Journal of Business Theory and Practice
ISSN 2372-9759 (Print) ISSN 2329-2644 (Online)
Vol. 8, No. 2, 2020
www.scholink.org/ojs/index.php/jbtp

Original Paper

Design of an Analysis Model for Strategic Behavior in the Digital Economy

Miguel Martin-Valmayor[1] & Luis A. Gil-Alana[1,2*]

[1] Faculty of Ciencias Empresariales y Jurídicas, Universidad Francisco de Vitoria, Madrid, Spain

[2] Faculty of Economics, University of Navarra, Pamplona, Spain

[*] Luis A. Gil-Alana, Faculty of Ciencias Empresariales y Jurídicas, Universidad Francisco de Vitoria, Madrid, Spain; Faculty of Economics, University of Navarra, Pamplona, Spain

Received: March 6, 2020 Accepted: March 20, 2020 Online Published: April 3, 2020
doi:10.22158/jbtp.v8n2p1 URL: http://dx.doi.org/10.22158/jbtp.v8n2p1

Abstract

Nowadays, multi-criteria decision-making techniques are highly developed, and are widely applied in multiple fields. They model and solve decisional problems by optimising multiple conflicting objectives. These techniques are very useful because they simultaneously analyse all the different criteria, and select the best alternatives according to the decision-maker's objectives and preferences. An important issue in this context is the adequacy of the structure of corporate long-term financing and its potential impact on the sustainable development of the long-term business plan. The purpose of this study is to advance the analysis of these strategic decisions, measuring the a posteriori results and analysing their coherence with the strategies followed a priori. To do this, sustainable strategic decisions will be mathematically modelled and parametrised, creating a system to study the preferences followed and to describe the corporate behaviour. This system is applied as a case example for two leading companies in the digital sector, and the corresponding results over the last few years are evaluated.

Keywords

strategic planning, finance, optimisation, multi-criteria decision-making, behavioural analysis

1. Introduction

In the field of decision theory, multi-criteria techniques are now highly developed, and are generally applied in several areas. They permit the formalisation of, and rational solution to, decisional problems by optimising multiple conflicting criteria. Their potential is fundamentally due to the way these techniques analyse different criteria in an integrated way, efficiently selecting possible alternatives according to the decision-maker's preferences. The important computational advances provided by computer calculation tools over the last few years have provided the necessary support for accessing numerical solutions without excessive complexity.

The initial germ of the multi-criteria theory is found in the development of Koopmans' mathematical concept of efficiency that, together with the work of Kuhn-Tucker, which deduces the conditions that guarantee the existence of efficient solutions for vector mathematical programming problems, allowed Charnes, Cooper and Ferguson to develop the concept of goal programming, a strategy that permits the search for satisfying solutions which can minimise the error of approximation. Later, Professor Ron Howard systematically applied statistics to solve decision problems and was the first person to use the term “decision analysis” in 1964.

Benayoun, Roy and Sussman proposed a new approach in 1966 based on the choice of a solution from among a finite number of alternatives. Thus, they developed the ELECTRE method as the first discrete method in which the decision strategy was the reduction of the solutions between a subset of favorable and less favorable solutions.

All these contributions culminated in the 1970s with the First International Conference of South Carolina in 1972, which saw the formal birth of multi-criteria methodology and allowed the development of the main multi-criteria optimisation methods. In 1973, Professors Yu and Zeleny developed Compromise Programming, which mathematically formalised the search for efficient solutions, such as those closest to the ideal solution, or a solution that individually optimises each criterion as if there were no restrictions.

After the publication of Compromise Programming, various calculation methods for its practical application were advanced, such as that of Zionts-Wallenius, which solves problems of linear programming with multiple objectives, or the Compromise Programming proposed by, among others, Michalowsky or Bardossy and Bogardi, which resulted in non-linear problems with complex formulations that are difficult to solve computationally. These difficulties encouraged the development and application of discrete methodologies for the resolution of practical problems such as the popular AHP model introduced by Saaty, which ranks the decision-maker’s criteria in a hierarchy to address a problem that requires choosing alternatives, and the PROMETHEE developed by Brans that proposed the inverse approach, building preference relationships between the criteria to rank the alternatives.

Sumpsi and Romero developed a methodology to analyse the *a posteriori* decision-maker’s behaviour by measuring the percentage of success achieved for each objective from the observed results. Finally, the computational problems raised in the optimisation issues were solved with the Extended Compromise Programming approach created by André and Romero that, under usual continuous and convex conditions in the formulation of objectives, linearises solutions to problems with complex metrics through linear combinations. This simplified the calculation process and facilitated efficient solutions in numerous areas, because these conditions are common in real problems.

One of these classic business management problems is choosing the appropriate financing structure and its potential impact on the subsequent development of the business plan. Many authors have built analysis models, analysing criteria individually and sequentially prioritizing these decisions iteratively. A classic example is the famous model designed by Donaldson Brown for the DuPont company, still used today by numerous businesses, which broke down the return on capital based on margin, turnover and financial leverage.

2. Literature Review

Similarly to multi-criteria techniques, more complex financial models were developed during the late 1970s and 1980s that eliminated arithmetic calculation errors thanks to the development of computational tools. The first multi-criteria model for applied management arose in 1979 with Kvanli’s approach, which integrated a financial planning model with a multi-criteria goal programming scheme using a flexible tree decision structure. A similar decision structure was later applied in Hayen, in which cash flow analysis was introduced to complement the purely accounting measures under a result simulation system for building corporate planning models based on scenarios.

The Linke and Withford model pioneered the use of multi-criteria techniques to develop a financial planning model to suggest efficient rates for the electricity market. In 1989, Batson's compilation work had already described up to 10 successful applications in economic-financial spheres that applied the goal programming methodology. However, it was limited by the amount of time taken to collect the data, and the indivisibility of the projects, which limited the different models to a simple “conflict resolution” tool.

These developments allowed for the expansion of more complex problems to more specialised environments, solving difficult problems. Thus, in 1995, the Goedhart and Spronk model of financial planning with fractional objectives emerged, which enabled the linear goal programming algorithms to be extended to financial objectives. In 1997, the Maranas et al. model addressed the problem of distributing financial assets based on investment categories with continuous and convex functions that guaranteed optimal solutions. In 1999, Tarrazo and Gutiérrez modelled the future uncertainty in the field of financial planning using neural networks and fuzzy logic. Recently, in 2011 Martin et al. proposed a long-term strategic planning model that allowed for the simultaneous collective optimisation of different criteria.

Currently, multi-criteria developments applied to financial problems are focusing mainly on using applied research to solve specific problems in different areas such as:

a) In the field of financial management, Mulvey and Shetty have proposed a model for the analysis of institutional investments that integrates statistical, risk management and other profit optimisation elements. Similarly, Xidonas et al. proposed a methodology for the selection of financial assets, evaluating basic ratios such as solvency or leverage by applying the ELECTRE methodology. Balibek and Köksalan published a study on the management of public debt with decision trees with stochastic variables. Shen et al. proposed a multi-criteria hybrid model applied to the banking market and insurance seeking synergies between different financial objectives, while Lin focused on the search and selection of clients in the field of private banking by applying ANP techniques.

b) In the field of risk management, Kou et al. studied the possibility of evaluating the probability of default or non-payment with multi-criteria techniques. Valladao et al. studied optimisation mechanisms for corporate debt management by integrating profitability and risk management with decision trees. Martins proposed an integrated financial model of loan management strategies and project scheduling, while Angilella and Mazzu examined how to use ELECTRE methodologies to finance entrepreneurial projects. Rezaie et al. focused on the evaluation of the performance of different industrial firms by also applying AHP.

c) In the field of operations Elgazzar et al. sought to optimise supply chain objectives with the fulfilment of strategic objectives and the maintenance of competitive advantages using AHP methodologies, which also integrated Büyüközkan and Göçer with fuzzy logic to select suppliers. Hu et al. focused on studying customer satisfaction in the field of mobile phones using VIKOR and ANP methodologies. Other works, such as those published recently by Pineda et al. and Chen et al., focus on the aeronautical industry, using multi-criteria analysis to address financial management and the decision whether to purchase or lease aeroplanes for the airlines.

Extensive links can be observed in the main bibliographical studies that combine multi-criteria decision developments in financial areas. In 2015, Zopounidis et al. updated a 1999 study, identifying more than 450 research articles in the field of financial management published between 2004 and 2015, of which more than 300 articles had been produced in the previous five years. This demonstrates how rapidly this number has grown, as Steuer and Na identified only 265 from the beginning until 2003.

Given the potential of multi-criteria decision-making techniques in these areas, the inverse question could be presented as a hypothesis of this study. Can it be verified that a company's strategy can be quantified based on the results it presents? Would it be reasonable to assume that, as maintained by economic behaviour theories, companies follow criteria other than those of profit maximisation as the sole strategic objective to guide their strategy?

Taking different models of strategic planning developed by and as a starting point, this work aims to give continuity to the hypotheses of these models and apply to the business environment the methodology developed by Sumpsi et al. in the field of agricultural research, which, based on the results obtained, evaluates the fulfilment of a company's objectives and the strategy followed. In general, given that any financial decision involves a balance or equilibrium between conflicting elements with different criteria (for example, increasing dividends to improve internal financing; increasing financial leverage for solvency; choosing whether to finance using internal or external resources, etc.), an issue of notable practical interest for decision-making techniques is raised when observing the results obtained by companies when different conflicting criteria are found.

3. Methodology: Mathematical Formulation of an Analysis Model for Strategic Behavior

The general formulation of a multi-criteria problem in which q represents relevant conflicting objectives is usually presented as follows:

$$Eff\left[f_1(x), f_2(x), \ldots, f_j(x), \ldots, f_q(x)\right] \tag{1}$$

Subject to $\boldsymbol{x} \in \boldsymbol{F}$

where "*Eff*" is an operator that indicates the search for efficient or Pareto-optimal solutions; $\boldsymbol{x}$ is a decision variables vector for the problem; $f_j(\boldsymbol{x})$ the mathematical expression of the j-th objective; and $\boldsymbol{F}$ is the feasible set, or those solutions that provide an answer to the problem's restrictions.

For the particular case of weighted goals, the following inputs can also be defined:

- w_j: Weight associated with the priorty of the j-th objective.
- f_j^*: Ideal or optimal value of the j-th objective.
- f_j: Observed value for the j-th objective.
- f_{ij}: Value obtained for the j-th objective, when the i-th objective is optimised (i.e., $f_{ij} = f_j\left(x^{*i}\right)$).
- n_j, p_j: Positive and negative deviations of the j-th objective with respect to the observed value.

3.1 Mathematical Formulation of a Strategic Planning Model

The multi-objective strategic planning problem proposed by Martin et al. focuses on five main strategic objectives of long-term sustainability (company expansion or growth, solvency, theoretical value of the share, shareholder dividends and operational efficiency), which are calculated from six strategic decision variables linked to the company's equity increases in its long-term balance sheet:

- x_1 = increase in cash reserves
- x_2 = increase in share capital
- x_3 = increase in depreciation
- x_4 = long-term increase
- x_5 = increase in property, plant and equipment
- x_6 = dividend to distribute

and from the following parameters referring to the initial situation of the company's balance sheet and its expected operating income for the year:

- P = Company's initial net equity
- A = Initial accumulated depreciation
- E = Initial long-term liabilities
- C = Initial subscribed capital
- I = Gross intangible assets, without amortisation
- G = Gross profit for the year, without amortisation, interest and taxes
- R= Profitability on fixed assets of profits before tax
- RIN = Net rate of return on fixed assets after taxes
- T = Profit tax
- i = Finance cost
- λ = Maximum legal coefficient of depreciation of fixed asset
- μ = Minimum level of capital distributed as a dividend

Using these parameters and decision variables, the mathematical model of strategic planning can be formulated as follows:

$$Eff[f_1(x), f_2(x), f_3(x), f_4(x), f_5(x)]$$

where

$$f_1(x) = x_1 + x_2 + x_3 + x_4 \qquad \text{(Growth)}$$

$$f_2(x) = \frac{P + A + x_1 + x_2 + x_3}{E + x_4} \qquad \text{(Solvency)}$$

$$f_3(x) = \frac{P + A + x_1 + x_2 + x_3}{C + x_2} \qquad \text{(Theoretic value of the shares)}$$

$$f_4(x) = x_6 \qquad \text{(Dividend)}$$

$$f_5(x) = R(F + x_5) - i(E + x_4) \qquad \text{(Operational Efficiency)}$$

Establishing the following restrictions to maintain the company's long-term sustainability:

- The solvency of the company must be higher than the prior value of solvency:

$$\frac{P + A + x_1 + x_2 + x_3}{E + x_4} \geq \frac{P + A}{E}$$

- The theoretic value of the share must grow:

$$\frac{P + A + x_1 + x_2 + x_3}{C + x_2} \geq \frac{P + A}{C}$$

- The company must distribute a minimum share, at least μ per cent of the capital, depending on each company:

  $x_6 \geq \mu C$

- The annual cost of amortisation must not exceed established legal limits:

  $x_3 \leq \lambda F^t$

- The annual increase in assets must be covered by permanent resources, i.e., capital increases, reserves and debts:

  $x_1 + x_2 + x_4 - x_5 = 0$

- The company's gross profit must be distributed in reserves and dividends:

$(G - x_3) - T(G - x_3) = x_1 + x_6$

- The internal rate of return of the benefit after tax must be higher than a certain level:

  $\frac{(1 - T)(G - x_3)}{(F + x_5)} \geq RIN$

- The decision variables cannot be negative,

$$x \geq 0; \quad x_i \geq 0 \; (i = 1..6) \tag{2}$$

3.2 Behaviour Analysis Model Based on the Observed Results

The methodology proposed by Sumpsi et al. allows us to estimate the decision-maker's observed behaviour "as if" it were subject to the defined mathematical model. To do this, we start with the individual estimation of the preferences based on the payment matrix and follow with a posterior approximation of the behavioural vectors with a weighted goals programming scheme.

Given that the payment matrix $f_{ij} = f_i(x^{*j})$ is by definition one in which the columns (j=1..q) correspond to the vectors associated with the individual optimisation of each of the objectives that meet the problem's restrictions, its calculation can identify the degree of conflict between each of the objectives:

$$[PM] = \begin{bmatrix} f_{11} = f_1(x^{*1}) = f_1^* & f_{12} = f_2(x^{*1}) & \cdots & f_{1q} = f_q(x^{*1}) \\ f_{21} = f_1(x^{*2}) & f_{22} = f_2(x^{*2}) = f_2^* & \cdots & f_{2q} = f_q(x^{*2}) \\ \vdots & \vdots & \cdots & \vdots \\ f_{q1} = f_1(x^{*q}) & f_{q2} = f_2(x^{*q}) & \cdots & f_{qq} = f_q(x^{*q}) = f_q^* \end{bmatrix} \tag{3}$$

The transposition of this matrix allows a system of equations to be presented such that if the vector of preferences **w** was canonical of its j-th component (for example, if **w**=[1,0,…,0]^T), the solution obtained by this system would correspond exactly with the optimisation of the j-th objective.

$$\underbrace{\begin{bmatrix} f_{11}=f_1^* & f_{21} & \cdots & f_{q1} \\ f_{12} & f_{22}=f_2^* & \cdots & f_{q2} \\ \vdots & \vdots & \cdots & \vdots \\ f_{1q} & f_{2q} & \cdots & f_{qq}=f_q^* \end{bmatrix}}_{[PM]^T} \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} = \underbrace{\begin{bmatrix} f_{11}=f_1^{*1} \\ f_{12} \\ \vdots \\ f_{1q} \end{bmatrix}}_{f(x^{*1})} \tag{4}$$

Therefore, a linear combination of these possible solutions associated with a different weighting of the w preferences would generate the following system:

$$\underbrace{\begin{bmatrix} f_{11}=f_1^* & f_{21} & \cdots & f_{q1} \\ f_{12} & f_{22}=f_2^* & \cdots & f_{q2} \\ \vdots & \vdots & \cdots & \vdots \\ f_{1q} & f_{2q} & \cdots & f_{qq}=f_q^* \end{bmatrix}}_{[PM]^T} \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_q \end{bmatrix} = \underbrace{\begin{bmatrix} f_1 \\ f_2 \\ \vdots \\ f_q \end{bmatrix}}_{f} \tag{5}$$

that is, that the combination of weights $\mathbf{w}=(w_1,\ldots,w_j)$ which, on the basis of the preferences shown in the payment matrix, generates the observations vector $\boldsymbol{f}=(f_1,\ldots,f_j)$.

This system, in general, has no solution because of the problem's restrictions and the existing conflict between the objectives. However, it is possible to seek an approximate solution under Goal Programming conditions by considering the observed values as the goals to be achieved. In this case, the achievement function would correspond to the minimisation of the sum of the deviation variables normalised to the value observed in each of the objectives.

The formulation of the problem of behaviour analysis would correspond to solving the following system of equations:

$$Min\left[\frac{n_1+p_1}{f_1}+\frac{n_2+p_2}{f_2}+\cdots+\frac{n_q+p_q}{f_q}\right]$$

Subject to the equations system:

$$\underbrace{\begin{bmatrix} f_{11}=f_1^* & f_{21} & \cdots & f_{q1} \\ f_{12} & f_{22}=f_2^* & \cdots & f_{q2} \\ \vdots & \vdots & \cdots & \vdots \\ f_{1q} & f_{2q} & \cdots & f_{qq}=f_q^* \end{bmatrix}}_{[PM]^T} \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_q \end{bmatrix} + \begin{bmatrix} n_1-p_1 \\ n_2-p_2 \\ \vdots \\ n_q-p_q \end{bmatrix} = \underbrace{\begin{bmatrix} f_1 \\ f_2 \\ \vdots \\ f_q \end{bmatrix}}_{f}$$

$$w_1+w_2+\cdots+w_q=1 \tag{6}$$

In general, the last restriction $w_1+w_2+\cdots+w_q=1$ is proposed so that the set of preferences is normalised. The resolution of this system would allow the decision-maker's behaviour and preferences to be identified, based on the observed results and the approximate solution.

3.3 Application Scenario

To study the applicability of this predictive analytical model (6) in the field of the digital economy, two leading companies, Apple and Microsoft, were selected, which have also demonstrated a deep rivalry over the past few years. For comparison, the last four exercises have been chosen.

The data selected for Apple Inc. are displayed in Table 1, while those for Microsoft are presented in Table 2.

Table 1. Values of the Exogenous Parameters of the Predictive Model for Apple Inc.

	Apple Inc.	2018	2017	2016	2015	2014
I_1	Long-term amortisable assets	82,683	70,257	57,482	46,242	34,700
I_2	Other non-amortisable assets (goodwill, investments)	210,593	184,601	174,603	138,542	112,938
I	Gross fixed assets	293,276	254,858	232,085	184,784	147,638
A	Accumulated amortisation	46,602	40,041	31,118	21,476	13,924
	Net fixed assets	246,674	214,817	200,967	163,308	133,714
C	Capital contributed	35,867	31.251	27,416	23,313	19,764
P	Net worth (capital and reserves)	134,047	128.249	119,355	111,547	123,549
E	Long-term liabilities	140,458	114.431	90,380	56,844	39,793
	Total long-term liabilities and net worth	274,505	242,680	209,735	168,391	163,342
G	EBITDA	70,744	69,824	81,730	60,503	55,759
R	Gross return	24%	26%	39%	36%	39%
T	Tax rate	25%	26%	26%	26%	26%
K_f	Financing cost	2,5%	2,8%	3,8%	3,2%	6,1%
U	Dividend rate on capital	35%	38%	42%	47%	53%
W_1	Amortisation rate	13%	17%	23%	23%	25%

Source. Thompson Reuters Eikon, 2018.

Table 2. Values of the Exogenous Parameters of the Predictive Model for Microsoft Inc.

	Microsoft Inc.	2018	2017	2016	2015	2014
I_1	Long-term amortisable assets	81,305	71,135	47,256	41,889	38,760
I_2	Other non-amortisable assets (goodwill, investments)	43,187	45,521	31,719	32,109	38,146
I	Gross fixed assets	124,492	116,656	78,975	73,998	76,906
A	Accumulated amortisation	37,106	30,740	25,167	22,323	18,768
	Net fixed assets	87,386	85,916	53,808	51,675	58,138
C	Capital contributed	47,981	48,175	48,800	50,169	51,494
P	Net worth (capital and reserves)	82,718	87,711	71,997	80,083	89,784
E	Long-term liabilities	117,642	106,856	62,114	44,742	36,975
	Total long-term liabilities and net worth	248,341	242,742	182,911	174,994	178,253
G	EBITDA	45,319	40,148	33,810	34,129	33,098
R	Gross return	30%	40%	37%	37%	49%
T	Tax rate	17%	15%	20%	34%	21%
K_f	Financing cost	-1,4%	-1,9%	-0,2%	2,2%	1,3%
U	Dividend rate on capital	27%	25%	23%	20%	18%

W_1	Amortisation rate	14%	19%	16%	15%	18%

Source. Thompson Reuters Eikon, 2018.

It can be observed that both companies are well financed in the long term, because the value of their resources is higher than that of their assets, and financial leverage has increased over the period.

4. Result

The first step is to obtain the payment matrices (3) associated with the two companies. The results for Apple Inc. are presented in Table 3, and after the application of the approximation model, the preferences vectors are displayed in Table 4.

Table 3. Payment Matrices Obtained for Apple Inc.

2018						**2017**					
	z1	z2	z3	z4	z5		z1	z2	z3	z4	z5
z1	39,908	1.819	6.662	13,150	65,525	z1	43,536	2.147	7.076	8,832	68,950
z2	39,908	1.819	6.662	13,151	65,525	z2	43,536	2.147	7.076	8,832	68,950
z3	39,908	1.819	6.662	13,151	65,525	z3	43,536	2.147	7.076	8,832	68,950
z4	0	1.471	5.385	53,058	56,266	z4	-	1.665	5.488	52,368	57,631
z5	39,908	1.819	6.662	13,151	65,525	z5	43,536	2.147	7.076	8,832	68,950
Ideal	39,908	1.819	6.662	53,058	65,525	Ideal	43,536	2.147	7.076	52,368	68,950
Anti-Ideal	-	1.471	5.385	13,150	56,266	Anti-Ideal	-	1.665	5.488	8,832	57,631
Real	**31,825**	**1.286**	**5.037**	**12,563**	**61,211**	**Real**	**32,945**	**1.471**	**5.385**	**11,965**	**58,829**
2016						**2015**					
	z1	z2	z3	z4	z5		z1	z2	z3	z4	z5
z1	30,265	2.873	7.004	29,948	79,445	z1	24,562	4.071	8.199	20,210	58,877
z2	30,265	2.873	7.004	29,949	79,445	z2	24,562	4.071	8.199	20,210	58,877
z3	30,265	2.873	7.004	29,949	79,445	z3	24,562	4.071	8.199	20,210	58,877
z4	-	2.340	5.706	60,214	67,944	z4	-	3.455	6.956	44,772	50,281
z5	30,265	2.873	7.004	29,948	79,445	z5	24,562	4.071	8.199	20,210	58,877
Ideal	30,265	2.873	7.004	60,214	79,445	Ideal	24,562	4.071	8.199	44,772	58,877
Anti-Ideal	-	2.340	5.706	29,948	67,944	Anti-Ideal	-	3.455	6.956	20,210	50,281
Real	**41,344**	**1.665**	**5.489**	**11,431**	**70,327**	**Real**	**5,049**	**2.340**	**5.706**	**11,031**	**52,192**

Table 4. Behaviour Model Results for Apple Inc.

Results	2018	2017	2016	2015	Average	Average exc 2015
w1	-	-	-	-	-	-
w2	-	-	-	-	-	-
w3	-	-	-	-	-	-
w4	-	0.071	-	0.794	0.21	0.024
w5	1.000	0.929	1.000	0.205	0.784	0.976
Mean squared error	11.8%	11.9%	36.4%	53.3%	28.3%	20.0%
Equipreferential case	16.4%	13.5%	46.0%	65.2%	35.3%	25.3%

Tables 5 and 6 display respectively the payment matrices and preferences for Microsoft Inc.

Table 5. Payment Matrices Obtained for Microsoft Inc.

2018						**2017**					
	z1	z2	z3	z4	z5		z1	z2	z3	z4	z5
z1	33,803	1.425	3.160	3,812	43,001	z1	21,871	1.114	2.439	12,254	37,123
z2	33,803	1.425	3.160	3,812	43,001	z2	21,871	1.114	2.439	12,254	37,123
z3	33,803	1.425	3.160	3,812	43,001	z3	21,871	1.114	2.439	12,254	37,123
z4	-	1.109	2.459	37,615	32,860	z4	-	0.909	1.991	34,125	28,592
z5	33,803	1.425	3.160	3,812	43,001	z5	21,871	1.114	2.439	12,254	37,123
Ideal	33,803	1.425	3.160	37,615	43,001	Ideal	21,871	1.114	2.439	34,125	37,123
Anti-Ideal	-	1.109	2.459	3,812	32,860	Anti-Ideal	-	0.909	1.991	12,254	28,592
Real	**12,159**	**1.019**	**2.497**	**12,917**	**37,996**	**Real**	**66,029**	**1.109**	**2.459**	**12,040**	**31,083**
2016						**2015**					
	z1	z2	z3	z4	z5		z1	z2	z3	z4	z5
z1	16,288	2.653	2.366	10,256	32,240	z1	36,385	3.382	2.506	-	40,748
z2	16,288	2.653	2.366	10,256	32,240	z2	36,385	3.920	2.393	-	40,838
z3	16,288	2.653	2.366	10,256	32,240	z3	28,024	3.694	2.652	-	36,447
z4	-	2.289	2.041	26,544	26,262	z4	-	2.936	2.108	27,303	27,485
z5	16,288	2.653	2.366	10,256	32,240	z5	36,385	3.920	2.393	-	40,838

Ideal	16,288	2.653	2.366	26,544	32,240	Ideal	36,385	3.920	2.652	27,303	40,838
Anti-Ideal	-	2.289	2.041	10,256	26,262	Anti-Ideal	-	2.936	2.108	-	27,485
Real	**12,130**	**1.564**	**1.991**	**11,329**	**25,717**	**Real**	**1,621**	**2.289**	**2.041**	**10,063**	**17,711**

Table 6. Results of the Behaviour Model for Microsoft Inc.

Results	2018	2017	2016	2015	Average	Average exc. 2015
w1	-	-	-	-	-	-
w2	-	-	-	-	-	-
w3	-	-	-	0.058	0.014	-
w4	0.640	-	0.255	0.942	0.459	0.298
w5	0.360	1.000	0.745	-	0.526	0.702
Mean squared error	19.9%	13.9%	14.7%	33.8%	20.6%	16.2%
Equipreferential case	26.0%	16.8%	14.6%	319.6%	94.3%	19.1%

The results from Tables 4 and 6 show a reasonable margin of error in both cases, so long as the real values remain within the ideal-anti-ideal range. When this is not the case, for example in the year 2015, the prediction error rises noticeably.

The main reason for this is that the model presents long-term sustainability as a starting hypothesis, based on the annual improvement of solvency and value creation ratios. If this does not occur, as in the case of solvency owing to the increase in financial leverage, the value obtained is outside the approximation range. The rest of the objectives (growth, dividend and efficiency) must maintain positive values, as is the case in reality, and so do not present a problem.

The data obtained show that the main difference between the two companies is that the creation of measured value as a ratio of Net Equity to Capital increases in the period for Microsoft and decreases for Apple. As expected, the prediction error is lower for Microsoft because its data fits the analysis model better. As a consequence, the forecast is of better quality during the years in which the actual solvency level is closer to the estimated range. Therefore, the hypothesis presented regarding the validity of the behaviour analysis study based on the results will depend primarily on whether the company fits the hypothesis of the proposed mathematical model.

5. Conclusions

In this article we have investigated the possibility of quantifying a company's strategy based on the presented results. Starting from this hypothesis, we have applied MCDM methodology to analyse the *a posteriori* decision-maker's behaviour "as if" the company were following a multi-criteria decision strategy model based on 5 key drivers in conflict to achieve long-term sustainability success: company expansion, solvency, theoretical value of the share, shareholder dividends and operational efficiency. By approaching the percentage of success achieved for each objective from the observed results in the payment matrix, we have been able to evaluate the corporate's behaviour according to the model.

Our first conclusion is to note the high correlation shown by the payment matrix in all the objectives except the dividend. The maximisation of the dividend objective creates the anti-ideals values of the matrix, while the ideal values are obtained simultaneously, optimising any of the remaining objectives. This result could be expected *a priori* because, if the resources generated are paid directly to the shareholder, the company's self-financing and potential for growth is reduced in the rest of the objectives.

Secondly, setting to one side the year 2015 in both cases because of the high margin of error, similar behaviour can be observed in the behaviour models for both companies because they prioritise efficiency and profitability over the dividend objective. For Apple, the weight that maintains the objective of efficiency reaches 97%, while for Microsoft it is 70% compared to 30% of the target dividend on average over the last three years.

Finally, it is important to highlight the improvement in these results with regard to the supposed equipreferential $w_i = 0.20$ (i=1..5), common in cases where there is little information about the decision-maker's habits. The prediction error rate has, in this instance, increased in the results that were obtained with the goal approach methodology.

These results lead us to believe that, in order to properly analyse a company and be able to make correct future predictions about it, it is essential to understand management's prior behaviour in order to subsequently create the strategic proposals that weigh up the company's preferences or new future strategy in the most effective way possible. This behavioural analysis model allows us to identify this information and present future objectives in a coherent way that can be complementary to multi-criteria interactive methods by analysing the previous behaviour of the decision-making centre before the objectives are set.

In terms of future lines of research in this area, the extension of this behaviour analysis model to other more precise financial planning models could be considered, whether in the long term or in the accounting balance that best adapts to the behaviour of the companies analysed during the study period.

References

André, F. J., & Romero, C. (2008). Computing Compromise Solutions: On the Connections between Compromise Programming and Composite Programming. *Applied Mathematics and Computation*, *195*, 1-10. https://doi.org/10.1016/j.amc.2007.04.064

Angilella, S., & Mazzù, S. (2015). Integrating financial planning, loaning strategies and project scheduling on a discrete-time model. *European Journal of Operational Research*, *244*, 540-554. https://doi.org/10.1016/j.ejor.2015.01.033

Balibek, E., & Köksalan, M. (2010). A Multi-Objective Multi-Period Stochastic Programming Model For Public Debt Management. *European Journal of Operational Research*, *205*(1), 205-217. https://doi.org/10.1016/j.ejor.2009.12.001

Bárdossy, A., & Bogárdi, I. (1983). Network Design for the Spatial Estimation of Environmental Variables. *Applied Mathematics and Computation*, *12*, 339-365. https://doi.org/10.1016/0096-3003(83)90046-2

Batson, R. G. (1989). Financial Planning Using Goal Programming. *Long Range Planning*, *22*, 112-120. https://doi.org/10.1016/0024-6301(89)90175-1

Benayoun, R., Roy, B., & Sussman, B. (1966). ELECTRE: Une méthode pour guider le choix en presence de points de vue multiples. In *Note de travail 49, SEMA-METRA International*. Direction Scientifique.

Brans, J. P., & Vincke, P. (1985). A Preference Ranking Organisation Method: The PROMETHEE Method for Multiple Criteria Decision-Making. *Management Science*, *31*(6), 647-656. https://doi.org/10.1287/mnsc.31.6.647

Büyüközkan, G., & Fethullah, G. (2016). Application of a New Combined Intuitionistic Fuzzy MCDM Approach Based on Axiomatic Design Methodology for the Supplier Selection Problem. *Applied Soft Computing*, *52*, 1222-1238. https://doi.org/10.1016/j.asoc.2016.08.051

Charnes, A., & Cooper, W. W. (1961). *Management Models and Industrial Applications of Linear Programming*. John Wiley and Sons.

Chen, W. T., Huang, K., & Ardiansyahb, M. N. (2018). A Mathematical Programming Model for Aircraft Leasing Decisions. *Journal of Air Transport Management*, *69*, 15-25. https://doi.org/10.1016/j.jairtraman.2018.01.005

Elgazzar, S. H., Tipi, N. S., Hubbard, N. J., & Leach, D. Z. (2012). Linking Supply Chain Processes' Performance to a Company's Financial Strategic Objectives. *European Journal of Operational Research*, *223*, 276-289. https://doi.org/10.1016/j.ejor.2012.05.043

Goedhart, M. H., & Spronk, J. (1995). Financial Planning with Fractional Goals. *European Journal of Operational Research*, *82*, 111-124. https://doi.org/10.1016/0377-2217(94)00034-A

Gudiel, P. P. J., James, J. H., Liou, H. C. C., & Chuang, Y. C. (2018). An Integrated MCDM Model for Improving Airline Operational and Financial Performance. *Journal of Air Transport Management*, *68*, 103-117. https://doi.org/10.1016/j.jairtraman.2017.06.003

Hayen, R. L. (1983). How to Design a Financial Planning Model. *Long Range Planning*, *16*(5). Pergamon Press. https://doi.org/10.1016/0024-6301(83)90086-9

Hu, S. K. A., Lu, M. T., & Tzeng, G. H. (2014). Exploring Smart Phone Improvements Based on a Hybrid MCDM Model. *Expert Systems with Applications*, *41*, 4401-4413. https://doi.org/10.1016/j.eswa.2013.12.052

Koopmans, T. C. (1951). *Analysis of Production as an Efficient Combination of Activities*. John Wiley and Sons.

Kuhn, H. W., & Tucker, A. W. (1951). Nonlinear Programming. In J. Neyman (Ed.), *Proceedings of the Second Berkeley Symposium on Mathematical Statistical and Probability*. University of California Press, Berkeley.

Kvanli, A. H. (1980). Financial Planning Using Goal Programming, OMEGA. *The International Journal of Management Sciences*, *8*, 207-218. https://doi.org/10.1016/0305-0483(80)90025-0

Lin, W. R. (2016). An Innovation Diffusion Perspective to Establish a Business Strategy Model for Wealth Management Banking Based on the MCDM Model Combining DEMATEL and ANP. *Journal of Accounting, Finance & Management Strategy*, *11*(2), 103-136.

Linke, C., & Withford, D. (1983). A Multiobjective Financial Planning Model for Electric Utility Rate Regulation. *Journal of Economics and Business*, *35*, 313-330. https://doi.org/10.1016/0148-6195(83)90015-2

Maranas, D., Androulakis, I. P., Floudas, C. A., Berger, A. J., & Mulvey, J. M. (1997). Solving Long-Term Financial Planning Problems via Global Optimization. *Journal of Economic Dynamics and Control*, *21*, 1405-1425. https://doi.org/10.1016/S0165-1889(97)00032-8

Martín, M. A., Cuadrado, M. L., & Romero, C. (2011). Computing Efficient Financial Strategies: An Extended Compromise Programming Approach. *Applied Mathematics and Computation*. https://doi.org/10.1016/j.amc.2011.02.106

Martin, M. A., Romero, M. S., & Romero, L. (2017). Un modelo de Planificación Financiera Sostenible, a través de un proceso de optimización. *Revista Internacional Jurídica y Empresarial*, *1*, 59-73. https://doi.org/10.32466/eufv-r.i.j.e.2017.1.234.59-73

Martins, P. (2017). Integrating financial planning, loaning strategies and project scheduling on a discrete-time model. *Journal of Manufacturing Systems*, *44*, 217-229. https://doi.org/10.1016/j.jmsy.2017.06.001

Michalowsky, W. (1981). The Choice of Final Compromise Solution. In J. N. Morse (Ed.), *Multiple Criteria Linear Programming Problem, Organizations: Multiple Agents with Multiple Criteria* (pp. 233-238). Springer-Verlag. https://doi.org/10.1007/978-3-642-45527-8_22

Mulvey, J., & Shetty, B. (2004). Financial Planning via Multi-Stage Stochastic Optimization. *Computers & Operations Research*, *31*, 1-20. https://doi.org/10.1016/S0305-0548(02)00141-7

Peng, Y., Kou, G., & Chen, L. (2014). MCDM Approach to Evaluating Bank Loan Default Models. *Technological and Economic Development of Economy*, *20*(2), 292-311. https://doi.org/10.3846/20294913.2014.913275

Peng, Y., Kou, G., Shi, Y., & Chen, Z. (2008). A Multi-Criteria Convex Quadratic Programming Model for Credit Data Analysis. *Decision Support Systems*, *44*(4), 1016-1030. https://doi.org/10.1016/j.dss.2007.12.001

Pereira, F., Ballarín, E., Rosanas, J. M., & Vázquez Dodero, J. C. (2003). *Contabilidad para dirección*. EUNSA, Madrid.

Rezaie, K., Saeidi-Ramiyani, D., Nazari-Shirkouhi, S., & Badizadeh, A. (2014). Evaluating performance of Iranian cement firms using an integrated fuzzy AHP-VIKOR method. *Applied Mathematical Modelling*, *38*, 5033-5046. https://doi.org/10.1016/j.apm.2014.04.003

Saaty, T. L. (1980). *The Analytic Hierarchy Process*. McGraw Hill. https://doi.org/10.21236/ADA214804

Shen, K. Y., & Tzeng, G. H. (2014). DRSA-Based Neuro-Fuzzy Inference Systems for the Financial Performance Prediction of Commercial Banks. *International Journal of Fuzzy Systems*, *16*(2), 173-183.

Shen, K. Y., Hu, S. K., & Tzeng, G. H. (2017). Financial Modelling and Improvement Planning for the Life Insurance Industry by Using a Rough Knowledge Based Hybrid MCDM Model. *Information Sciences*, *375*, 296-313. https://doi.org/10.1016/j.ins.2016.09.055

Steuer, R., & Na, P. (2003). Multiple criteria decision making combined with finance: A categorized bibliographic study. *European Journal of Operational Research*, *150*, 496-515. https://doi.org/10.1016/S0377-2217(02)00774-9

Sumpsi, J. M., Amador, F., & Romero, C. (1996). On Farmers' Objectives: A Multi-Criteria approach. *European Journal of Operational Research*, *96*, 64-71. https://doi.org/10.1016/0377-2217(95)00338-X

Tarrazo, M., & Gutierrez, L. (2000). Economic Expectations, Fuzzy Sets and Financial Planning. *European Journal of Operational Research*, *126*, 89-105. https://doi.org/10.1016/S0377-2217(99)00283-0

Thompson Reuters Eikon data base. (2018).

Valladão, D. M., Veiga, A., & Veiga, G. (2014). A multistage linear stochastic programming model for optimal corporate debt management. *European Journal of Operational Research*, *237*, 303-311. https://doi.org/10.1016/j.ejor.2014.01.028

Xidonas, P., Mavrotas, G., & Psarras, J. (2009). A Multicriteria Methodology for Equity Selection Using Financial Analysis. *Computers and Operations Research*, *36*(12), 3187-3203. https://doi.org/10.1016/j.cor.2009.02.009

Xidonas, P., Mavrotas, G., Krintas, T., Psarras, J., & Zopounidis, C. (2012). *Multicriteria Portfolio Management*. Springer, New York. https://doi.org/10.1007/978-1-4614-3670-6

Yu, P. L. (1973). Introduction to Domination Structures in Multicriteria Decision Problems. In J. L. Cochrane, & M. Zeleny (Eds.), *Multiple Criteria Decision Making* (pp. 249-261). University of South Carolina Press.

Zeleny, M. (1973). Compromise Programming. In J. L. Cochrane, & M. Zeleny (Eds.), *Compromise Programming in Multiple Criteria Decision Making* (pp. 262-301). University of South Carolina Press.

Zionts, S., & Wallenius, J. (1983). An Interactive Multiple Objective Linear Programming Method for a Class of Underlying Nonlinear Utility Functions. *Management Science*, *29*, 519-529. https://doi.org/10.1287/mnsc.29.5.519

Zopounidis, C., Galariotis, E., Doumpos, M., Sarri, S., & Andriosopoulos, K. (2015). Multiple Criteria Decision Aiding for Finance: An Updated Bibliographic Survey. *European Journal of Operational Research*, *247*, 339-348. https://doi.org/10.1016/j.ejor.2015.05.032