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A composite indicator from an environmental perspective

Zeng, Qinqin; Beelaerts Van Blokland, Wouter W.A.; Santema, Sicco C.; Lodewijks, Gabriel

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Company Performance Measurement for Automobile Companies: a Composite Indicator from an Environmental Perspective

Qinqin Zeng, Wouter W. A. Beelaerts van Blokland, Sicco C. Santema
Delft University of Technology
Delft, the Netherlands
e-mail: Q.Zeng-1@tudelft.nl, W.W.A.BeelaertsvanBlokland@tudelft.nl, S.C.Santema@tudelft.nl

Gabriel Lodewijks
School of Aviation
University of New South Wales,
Sydney, Australia
e-mail: g.lodewijks@unsw.edu.au

***Abstract*—Current research in the field of performance measurement hasn't presented a rigorous composite indicator for quantifying company performance, with environmental indicators for automobile companies. This paper aims to construct this missing composite indicator. A new approach is developed, including techniques of fuzzy logic, analytic network process, the entropy theory and a geometric mean with unequal weights. The method is transparent, and the composite indicator derived can serve as a statistical tool for benchmarking. A case study is conducted in six leading automobile companies with data from the fiscal year 2016.**

Keywords-environmental concerns; composite indicator; multi-criteria decision making

I. INTRODUCTION

Investors and financial institutions are becoming increasingly concerned about company environmental policies [1]. Consequently automobile companies are supposed to improve profitability with considerable environmental concerns, such as developing eco-friendly products, reducing overconsumption of energy, reducing greenhouse gas emissions. A composite indicator may be defined as "a single index which is formed when individual indicators are compiled on the basis of an underlying model of the multidimensional concept" (OECD, Glossary of Statistical Terms). By conveying rich and relevant information into a single figure, composite indicators are getting increasingly accepted among performance analysts.

TABLE I. A LIST OF SHORTCOMINGS OF CURRENT METHODS

Application	Shortcoming(s)
Indicators' selection	SC_1: Without particular emphasis on environmental concerns
	SC_2: With general indicators not for specific sectors
Indicators' weights	SC_3: With *AHP/ PCA/* Experts' scoring as the sole tool
	SC_4: With the interdependencies of the different indicators not tackled
Fuzzy logic	SC_5: With the fuzzy/ grey rules which are rather similar to the judgment elicitation used by *AHP* SC_6: Without adoption for tackling the inherent uncertainty
Measures' normalization	SC_7: With unclear techniques
Measures' aggregation	SC_8: Without aggregating procedure
Post analysis	SC_9: Impractical for computational demonstration due to its complex scenarios designed
	SC_{10}: Without sensitivity/ uncertainty analysis

It's necessary to construct a composite indicator of company performance, with realistic assumptions rather than directly adopt controversial or misleading techniques. However this composite indicator is missing. This paper summaries the shortcomings of current methods for constructing composite indicators in Table I. This research has no focus on post analysis application. Thus the research question is proposed as: how to construct a composite indicator, which counters the nine shortcomings, for automobile companies to benchmark their performance with an environment perspective?

II. METHODOLOGY

To solve this research question, the paper is organized as follows: 1) in phase I, a conceptual framework of performance measurement for automobile companies is developed; referring to literature, reports released by automobile companies, and opinions from three industry professionals (one in environmental management and the other two in automobile assembly process management, and all with more than 5 years' work experience); 2) during phase II to phase IV, an approach is developed for getting the composite indicator function, including techniques of fuzzy logic, analytic network process (ANP), Shonna entropy and a geometric mean with unequal weights; 3) in phase V, a case study is conducted in six leading automobile companies with data from the fiscal year 2016.

A. Environmental Performance

Environmental impacts can be measured in terms of resource consumption, emissions or environmental damage [2]. Thus this paper identifies three indicators for environmental performance.

- CO_2 emission: considering the availability and comparability of data from automobile companies, this paper adopts CO_2 emission reduction as a measure for CO_2 emission performance, and the calculation be as follows: CO_2e reduction[%] = (CO_2e_t[Kg]-CO_2e_{t-1}[Kg])/CO_2e_{t-1}[Kg], where CO_2e represents for the volume of CO_2 emission, t and t-1 for the fiscal year t and t-1 respectively.
- Water consumption: water consumption can be regarded as the indicator of the company's impact on water resources [3]. It can be calculated as the difference between the amount of input water (water use) [4] and water discharge respectively in the reports. This suits for companies who directly release data of water flows and water discharges rather than water consumption, such as Hyundai, Nissan, and Mazda. This paper adopts water consumption on a per-unit (cars produced) basis as a measure, and the calculation can be as follows: Water consumption per car produced[m^3/#]= Water consumption [m^3]/N[#]= (Water input[m^3] - Water discharge[m^3])/N[#], where N is for cars' production volume.
- Energy consumption: as one of the most important sector in manufacturing industry, car manufacturing consumed a large volume of energy [5]. This paper adopts energy consumption on a per-unit as a measure, and the calculation can be as follows: EC per car produced[MWh /#]=EC[MWh])/N[#], where EC represents for the volume of energy consumption.

B. A conceptual Framework Developed

Mainly referring to some references and the prior research by the authors of this research, this paper develops a new conceptual framework of performance measurement for automobile companies (Table II). Noted: the last two dimensions are the authors' own source, "+"denotes indicators with the category "the larger the better", and "-" denotes indicators with the category "the smaller the better".

TABLE II. THE PERFORMANCE MEASUREMENT FRAMEWORK FOR AUTOMOBILE COMPANIES

Dimension	Indicator (category)	Measure(s) [Unit]	Reference (s)
Competitive Performance	C_1 (+)Sales	Sales [$], S for sales	[6, 7]
	C_2 (+) Market share	Market share [%]	[8, 9]
Financial performance	C_3 (+) Profitability	Net profit margin [%]	[10-12]
	C_4 (+) Market capitalization	Market capitalization [$]	[13-15]
	C_5 (+) Cash flow margin	Operating cash flow margin ratio [%]	[16-18]
Manufacturing capability	C_6(+) Productivity	Cars produced per employee [#]=N/E, E for the number of employees	[19, 20]
	C_7 (+) Continuity	Profit per employee [$]=$P/E$	[21, 22]
Innovation capability	C_8(+) Conception	R&D expenditure per employee [$]	[23]
Supply chain management	C_9(+) Configuration	Turnover per employee [$]	[24, 25]
Inventory performance	C_{10}(+) Inventory turnover	$COGS_t$ / [$0.5*(I_t + I_{t-1})$], $COGS$ for cost of goods sold	[26]
	C_{11} (-) Inventory efficiency	Inventory to sales ratio= [$0.5*(I_t + I_{t-1})$]/ NS_t, GS for gross sales	[27, 28]
Environmental performance	C_{12}(-) Water consumption	Water consumption /car produced [m^3/#]	[4]
	C_{13}(-) Energy consumption	EC per car produced [MWh /#]	–
	C_{14}(+) CO_2 emission	CO_2 emission reduction [%]	–

C. Fuzzy ANP for Weighting

Basically, there are two categories for weighting: 1) direct explication, with subjective judgments, and sometimes together with multi-criteria decision making methods, 2) indirect explication, with mathematical methods or statistical methods. This research develops an integrated approach with both the two categories for weight determination, including fuzzy logic, ANP and Shannon entropy. This new integration approach suits well for this research for three main reasons as follows: 1) the existence of interactions, dependencies and feedback between the seven dimensions and fourteen indicators; 2) the good use of experts' practical opinions; and 3) the extra use of objective weighting technique, making the weighting more accurate and valid. The steps of fuzzy ANP for weighting are as follows:

- Construct the ANP structure hierarchically with control layer, dimensions, and indicators. As is constructed in equation (1), where w_1 is a vector that represents the impact of "company performance" on the six dimensions; W_2 is a matrix with inner dependence between the six dimensions; W_3 is a matrix that denotes the impact of the dimensions on the indicators; and W_4 is a matrix with inner dependence between the fourteen indicators.

$$W = \begin{bmatrix} 0 & 0 & 0 \\ w_1 & W_2 & 0 \\ 0 & W_3 & W_4 \end{bmatrix} \tag{1}$$

- Construct the pairwise comparison matrices A. The linguistic variables and their corresponding importance levels are shown in the first two columns in table III [29, 30].
- Construct the fuzzy pairwise comparison matrices $\tilde{A}$ and get it reconstructed with crisp values. Replace the crisp importance levels with the corresponding triangular fuzzy numbers in the third columns in table III as in equation (2), where reciprocal values are automatically assigned to the reverse comparison. Denote α as the confidence level,∀α ∈

[0,1], $a_\alpha = \{x \mid \mu_{\tilde{a}}(x) \ge \alpha\}$ as α - cut set, and calculate α - cut fuzzy comparison matrix as equation (3) [31]. Denote μ as the index of optimism, which expresses the degree of satisfaction from the experts, ∀μ ∈ [0, 1], and calculate the crisp $\tilde{a}^{\alpha}$ value as in equation (4). Therefore $\tilde{A}$ is reconstructed as in equation (5).

TABLE III. THE LINGUISTIC TERMS AND THE CORRESPONDING TRIANGULAR FUZZY NUMBERS

Importance levels	**Linguistic variable**	**Fuzzy number**	**Membership function**
1	Equal importance	$\tilde{1}$	(1,1,2)
3	Moderate importance	$\tilde{3}$	(2,3,4)
5	Essential/strong importance	$\tilde{5}$	(4,5,6)
7	Very strong importance	$\tilde{7}$	(6,7,8)
9	Extreme importance	$\tilde{9}$	(8,9,10)

$$\tilde{A} = \begin{bmatrix} 1 & \tilde{a}_{12} & \cdots & \tilde{a}_{1n} \\ \tilde{a}_{21} & 1 & \cdots & \tilde{a}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{a}_{n1} & \tilde{a}_{n2} & \cdots & 1 \end{bmatrix} = \begin{bmatrix} 1 & \tilde{a}_{12} & \cdots & \tilde{a}_{1n} \\ \tilde{a}_{12}^{-1} & 1 & \cdots & \tilde{a}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{a}_{1n}^{-1} & \tilde{a}_{2n}^{-1} & \cdots & 1 \end{bmatrix} \tag{2}$$

$$\tilde{a}_\alpha = \left[a_\alpha^l, a_\alpha^u\right] = \left[\alpha\left(a^m - a^l\right) + a^l, -\alpha\left(a^u - a^m\right) + a^u\right] \tag{3}$$

$$\tilde{a}^\alpha = \mu \tilde{a}_\alpha^u + \left(1-\mu\right)\tilde{a}_\alpha^l \tag{4}$$

$$A_\alpha = \begin{bmatrix} 1 & \tilde{a}_{12,\alpha} & \cdots & \tilde{a}_{1n,\alpha} \\ \tilde{a}_{21,\alpha} & 1 & \cdots & \tilde{a}_{2n,\alpha} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{a}_{n1,\alpha} & \tilde{a}_{n2,\alpha} & \cdots & 1 \end{bmatrix} = \begin{bmatrix} 1 & \tilde{a}_{12,\alpha} & \cdots & \tilde{a}_{1n,\alpha} \\ \tilde{a}_{12,\alpha}^{-1} & 1 & \cdots & \tilde{a}_{2n,\alpha} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{a}_{1n,\alpha}^{-1} & \tilde{a}_{2n,\alpha}^{-1} & \cdots & 1 \end{bmatrix} \tag{5}$$

- Calculate the vector w_1 and the matrix W_3, with assumption that there is no dependence between the six dimensions or between the fourteen indicators. Similarly, calculate the matrix W_2 and W_4. Verify (and revise) the consistency ratio (CR) of each matrix. All the CR values must be less than 0.10, which means the judgments are consistent enough to be acceptable, otherwise the comparison matrix should be revised.
- Calculate the interdependent priorities of the dimensions as $w_d = w_1 * W_2$, and calculate the interdependent priorities of the indicators as $W_{id} = W_3 * W_4$, and finally calculate the overall weights of the indicators on company performance as $w = w_d * W_{id}$, and w ∈ (0,1)
- Get the objective weights of the indicators by Shannon entropy. Here x_{ij} represents the value of the indicator j of alternative i, p_{ij} for the relative frequency, d_j for the degree of diversification. Do the data transformation in equation (6) for commensurability on indicators with negative values or not satisfied for logarithm application, $x'^t_{ij} \in [1, 2]$; calculate the entropy value of indicator j as equation (7); calculate the weight of d_j and get objective weights for each indicator W_{obj}, and then get the final weights w_j by the arithmetic mean of subjective weights and its objective weights.

$$x'^t_{ij} = \begin{cases} \dfrac{x_{ij}^t - \min\limits_i x_{ij}^t}{\max\limits_i x_{ij}^t - \min\limits_i x_{ij}^t} + 1, \text{ for } (+) \\ \dfrac{\max\limits_i x_{ij}^t - x_{ij}^t}{\max\limits_i x_{ij}^t - \min\limits_i x_{ij}^t} + 1, \text{ for } (-) \end{cases} \tag{6}$$

$$e_j = -k \sum_{i=1}^{m} p_{ij} \ln(p_{ij}), \mathrm{k} = \left(\ln\left(\mathrm{m}\right)\right)^{-1} > 0, \mathrm{e_j} \ge 0 \tag{7}$$

- Construct a decision matrix $B_{m\times n}$ and normalize the elements with the procedure in equation (8), where i (i=1,2,...,m) represents for the alternative automobile companies, j (j=1,2,...,n) for the individual indicators for company performance, x_{ij}^t for the value of indicator j on alternative i at fiscal year t (t=0,1,...,T), x^{*t}_{ij} for the normalized value of x_{ij}^t, and $x^*_{ijt} \in (0,1]$

$$x^{*t}_{ij} = \begin{cases} \dfrac{x_{ij}^t}{\max\limits_i x_{ij}^t}, for(+) \\ \dfrac{\min\limits_i x_{ij}^t}{x_{ij}^t}, for(-) \end{cases} \tag{8}$$

- Aggregate and calculate the values for the nine companies as equation (9), where I_i^t is the index of company performance for truck manufacturers i at fiscal year t, and $I_i^t \in (0,1)$.

$$I_i^t = f\left[x_{ij}^{*t}, w_j\right] = \prod_{j=1}^{n} {x^{*t}_{ij}}^{w_j} \tag{9}$$

III. NUMERICAL EXAMPLE

To demonstrate the method's applicability for quantifying company performance, a case study is conducted in 6 leading automobile companies , Bayerische Motoren Werke AG (BMW), Audi AG (Audi), Toyota Motor Corporation (Toyota), Nissan Motor Company (Nissan), General Motors (GM), Ford Motor Company (Ford), with data from the fiscal year 2016. In order to obtain the subjective importance level of the indicators, a questionnaire of pairwise comparison is designed and filled up by the three industry professionals in phase I.

A. Calculate the Pairwise Comparison Matrices

Here is an example is given for obtaining A_1, which is the pairwise comparison matrix of the seven dimensions with respect to the company performance. Create the fuzzy pairwise comparison matrix $\tilde{A}_1$, calculate $\tilde{A}_1$ for α = 0.5 and μ = 0.5, and then A_1 is constructed.

$$\tilde{A}_1 = \begin{bmatrix} 1 & [1,2] & [4,6] & [1,2] & [1,2] & [2,4] & [2,4] \\ [1/2,1] & 1 & [2,4] & [1,2] & [6,8] & [2,4] & [1,2] \\ [1/6,1/4] & [1/4,1/2] & 1 & [2,4] & [1,2] & [2,4] & [2,4] \\ [1/2,1] & [1/2,1] & [1/4,1/2] & 1 & [1,2] & [4,6] & [2,4] \\ [1/2,1] & [1/8,1/6] & [1/2,1] & [1/2,1] & 1 & [2,4] & [4,6] \\ [1/4,1/2] & [1/4,1/2] & [1/4,1/2] & [1/6,1/4] & [1/4,1/2] & 1 & [4,6] \\ [1/4,1/2] & [1/2,1] & [1/4,1/2] & [1/4,1/2] & [1/6,1/4] & [1/6,1/4] & 1 \end{bmatrix}$$

$$A_1 = \begin{bmatrix} 1.000 & 1.500 & 5.000 & 1.500 & 1.500 & 3.000 & 3.000 \\ 0.750 & 1.000 & 3.000 & 1.500 & 7.000 & 3.000 & 1.500 \\ 0.208 & 0.375 & 1.000 & 3.000 & 1.500 & 3.000 & 3.000 \\ 0.750 & 0.750 & 0.375 & 1.000 & 1.500 & 5.000 & 3.000 \\ 0.750 & 0.146 & 0.750 & 0.750 & 1.000 & 1.500 & 5.000 \\ 0.375 & 0.375 & 0.375 & 0.208 & 0.375 & 1.000 & 5.000 \\ 0.375 & 0.750 & 0.375 & 0.375 & 0.208 & 0.208 & 1.000 \end{bmatrix}$$

B. Calculate the Pairwise Comparison Matrices

Take A_1 for example. With the mathematical programming software Matlab, λ_{max} is calculated as 8.7148, *RI* is assigned as 1.32 [32], $CR=CI/RI = 0.2858/1.32 \approx 0.2165 > 0.10$, which means the judgments needs being revised. This time, a maximum eigenvalue of 7.6516 is obtained, and $CI=(7.6516-7)/6 \approx 0.1086$, $CR=0.1086/1.32 \approx 0.0823 < 0.10$, which means the judgments are consistent enough to be acceptable. Calculate the priorities from limiting matrix *W*, get the limit matrix and calculate the normalized priorities W_{sub} as in Table IV.

TABLE IV. THE WEIGHTS OF THE INDICATORS BY FUZZY ANP

	C_1	C_2	C_3	C_4	C_5	C_6	C_7
W	0.088	0.052	0.073	0.087	0.015	0.046	0.068
W_{sub}	0.108	0.064	0.089	0.106	0.018	0.056	0.083
	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}
W	0.021	0.047	0.190	0.009	0.025	0.029	0.067
W_{sub}	0.026	0.058	0.232	0.011	0.031	0.035	0.082

C. Calculate the Values of the Composite Indicators

Calculate the objective weights W_{obj} and the final weights as W_j, normalize the measures, and calculate the values of the composite indicators in the year 2016 for the six companies as in Table V.

TABLE V. THE WEIGHTS BY SHONNA ENTROPY AND THE FINIAL WEIGHTS OF THE INDICATORS AND THE VALUE OF I^{2016}

	Audi	**BMW**	**Toyota**	**Nissan**	**GM**	**Ford**	d_j	W_{obj}	W_j
C_1	62416.609	90940.085	235934.949	100197.410	166380.000	141546.000	0.050	0.127	0.117
C_2	7.827	11.404	29.587	12.565	20.865	17.751	0.050	0.127	0.095
C_3	5.137	9.159	7.227	6.333	5.570	6.656	0.010	0.026	0.058
C_4	28550.834	60435.049	199260.000	79967.700	50451.446	48232.220	0.120	0.304	0.205
C_5	12.673	13.265	12.372	11.395	9.944	4.511	0.025	0.064	0.041
C_6	21.848	20.907	24.615	40.701	27.764	34.345	0.017	0.042	0.049
C_7	36805.732	73799.276	46784.451	45678.234	41191.111	48567.010	0.015	0.038	0.061
C_8	43968.777	40032.098	24337.921	30180.222	36000.000	37628.866	0.010	0.024	0.025
C_9	716509.881	805713.567	647381.495	721275.369	739466.667	729618.557	0.001	0.003	0.030
C_{10}	-6.559	-6.365	-9.808	-7.501	-9.896	-14.705	0.026	0.065	0.149
C_{11}	11.596	12.903	7.959	10.718	8.280	6.082	0.017	0.043	0.027
C_{12}	2.223	2.250	4.600	2.560	4.180	3.700	0.024	0.060	0.045
C_{13}	1.515	2.210	1.780	1.800	2.050	2.133	0.004	0.011	0.023
C_{14}	8.333	5.263	4.878	7.018	3.016	5.127	0.026	0.065	0.073
I^{2016}	0.394	0.511	0.791	0.561	0.529	0.565			
Ranking	6	5	1	3	4	2			

IV. CONCLUSION

This paper proposed the research question as: how to construct composite indicators of company performance for automobile companies from an environment perspective? To answer this question, this paper developed a multiplicative function $I_i^t = f\left[x_{ij}^{*t}, w_j\right] = \prod_{j=1}^{n} {x_{ij}^{*t}}^{w_j}$ with five steps. It involves developing a new conceptual framework including three environmental indicators; calculating the values of I_i^t with techniques of fuzzy logic, ANP, Shannon entropy, and a geometric mean with unequal weights for aggregation. The research question was answered by the multiplicative function. With this function, the performance of the sampled companies can be measured and ranked. The steps are transparent and logically reasoned with the realistic assumptions for automobile companies.

This approach developed can better overcome the 9 shortcomings mentioned in the introduction section. For the further research, 1) for a time series analysis, data from more fiscal years needs included, which might involve concerns about data preprocessing, such as data imputation and data inconsistency; 2) robustness and effectiveness of method developed needs being conducted by a post analysis; and 3) detailed discussion about benchmarking companies considering the outcome of the composite indicators needs analyzed.

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