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

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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

<table>
<thead>
<tr>
<th>Application</th>
<th>Shortcoming(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Indicators’ selection</td>
<td>SC1: Without particular emphasis on environmental concerns</td>
</tr>
<tr>
<td></td>
<td>SC2: With general indicators not for specific sectors</td>
</tr>
<tr>
<td>Indicators’ weights</td>
<td>SC3: With AHP/PCA/Experts’ scoring as the sole tool</td>
</tr>
<tr>
<td></td>
<td>SC4: With the interdependencies of the different indicators not tackled</td>
</tr>
<tr>
<td>Fuzzy logic</td>
<td>SC5: With the fuzzy/grey rules which are rather similar to the judgment elicitation used by AHP</td>
</tr>
<tr>
<td></td>
<td>SC6: Without adoption for tackling the inherent uncertainty</td>
</tr>
</tbody>
</table>

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.
• CO₂ emission: considering the availability and comparability of data from automobile companies, this paper adopts CO₂ emission reduction as a measure for CO₂ emission performance, and the calculation be as follows: \( \text{CO}_2\text{e reduction}\% = \frac{(\text{CO}_2\text{e}_2[\text{Kg}] - \text{CO}_2\text{e}_1[\text{Kg}])}{\text{CO}_2\text{e}_1[\text{Kg}]} \), where \( \text{CO}_2\text{e} \) represents the volume of CO₂ emission, and \( t \) 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 \( \text{m}^3/\# \) = Water input \( \text{m}^3 \) - Water discharge \( \text{m}^3 \), 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 \( \text{MWh}/\# \) = EC \( \text{MWh} \)/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>
<thead>
<tr>
<th>Dimension</th>
<th>Indicator (category)</th>
<th>Measure(s) [Unit]</th>
<th>Reference (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Innovation capability</td>
<td>( C_{i(+)} )</td>
<td>R&amp;D expenditure per employee [$]</td>
<td>[23]</td>
</tr>
<tr>
<td>Supply chain management</td>
<td>( C_{i(+)} )</td>
<td>Turnover per employee [$]</td>
<td>[24, 25]</td>
</tr>
<tr>
<td>Inventory performance</td>
<td>( C_i(-) )</td>
<td>COGS, Inventory turnover</td>
<td>[26]</td>
</tr>
<tr>
<td>Environmental performance</td>
<td>( C_i(-) )</td>
<td>Inventory to sales ratio</td>
<td>[27, 28]</td>
</tr>
</tbody>
</table>

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:

1. Construct the ANP structure hierarchically with control layer, dimensions, and indicators. As is constructed in equation (1), where \( W \) is a vector that represents the impact of “company performance” on the six dimensions; \( W \) is a matrix with inner dependence between the six dimensions; \( W_1 \) 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.

\[
W = \begin{bmatrix}
0 & 0 & 0 \\
W_1 & W_2 & 0 \\
0 & W_3 & W_4
\end{bmatrix}
\]

2. 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].

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

<table>
<thead>
<tr>
<th>Importance levels</th>
<th>Linguistic variable</th>
<th>Fuzzy numbers</th>
<th>Membership function</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Equal importance</td>
<td>1</td>
<td>(1, 1, 2)</td>
</tr>
<tr>
<td>3</td>
<td>Moderate importance</td>
<td>3</td>
<td>(2, 3, 4)</td>
</tr>
<tr>
<td>5</td>
<td>Essential/strong importance</td>
<td>5</td>
<td>(4, 5, 6)</td>
</tr>
<tr>
<td>7</td>
<td>Very strong importance</td>
<td>7</td>
<td>(6, 7, 8)</td>
</tr>
<tr>
<td>9</td>
<td>Extreme importance</td>
<td>9</td>
<td>(8, 9, 10)</td>
</tr>
</tbody>
</table>

\[
\tilde{A} = \begin{bmatrix}
1 & \tilde{a}_{12} & \cdots & \tilde{a}_{1n} \\
\tilde{a}_{21} & 1 & \cdots & \tilde{a}_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
\tilde{a}_{n1} & \tilde{a}_{n2} & \cdots & 1
\end{bmatrix}
\]

\[
\tilde{a}_\alpha = [\alpha_0, \alpha_n] = [\alpha (a^n - a^\mu), \alpha (a^\mu - a^\alpha) + a^\mu]
\]

\[
\tilde{a}^\mu = \mu \tilde{a}_\alpha + (1 - \mu) \tilde{a}_\alpha
\]

\[
\tilde{A}_\alpha = \begin{bmatrix}
1 & \tilde{a}_{12,\alpha} & \cdots & \tilde{a}_{1n,\alpha} \\
\tilde{a}_{21,\alpha} & 1 & \cdots & \tilde{a}_{2n,\alpha} \\
\vdots & \vdots & \ddots & \vdots \\
\tilde{a}_{n1,\alpha} & \tilde{a}_{n2,\alpha} & \cdots & 1
\end{bmatrix}
\]

- Calculate the vector \( w_i \) 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 \( w_\alpha = w_1 \ast W_2, \) and calculate the interdependent priorities of the indicators as \( W_\alpha = W_2 \ast W_\alpha \) and finally calculate the overall weights of the indicators on company performance as \( w = w_\alpha \ast W_\alpha \), and \( w \in (0, 1) \).

- Get the objective weights of the indicators by Shannon entropy. Here \( x_\alpha \) 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, \( x_j \in [1, 2] \); calculate the entropy value of indicator \( j \) as equation (7); calculate the weight of \( d_j \) and get objective weights for each indicator \( W_{ij} \), and then get the final weights \( w_j \) by the arithmetic mean of subjective weights and its objective weights.

\[
x_j^* = \begin{cases}
\frac{x_j^* - \min x_j^*}{\max x_j^* - \min x_j^*} + 1, & \text{for } (+) \\
\frac{\max x_j^* - x_j^*}{\max x_j^* - \min x_j^*} + 1, & \text{for } (-)
\end{cases}
\]

\[
e_j = -k \sum_{i=1}^{m} p_{ij} \ln(p_{ij}), k = (\ln(m))^{-1} > 0, e_j \geq 0
\]

- 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, \( x_j^* \) for the value of indicator \( j \) on alternative \( i \) at fiscal year \( t \) (\( t=0, 1, ..., T \)), \( x_j^* \) for the normalized value of \( x_j^* \), and \( x_j^* \in (0, 1] \)

\[
x_j^* = \begin{cases}
\frac{x_j^*}{\max x_j^*}, & \text{for } (+) \\
\frac{\min x_j^*}{x_j^*}, & \text{for } (-)
\end{cases}
\]

- 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 \( I_i^t \in (0, 1) \).

\[
I_i^t = f \left[ x_j^*, w_j \right] = \prod_{j} x_j^*^{w_j}
\]

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 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 $\tilde{A}$, calculate $\lambda_i$ for $\alpha=0.5$ and $\mu=0.5$, and then $A_1$ is constructed.

\[
\tilde{A} = \begin{bmatrix}
\end{bmatrix}
\]

Calculate the Pairwise Comparison Matrices

Take $A_1$ for example. With the mathematical programming software Matlab, $\lambda_{max}$ is calculated as 8.7148, $RI$ is assigned as 1.32 [32], $CR=CI/RI=0.2858/1.32$

B. Calculate the Pairwise Comparison Matrices

Take $A_1$ for example. With the mathematical programming software Matlab, $\lambda_{max}$ is calculated as 8.7148, $RI$ is assigned as 1.32 [32], $CR=CI/RI=0.2858/1.32$

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 $I'_i = f(x'_i, w_j) = \prod x'_i^{w_j}$ with five steps. It involves developing a new conceptual framework including three environmental indicators; calculating the values of $I'_i$ 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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