOMER (30%)	Customer satisfaction
	New customer acquisition
	Target market share
	Customer retention
INTERNAL BUSINESS PROCESS (10%)	Product and service development
	Manufacturing process
	Product delivery
	New technologies
LEARNING AND GROWTH (20%)	Job satisfaction
	Training and skill
	Innovation
	Knowledge sharing

Source*:* Ihsan and Dagdeviren (2010)

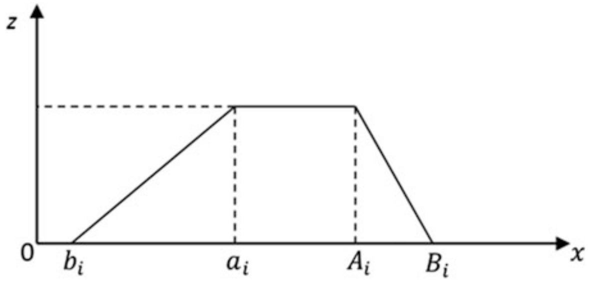

Fig. 2 Normalization of basic indicator *c*

quality issues that may arise from the cumulative effects of past corporate pressures, data availability, and data accuracy, we use weighted sums of data for current and previous model inputs. So, the value z of the indicator can be computed using weighted sum Eq. (2)

$$z = w_1 y_1 + w_2 y_2 + \ldots. + w_n y_n \tag{2}$$

Where $w_1 + w_2 + \ldots + w_n = 1$. The weighted sum of parameters used in the fuzzy model is performed based on their past data process called smoothing of normalized values. The fuzzification of the normalized value z, of indicator c, it is transformed from a crisp value into a linguistic variable to make it compatible with the rule base. Broadly, a linguistic variable is a variable whose values is formed of words).

Table 2 Parameters values of basic indicators and corresponding normalized ones

Indicator	Annual indicator value (normalized value)			
	2012	2013	2014	2015
Assets profitability	0.624 (1)	0.649 (1)	0.679 (1)	0.595 (0.985)
Sale profitability	0.411 (0.853)	0.397 (0.794)	0.423 (0.872)	0.503 (0.912)
Equity profitability	0.712 (0.814)	0.694 (0.798)	0.688 (0.764)	0.738 (0.852)
Cash flow	0.649 (0.549)	0.759 (0.572)	0.814 (0.612)	0.802 (0.605)
Customer satisfaction	NA	NA	0.87 (0.91)	0.88 (0.92)
New customer acquisition	NA	NA	0.54 (0.54)	0.57 (0.57)
Target market share	0.195 (0.21)	0.204 (0.23)	0.217 (0.26)	0.301 (0.34)
Customer retention	NA	NA	NA	0.114 (0.41)
Product and service development	0.347 (0.644)	0.409 (0.712)	0.434 (0.748)	0.530 (0.911)
Manufacturing process	NA	NA	0.719 (1)	0.722 (1)
Product delivery	0.914 (1)	0.935 (1)	0.938 (1)	0.941 (1)
New technologies	0.642 (0.541)	0.645 (0.542)	0.803 (0.796)	0.899 (0.871)
Job satisfaction	NA	0.501 (0.398)	0.350 (0.263)	0.514 (0.402)
Training and skill	NA	0.629 (0.431)	0.547 (0.402)	0.812 (0.657)
Innovation	NA	NA	0.235 (0.519)	0.472 (0.723)
Knowledge sharing	NA	NA	0.980 (1)	0.980 (1)

Source: Data collected from a textile company in Iasi County
NA mean the lack of data for the respective year

The values of the basic indicator and the corresponding normalized ones in parentheses are given in Table 2. Unfortunately, the data wasn't available for all the period considered and sometimes not even for all indicators. Despite of this, the calculations were made and should not be forgotten that the main purpose of the fuzzy system is to show that such an assessment is feasible and such analysis can be made on solid and pertinent considerations.

A fuzzy assessment of performance implies fuzzy inputs and fuzzy outputs. Because all performance indicators, basic or composite, are normalized, appropriate fuzzy partitions must be defined in the [0, 1] interval. Each linguistic variable has a number of fuzzy sets. The linguistic variables of basic indicators used in the model have three fuzzy sets with linguistic values *weak (W)*, *average* (A), and *strong* (S). The fuzzy sets used in the model are presented in Fig. 3.

In order to obtain a composite indicator a combination of two or more fuzzy sets is required. Thus for the composite indicator presented in Fig. 4 has five linguistic values: *very bad* (VB), *bad* (B), *average* (A), *good* (G), *and very good* (VG).

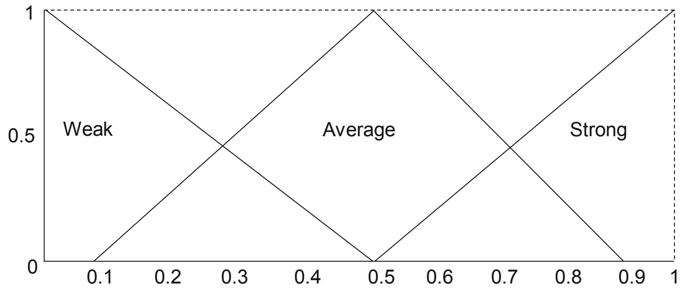

Fig. 3 Membership functions for basic indicator used in the fuzzy performance model

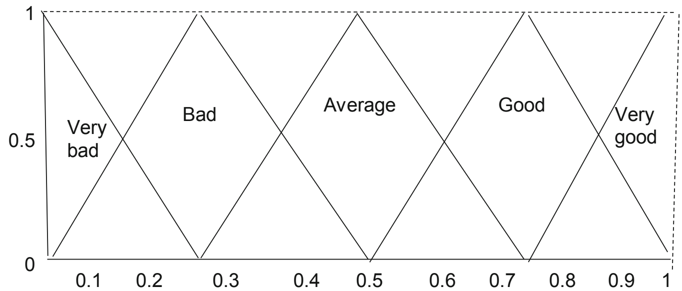

Fig. 4 Membership functions for composite indicator used in the fuzzy performance model

For an accurate representation of the final indicator, namely CPS, an even larger number of fuzzy sets must be used. The number of linguistic values for CPS is determined by assigning positive weights $\alpha(0.4)$,$\beta(0.3)$, $\delta(0.1)$, $\gamma(0.2)$ representing the relative importance of respectively FINANCIAL, CUSTOMER, INTERNAL BUSINESS PROCESS and LEARNING AND GROWTH in the calculation of CPS. The integer values 0,1,2,3 and 4 to the five linguistic values will be also assigned as follows: 0 corresponds to *Very Bad*, 1 corresponds to *Bad*, and so on. The computation of CPS will be performed as in Eq. (3):

$$CPS = \alpha FINANCIAL + \beta CUSTOMER + \delta INTERNAL + \gamma LEARNING \tag{3}$$

The minimum index for CPS is 0 and the maximum is $4 \times 4 = 16$. Therefor we have to use 17 fuzzy sets in order to describe CPS precisely. But to avoid an explosion of linguistic variables we used five representative linguistic values for all composite indicators. For CPS we used nine fuzzy sets in order to aggregate the four parameters more precisely. These fuzzy sets are: *extremely low* (EL = 0), *very low* (VL = 1), *low* (L = 2), *rather low* (RL = 3), *intermediate* (I = 4), *rather high* (RH = 5), *high* (H = 6), *very high* (VH = 7), and *extremely high* (EH = 8; see Fig. 5).

The rule base for CPS is obtained from the Eq. (4) by assigning values from the set {0,1,2, 3,4} to the term sets {VB, B, A, G,VG} and to the term sets {EL,VL,L,

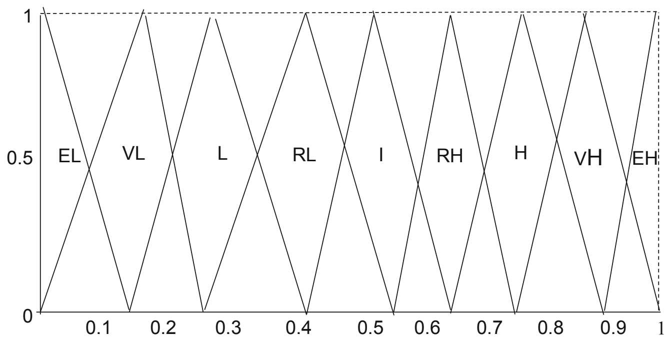

Fig. 5 Membership function of CPS (own compilation)

RL,I,RH,H,VH,EH}. For example, if FINANCIAL = A = 2 and CUSTOMERS = G = 3 and INTERNAL = B = 1 and LEARNING = A = 2 then CPS is computed as $0.4 \times 2 + 0.3 \times 3 + 0.1 \times 1 + 0.2 \times 2 = 2.2$, which corresponds to a greater extent the fuzzy set L.

$$CPS = \begin{cases} EL, & 0 \leq SUM < 0.5 \\ VL, & 0.5 \leq SUM < 1 \\ L, & 1 \leq SUM < 1.5 \\ RL, & 1.5 \leq SUM < 2 \\ I, & 2 \leq SUM < 2.5 \\ RH, & 2.5 \leq SUM < 3 \\ H, & 3.5 \leq SUM < 4 \\ VH, & SUM = 4 \\ EH, & SUM = 4 \end{cases} \tag{4}$$

FINANCIAL has four inputs in our particular case, namely, *Assets profitability (AP)*, *Sale profitability (SP)*, *Equity profitability (EP)* and *Cash flow (CF)*. For ease of calculation and understanding we assumed that the weight of each parameter is equal to a unit. So its fuzzy set is determined from the following equations:

$$\mathrm{SUM} = \mathrm{AP} + \mathrm{SP} + \mathrm{EP} + \mathrm{CF} \tag{5}$$

And

$$FINANCIAL = \begin{cases} VB, & 0 \leq SUM \leq 1 \\ B, & 1 < SUM \leq 3 \\ A, & 3 < SUM \leq 4 \\ G, & 4 < SUM \leq 6 \\ VG, & 7 < SUM \leq 8 \end{cases} \tag{6}$$

Taking into consideration that the other three parameters have four inputs as *FINANCIAL* we can presume that the fuzzy sets for *CUSTOMERS*, *INTERNAL* and

LEARNING is computed in a similar way. Of course the rule base of basic indicators could be more pessimistic or more optimistic relative to the influence each indicator has on the system.

4 Results

Products and sums of the membership grades of basic indicators are propagated to the composite variables and, finally, to CPS (corporate performance assessment). The result of the computation is presented below, showing the values obtained after compiling the data presented in Figs. 3–5 (Table 3).

Starting with membership grades of the basic indicators computation and continuing with membership grades of composite indicators we have all the data needed to determine the membership grades of CPS using the following rules (Phillis and Davis 2008; Phillis and Kouikoglou 2009):

$$\begin{aligned}&(\mathrm{B})\mathrm{FINANCIAL} + (\mathrm{B})\mathrm{CUSTOMER} + (\mathrm{B})\mathrm{INTERNAL} + (\mathrm{B})\mathrm{LEARNING}\\&\quad = 0.4 \times 1 + 0.3 \times 1 + 0.1 \times 1 + 0.2 \times 1 = 1\\&\quad \Rightarrow \text{CPS is B with grade } 0.16 \times 0.9 \times 0.29 \times 0.42 = 0.001753\end{aligned}$$

$$\begin{aligned}&(\mathrm{A})\mathrm{FINANCIAL} + (\mathrm{A})\mathrm{CUSTOMER} + (\mathrm{B})\mathrm{INTERNAL} + (\mathrm{G})\mathrm{LEARNING}\\&\quad = 0.4 \times 2 + 0.3 \times 2 + 0.1 \times 1 + 0.2 \times 3 = 2.1\\&\quad \Rightarrow \text{CPS is A with grade } 0.68 \times 0.72 \times 0.58 \times 0.43 = 0.1221\end{aligned}$$

The calculation, in the end, for CPS parameter:

$$\begin{aligned}\mathrm{CPS} &= (0.07 \times 0.5 + 0.64 \times 0.65 + 0.29 \times 0.75)/(0.07 + 0.64 + 0.29)\\&= 0.6685\end{aligned} \tag{7}$$

The overall performance indicator CPS score is computed using centroid method defuzzification. Accordingly, the performance of the concerned business was

Table 3 Membership grades of performance indicators

Indicator	Value								
	VB (0)	B (1)	A (2)	G (3)	VG (4)				
FINANCIAL	0	0.16	0.7	0.14	0				
CUSTOMER	0	0.09	0.72	0.19	0				
INTERNAL BUSINESS PROCESS	0	0.29	0.58	0.13	0				
LEARNING AND GROWTH	0	0.42	0.43	0.15	0				
	EL	VL	L	RL	I	RH	H	VH	EH
CPS	0	0	0	0.07	0.64	0.29	0	0	0

calculated as 66.85% at the end of the implementation made by using fuzzy BSC model. The interpretation of the result is dependent of the distance between the value obtained and 1: the closer the value is to 1 the more the corporate performance is improving and vice versa. The value obtained reflects the performance of the company based on BSC approach. Also after fuzzy system performing the conclusion riched is that the most important performance indicators that have a negative effect on business performance are: sales profitability and adaptation to innovations.

5 Conclusion

The model we proposed and tested is modular and flexible and it can also be adapted to assess different types of organizations. In practice, the analytical structure of the model—namely strategies, BSC perspectives and performance indicators may need to be adjusted according to the company's profile, industry or other specific requirements. The proposed model, represents an attempt to provide a tool for corporate performance assessment via computing techniques in order to ensure corporate sustainability. Based on linguistic variables and linguistic rules, the model provides quantifiable values of performance assessment. Based on these, the user can design appropriate policies according to the purpose it has to achieve in order to move on toward the path of sustainable development. The model we proposed provides new approaches in the field of performance assessment, and proves to be a useful tool for managers or policy makers. We also intend to further perform a sensitivity analysis in order to determine the effects of a change in a decision parameter on the entire system's performance.

Acknowledgement This research was undertaken within the framework of the National Research Program PN II, financed by MEN – UEFISCDI, project PN-II-PT-PCCA-2013-4-1811.

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