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Measuring Sustainability Performance with Multi Criteria Model: A Case Study

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Abstract: The proposal of this research is the development of a hybrid multi-criteria decision analysis (MCDA) model of sustainability performance. The model is applied to a Brazilian oil and gas company and is constructed from the MCDA associated with statistical analysis. The MCDA technique is a preference ranking organization method for enrichment evaluation (PROMETHEE), with analysis of 20 indicators of the dimensions of sustainability. In the statistical analysis, the Principal Component Analysis (PCA) and Multiple Linear Regression (MLR) are used. The results of PROMETHEE showed that the company's best sustainability performance was in 2011 and 2010. The worst sustainability performance was in 2015 and 2016. The application of the PCA technique aims to eliminate the existing multicollinearity and capture the direction of variability of the indicators. The first PC with 53.2%, the second PC with 25.6%. An estimate based on the MLR equation was performed. The limitation of the paper is with data from the company's sustainability reports as well as the choice and quantity of indicators. The analysis of the sustainability performance of the company through multi-criteria models is not new but their combination with mathematical models, comparing the sustainability reports per year, brings more complete results on the sustainability performance of the company.

Keywords: sustainability performance; MCDA; MCDM; PROMETHEE; PCA; MLR

1. Introduction

The most popular definition of sustainability was presented by the World Commission on Environment and Development in 1987 as, "sustainable development is development that meets the needs of the present without compromising the ability of future generations to meet their own needs." Sustainability seeks to ensure that the resources available today is not used to deprive the economic, environmental and social benefits of future generations [1].

Faced with the need for sustainability assessment, researchers and practitioners indicate evaluation systems that track the progress of sustainability over time [2]. The greatest difficulty for sustainability is the integration of multiple criteria into several dimensions, with many criteria conflicting with each other. Sustainability has been the focus of most organizational initiatives and innovations [3].

Although there are advances in practices and theories that are contributing to the sustainability of organizations, the issue is still far from maturing [4]. Many efforts were directed towards the development of indicators in the measurement, prevention and classification of sustainability. These indicators provide a standardized form of data for decision making. However, indicators alone may not be enough to measure sustainable development. Many of these sustainability indicators have been proposed and adopted in practice but most of them focus only on classifying organizations [5].

Companies need to integrate techniques that take into account social and environmental dimensions, not just the economic dimension of traditional cost minimization techniques. Thus sustainability decisions are increasingly becoming an integral part of business decision making [6]. The dimensions that are studied in sustainability influence all the constituent organizations of a supply chain, not just an organization or focal company. References [7,8] in their papers reported that research on innovation, sustainability and sustainable supply chain is growing, thus demonstrating the relevance of research related to measuring corporate sustainability performance.

The aggregation of these indicators is carried out through models and techniques of different approaches. As an example, we have analytical models, mathematical programming methods, simulation models, heuristic methods and a combination of two or more in hybrid models [9]. Many models currently designed are insufficient for a complete assessment of sustainability, such as models that are based only on environmental parameters or models that work only with deterministic variables. The lack of more comprehensive models for measuring sustainability has led to the development of many different methods, resulting in incomplete structures and partial solutions [10].

There is a research gap when it comes to complete sustainable models. There is a need to create hybrid models that offer complete results for companies decision support systems [11]. A decision support system (DSS) is defined as a software-based tool that assists the decision-making process in an integrated way with the company's management processes [12].

The analytical models are the most used for analysis of sustainability in organizations. The focus of the analytical models is the study of the conflicting criteria. Usually it does not aim at the equilibrium among the parameters. The analytical models are divided into multicriteria decision aid (MCDA), game theory and systemic models [13]. Some MCDA models are highlighted in the literature, such as the models based on analytic hierarchy process (AHP) and analytic network process (ANP), data envelopment analysis (DEA), technique for order preference by similarity to ideal solution (TOPSIS), elimination and chox traduisant la realité (ELECTRE), a multi-attribute utility theory (MAUT), decision-making trial and evaluation laboratory (DEMATEL) and preference ranking organization method for enrichment evaluation (PROMETHEE) [14]. Other authors combine multicriteria models with heuristic models such as the authors who used DEMATEL combined with fuzzy logic to evaluate the sustainability of small and medium enterprises [15].

The PROMETHEE method was developed in the 1980s by J.P. Brans and B. Mareschal. PROMETHEE is a method that assists in decision making in business sectors and government institutions. The method quantifies the criteria and their conflicts highlighting the main alternatives for reaching these goals [16]. The method is widely used for multi-criteria assessments and has a strong application in sustainability. It stands out from the other methods by dealing with uncertain data and by the Visual Gaia PROMETHEE software where it offers visual tools as well as having high practicality in re-evaluations [17].

The main objective of this paper is the development of a hybrid model using MCDA and statistical techniques for the analysis of corporate sustainability performance, study of the correlation of input data to formulate an equation for future forecasts.

2. Materials and Methods

The proposal is the combination of PROMETHEE, an MCDA tool, with the PCA and MLR statistical techniques to analyze the sustainability performance of an Brazilian oil and gas company. The scope is shown in Figure 1 is presented in three steps.

2.1. Selection

The indicators are selected from the Global Reporting Initiative (GRI). According to Reference [18] these are the most prominent and consolidated indicators. Based on the company's sustainability reports, around 60 key indicators were identified, of which 20 were chosen for the assessment, 5 economic, 7 environmental and 8 social indicators. Reference [19] reported in their paper that social indicators are often used to assess the sustainability performance of production processes. Reference [20] suggested using quantifiable social indicators such as equity and safety at work in measuring sustainability.

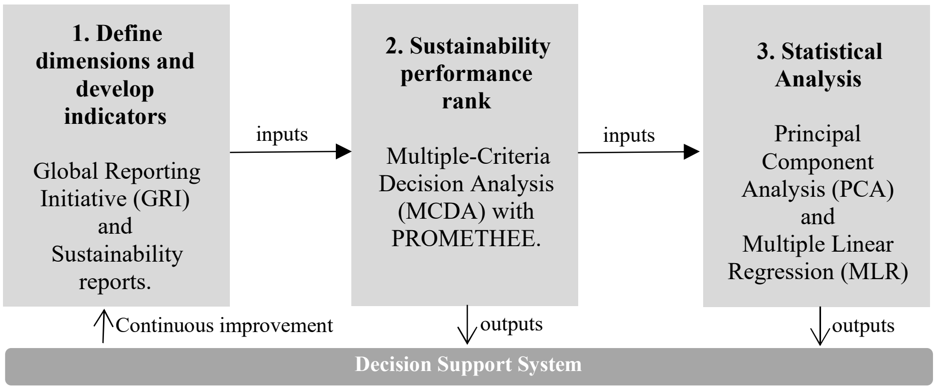

Figure 1. Scope of paper.

2.2. *Sustainability Performance*

The evaluation of the sustainability performance of the Brazilian oil and gas company is carried out through the multi criteria modeling with the PROMETHEE technique. Preference flows, which are the results of the multi criteria analysis. In the third step, statistical analysis techniques with principal component analysis and multiple linear regression.

PROMETHEE consists of an array with a set of possible alternatives or actions (A). In the case of this paper, the alternatives are years. Sustainability performance of the company obtained from the PROMETHEE is compared on an annual time scale (2009 to 2017). For these alternatives there are the criteria that are evaluated from their function F (a). PROMETHEE I classifies alternatives partially through the Phi+ and Phi− flows, and PROMETHEE II classifies the alternatives globally through the Phi flow. Steps for PROMETHEE method are the determination of deviations based on parity comparison; application of the preference function; calculation of an overall or global preference index; calculation the PROMETHEE I partial ranking and the PROMETHEE II complete ranking. Steps are given below.

$$\forall a, b \epsilon A; \pi(a,b) = \sum_{j=1}^{k} Pj(a,b)wj \tag{1}$$

$$\phi^{+}(a) = 1/(n-1) \sum_{X \epsilon A} X \epsilon A \tag{2}$$

$$\phi^{-}(a) = 1/(n-1) \sum_{X \epsilon A} X \epsilon A \tag{3}$$

where $\phi^{+}(a), \phi^{-}(a)$ denote the positive outranking flow and negative outranking flow.

$$\phi(a) = [\phi^{+}(a)] - [\phi^{-}(a)], \tag{4}$$

where ϕ denotes the global flow.

2.2.1. Sensitivity Test

A sensitivity test is performed from the input data change. Analysis is the act of studying the effect that variation of an input data can have on the results. Methods for sensitivity analysis are divided into mathematical, statistical and graphs. Statistical methods involve simulations with variations of inputs and analysis of the effect outputs [21].

2.2.2. Principal Component Analysis

The Principal Component Analysis (PCA) is a multivariate statistical technique that seeks to capture information about the linear correlation structure for correlated group variables [22]. This information is condensed into a smaller number of uncorrelated variables, called principal components (PCs), which represent the projections of the original variables on new orthogonal axes.

Let X_{nXk} a matrix of set of data centered on k correlated variables, where each row contains a k-variant observation, represented by x'_{j1xp}. The correlation structure of the matrix X is obtained in the sample co-variance matrix (or correlations) S_{kXk} As such matrix is symmetric and not singular, there exists an orthogonal matrix U_{kXk} which diagonalizes S. Thus, we have $U'SU = S_c$, where S_c is a diagonal matrix containing the k eigenvalues λ_t positive values for S. The matrix U presents in its columns the k-eigenvectors u_t that carry the charges of the linear combination for projects the original variables on the th^{th} orthogonal axis given by the t^{th} PC, for $t = 1, \ldots, k$. The eigenvector λ_t describes the variance of the th^{th}. The vector $z_{t(nX1)}$, brings the scores for the t^{th} PC of the n initial observations, obtained through $z_t = Xu_t$, for $t = 1, \ldots, l$. Considering that each variable follows a Normal distribution, the th^{th} PC follows a Normal distribution with mean 0 and variance λ_t.

The projection of a new k observation varied by the vector $x(kx1)$, in orthogonal axes defined by the PCs, is obtained by $z = U'x$, Where $z = [z_1, z_2, \ldots, z_w]$ is the vector containing the w scores for the new observations; the matrix $U = [u_1|u_2|\ldots|u_w]$ contains in its columns the associated eigenvectorsand U' represents its transpose [23].

2.2.3. Multiple Linear Regression

Multiple Linear Regression (MLR) is a generalization of simple linear regression when there is more than one independent variable. The basic model for multiple linear regression is:

$$\gamma_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_p X_{ip} + \epsilon i \tag{5}$$

for each observation $i = 1, \ldots, n$.

The value n are the observations of a dependent variable and p the independent variables. Where γ_i is the i-observation of the dependent variable, X_{ij} is with the observation of the independent j-variable, $j = 1, 2, \ldots, p$. The values βj are the parameters to be estimatedand ϵi is the ith normal error independently distributed identically. In the multivariate linear regression, there is an equation for each of the dependent variables $m > 1$ that share the same set of independent variables and are therefore estimated simultaneously [24].

3. Results and Discussions: Case Study

The case study company is a large Brazilian oil. Main producer, distributor and seller of oil and gas the company has more than 150 thousand employees. The publicly traded reports its sustainability through annual in its media. From these reports were collected the essential information for the development of this research. Section presents the development with results of the PROMETHEE evaluation, PCA and the MLR.

3.1. Dimension, Themes, Indicators

The company's sustainability reports are based on The Global Reporting Initiative (GRI) which is an international organization that helps companies communicate their economic, environmental and social impacts. About 60 quantitative indicators were identified in the report. Were divided into three dimensions (social, environmental and economic). Five indicators of the economic dimension, seven of the environmental and eight of the social were selected. The selection of 20 indicators was made according to the criteria of data availability, comprehensiveness of the themes and dimensions. Table 1 illustrates the selected indicators.

Table 1. Dimension, GRIthemes and indicators.

Dimension	Theme by GRI	Indicators
Economic	Economic performance	X_1 = Net Debt (millions)
Economic	Economic performance	X_2 = Volume of Production (boed)
Economic	Economic performance	X_3 = Net Margin
Economic	Economic performance	X_4 = Sales Revenue (millions)
Economic	Economic performance	X_5 = Total Investments (millions)
Environmental	Biodiversity	X_6 = Protected Areas (un)
Environmental	Effluents	X_7 = Oil Leaks (m^3)
Environmental	Waste	X_8 = Hazardous Waste (thousand tons)
Environmental	Energy	X_9 = Energy Consumption(Tj)
Environmental	Water	X_{10} = Water Consumption (millions m^3)
Environmental	Emissions	X_{11} = CO_2 Emissions (ton)
Environmental/Social	Local communities	X_{12} = Social-environmental Projects (un)
Social	Diversity	X_{13} = Female Employees (%)
Social	Diversity	X_{14} = Black Employees(%)
Social	Equality	X_{15} = Female Heads(%)
Social	Equality	X_{16} = Black Bosses(%)
Social	Equality	X_{17} = Wage Relation (min max)
Social	Health and safety at Work	X_{18} = Rate of Fatal Accidents
Social	Health and safety at Work	X_{19} = Number of Accidents (un)
Social	Job	X_{20} = Total Job (un)

Selected 20 criteria in PROMETHEE through the bases of sustainability indicators, are determined the functions of each of them preference and the objective of each criterion in the maximization or minimization. It is observed that the preference functions used are the v-Shape and the linear function. Table 2 shows the inputs of PROMETHEE.

Table 2. Inputs of PROMETHEE. Adapted from Reference [18].

Criteria	Max/Min	Preference Fn	-Q	-P
X_1	Min	V-Shape	na	238,519.30
X_2	Max	V-Shape	na	175.07
X_3	Max	V-Shape	na	0.25
X_4	Max	V-Shape	na	112,185.10
X_5	Max	Linear	9480	24.50
X_6	Max	Linear	394.620	874.43
X_7	Min	Linear	174.060	411.51
X_8	Min	Linear	25.530	59.72
X_9	Min	Linear	171,956.900	451,237.10
X_{10}	Min	Linear	9.480	24.05
X_{11}	Min	Linear	7.210	19.52
X_{12}	Max	Linear	166.330	426.14
X_{13}	Max	Linear	0.030	0.25
X_{14}	Max	Linear	0.030	0.25
X_{15}	Max	Linear	0.030	0.25
X_{16}	Max	Linear	0.030	0.25
X_{17}	Min	V-Shape	na	9.90
X_{18}	Min	Linear	0.025	0.25
X_{19}	Min	V-Shape	na	5062.90
X_{20}	Max	Linear	64,052.400	141,584.70

3.2. PROMETHEE Analysis

From these selected indicators were parametric and the functions of preference were defined. Evaluating according to the PROMETHEE method, individual flows (Phi− and Phi+) and global flows (Phi) were generated. According to the Phi results a ranking is performed as the final result of the evaluation. As shown in Table 3. The results showed that the company had its best performance in

2011 and its worst performance in the year 2015. From the ranking highlighted in Table 2 it can be inferred that the results can be related to two external indices, oil price.and exchange rate. For this understanding a multi criteria correlation analysis is performed using the PCA technique.

Table 3. Flows, Global flows and rank. Adapted from Reference [18].

Year	Phi+	Phi−	Phi
2011	0.3100	0.2058	0.1042
2010	0.3194	0.2423	0.0770
2013	0.2565	0.2038	0.0528
2009	0.3279	0.2815	0.0464
2012	0.2444	0.2240	0.0204
2014	0.2354	0.2688	−0.0334
2017	0.2675	0.3105	−0.0430
2016	0.2497	0.3260	−0.0762
2015	0.2151	0.3633	−0.1482

3.3. Sensitivity Test

A sensitivity test of the model with respect to the input data is performed. Based on two modifications, the sensitivity of evaluation model is performed. The first modification is based on the number of indicators. The second is based on indicator weights. In a first test 3 indicators, 2 social (Total Jobs and Accidents) 1 environmental indicator (Projects) were removed. In a second test, 1 more environmental indicator and 1 social (Fatal Accidents) were removed, balancing the number of indicators with 5 economic, 5 environmental and 5 social

With the first sensitivity test it can be observed that the change in number of indicators does not significantly the rank results. Ranking maintains the first place of the year 2011 and last place of the year 2015, there were no significant changes in the positioning of other years. Shown in Table 4.

Table 4. Sensitivity Test: Number of Indicators.

Year	Phi 20 Indicators	Phi 17 Indicators	Phi 15 Indicators
2011	0.1042	0.0834	0.0920
2010	0.0770	0.0621	0.0284
2013	0.0528	0.0720	0.0204
2009	0.0464	0.0409	0.0070
2012	0.0204	−0.0148	0.0645
2014	−0.0334	−0.0362	−0.0559
2017	−0.0430	−0.0267	−0.0226
2016	−0.0762	−0.0721	−0.0330
2015	−0.1482	−0.1086	−0.1009

In the second robustness test the weights relative to the indicators were changed. Initially, equal to all size independent were entered. Then, greater weights were added to economic indicators (50%) and environmental (35%) and the weights of social (15%) were decreased. Shown in Table 5.

Table 5. Sensitivity Test: Dimensions Weights.

Year	Phi 33% all	Phi Equal Weights	Phi 50%, 35%, 15%
2011	0.1042	0.1100	0.0955
2010	0.0770	0.0676	0.0892
2013	0.0528	0.0449	0.0577
2009	0.0464	0.0693	−0.0030
2012	0.0204	0.0109	0.0304
2014	−0.0334	−0.0405	−0.0307
2017	−0.0430	−0.0350	−0.0437
2016	−0.0762	−0.0732	−0.0617
2015	−0.1482	−0.1540	−0.1337

With the second robustness test it can be observed that the change in indicator weights does not significantly the rank results. Ranking maintains the first place of the year 2011 and last place of the year 2015, there were no significant changes in the positioning of other years.

The Pearson correlation demonstrates the level of correlation between Uni-criteria, shown in Tables 6 and 7 . Red a negative and in blue a positive. The color intensity indicates whether the correlation is high, medium or low. These data are shown in Figure 2.

The application of PCA technique aims to eliminate the existing multicollinearity and capture the direction of variability the indicators. Technique allows obtaining orthogonal main principal components PCs forming a linear combination distinct from the original indicators. PC eigenvectors represent the load and direction of variability in the indicators. PCs is listed in Table 8.

With a biplot chart, shown in Figure 3, you can see a split between two PCs. On PC1 with 53.2% the Protected Areas, Hazardous Waste, Volume of Production, Net Debt, Black Employees, Female Heads, Net Margin, Sales, Female Employees. In PC2, with 25.6%, Total Investments, Energy Consumption, Water Consumption, Emissions, Social-Environmental Projects, Black Bosses, Wage Relation, Rate of Fatal Accidents, Number of Accidents, Total Jobs. This shows at what level of correlation the indicators have with each other.

With the Pearson correlation coefficient of 0.829 it can be inferred that the multiple linear equation is an adequate technique to predict future values of sustainability from the parameters of the global flows generated in PROMETHEE. From these results can be realized a prediction with a multiple linear regression having as dependent variable the global flows and independent variables the exchange rate and Oil Price.

Table 6. Uni-criteria Phi: Part A.

Year	S. Revenue	Net Debt	Net Margin	Vol of Prod	T. Invest.	Energy	Oil Leaks	Emissions	Haz. Waste
2009	−0.8090	0.5937	0.7500	−0.6487	−0.5000	0.5768	0.0771	0.4090	−0.3696
2010	−0.5911	0.6392	1.0000	−0.4045	0.2500	0.3638	−0.9313	0.2842	−0.4389
2011	−0.2816	0.4707	0.5000	−0.2037	−0.2500	0.4358	0.1081	0.4740	−0.4735
2012	0.0915	0.2829	0.1250	−0.3359	0.5000	−0.0873	−0.2853	0.0152	−0.3804
2013	0.3163	−0.0620	0.1250	−0.5874	1.0000	−0.2835	0.1387	−0.2677	−0.3767
2014	0.5901	−0.3475	−0.7500	0.1047	0.7500	−0.4438	0.2060	−0.5809	−0.1352
2015	0.4655	−0.7460	−1.0000	0.7135	0	−0.4438	0.2038	−0.4628	0.4242
2016	0.1036	−0.4898	−0.5000	0.7242	−0.7500	−0.0051	0.2288	0.0811	0.8750
2017	0.1147	−0.3412	−0.2500	0.6378	−1.0000	−0.1129	0.2542	0.0558	0.8750

Table 7. Uni-criteria Phi: Part B.

Year	P. Areas	Projects	Water	Fem. Emplo.	B. Emplo.	Fem. Heads	B Bosses	W. Relation	Rate F. Accid	N of Accid.	T. Jobs
2009	−0.2893	−0.2346	0.5022	−0.0268	−1.0000	−0.3138	0.8304	0.2580	0.7500	0.4970	0.3343
2010	−0.2893	0.5394	0.1917	−0.0121	−0.5606	−0.4232	0.1543	0.5500	0.2121	0.4842	0.3340
2011	−0.2893	0.7834	0.0849	0.0146	−0.1836	−0.0500	0.1286	0.7168	−0.6122	0.4510	0.3750
2012	−0.2809	0.1376	−0.0009	0.0371	0.0389	0.1023	0.1120	0.6989	−0.1863	−0.7864	0.4200
2013	−0.2358	0.2819	−0.0077	−0.0068	0.1252	0.1518	0.1466	−0.3903	1.0000	−0.5932	0.4241
2014	−0.0311	0.0875	−0.4928	0.0038	0.1837	0.1270	0.0914	−0.3443	0.2037	−0.3579	0.3334
2015	−0.0655	0.1549	−0.7678	0.1006	0.3168	0.1394	0.1543	−0.4963	−0.9832	−0.0668	−0.7200
2016	0.8055	−0.7746	0.0609	−0.0570	0.5044	0.1270	−0.6552	−0.4963	−0.5963	0.0995	−0.7500
2017	0.6756	−0.9754	0.4293	−0.0533	0.5751	0.1394	−0.9624	−0.4963	0.2121	0.2728	−0.7500

Pearson´s	Sales R.	Net Debt	Net Margin	Vol. Prod.	Total Invest.	Energy	Oil Leaks	Emissions	Haz. Waste	Prot. Areas	Projects	Feme Empl.	Water	Black Empl.	Fem. Heads	B. Bosses	Wage Rel.	% Fatal Accidents	N. Accidents	Jobs	Oil Price	Ex. rate
Sales R.	-	-0.84	-0.885	0.54	0.364	-0.967	0.512	-0.897	0.396	0.305	-0.146	0.345	-0.744	0.835	0.9	-0.406	-0.65	-0.257	-0.699	-0.335	0.096	0.522
Net Debt	-0.84	-	0.961	-0.84	0.097	0.836	-0.64	0.758	-0.776	-0.634	0.493	-0.182	0.619	-0.85	-0.8	0.554	0.879	0.395	0.335	0.757	0.445	-0.89
Net Margin	-0.89	0.961	-	-0.789	0	0.859	-0.65	0.808	-0.656	-0.508	0.389	-0.314	0.727	-0.802	-0.823	0.431	0.762	0.461	0.427	0.63	0.305	-0.78
V. Production	0.54	-0.84	-0.789	-	-0.514	-0.5	0.469	-0.37	0.918	0.801	-0.58	0.036	-0.382	0.785	0.562	-0.736	-0.654	-0.661	0.075	-0.926	-0.65	0.912
T. Investments	0.364	0.097	0	-0.514	-	-0.409	-0.27	-0.523	-0.646	-0.648	0.645	0.443	-0.485	-0.095	0.106	0.463	0.133	0.314	-0.695	0.663	0.741	-0.49
Energy	-0.97	0.836	0.859	-0.5	-0.409	-	-0.41	0.954	-0.39	-0.263	0.182	-0.374	0.739	-0.768	-0.817	0.345	0.691	0.152	0.718	0.345	-0.01	-0.54
Oil Leaks	0.512	-0.64	-0.654	0.469	-0.272	-0.405	-	-0.353	0.496	0.45	-0.458	-0.041	-0.213	0.506	0.704	-0.264	-0.643	-0.126	-0.146	-0.435	-0.22	0.554
Emissions	-0.9	0.758	0.808	-0.37	-0.523	0.954	-0.35	-	-0.238	-0.098	0.067	-0.425	0.806	-0.571	-0.66	0.113	0.663	0.054	0.669	0.203	-0.03	-0.43
Haz. Waste	0.396	-0.78	-0.656	0.918	-0.646	-0.39	0.496	-0.238	-	0.938	-0.828	-0.263	-0.074	0.732	0.507	-0.806	-0.739	-0.393	0.118	-0.964	-0.78	0.958
Prot. Areas	0.305	-0.63	-0.508	0.801	-0.648	-0.263	0.45	-0.098	0.938	-	-0.863	-0.54	0.129	0.698	0.457	-0.88	-0.656	-0.249	0.135	-0.828	-0.67	0.834
Projects	-0.15	0.493	0.389	-0.58	0.645	0.182	-0.46	0.067	-0.828	-0.863	-	0.569	-0.31	-0.451	-0.336	0.639	0.616	-0.055	-0.073	0.705	0.715	-0.74
Fem. Empl.	0.345	-0.18	-0.314	0.036	0.443	-0.374	-0.04	-0.425	-0.263	-0.54	0.569	-	-0.764	0.024	0.181	0.426	0.137	-0.477	-0.353	0.077	0.244	-0.06
Water	-0.74	0.619	0.727	-0.382	-0.485	0.739	-0.21	0.806	-0.074	0.129	-0.31	-0.764	-	-0.412	-0.487	-0.095	0.342	0.502	0.469	0.156	-0.1	-0.29
Black Empl.	0.835	-0.85	-0.802	0.785	-0.095	-0.768	0.506	-0.571	0.732	0.698	-0.451	0.024	-0.412	-	0.888	-0.82	-0.662	-0.408	-0.423	-0.659	-0.18	0.738
Fem. Heads	0.9	-0.8	-0.823	0.562	0.106	-0.817	0.704	-0.66	0.507	0.457	-0.336	0.181	-0.487	0.888	-	-0.531	-0.609	-0.278	-0.658	-0.426	0.051	0.582
B. Bosses	-0.41	0.554	0.431	-0.736	0.463	0.345	-0.26	0.113	-0.806	-0.88	0.639	0.426	-0.095	-0.82	-0.531	-	0.489	0.278	0	0.701	0.367	-0.66
Wage Relation	-0.65	0.879	0.762	-0.654	0.133	0.691	-0.64	0.663	-0.739	-0.656	0.616	0.137	0.342	-0.662	-0.609	0.489	-	-0.014	0.176	0.681	0.544	-0.83
% Fatal Accid.	-0.26	0.395	0.461	-0.661	0.314	0.152	-0.13	0.054	-0.393	-0.249	-0.055	-0.477	0.502	-0.408	-0.278	0.278	-0.014	-	-0.101	0.516	0.243	-0.42
N. Accidents	-0.7	0.335	0.427	0.075	-0.695	0.718	-0.15	0.669	0.118	0.135	-0.073	-0.353	0.469	-0.423	-0.658	0	0.176	-0.101	-	-0.202	-0.49	-0.02
Jobs	-0.34	0.757	0.63	-0.926	0.663	0.345	-0.44	0.203	-0.964	-0.828	0.705	0.077	0.156	-0.659	-0.426	0.701	0.681	0.516	-0.202	-	0.834	-0.95
Oil Price	0.096	0.445	0.305	-0.651	0.741	-0.012	-0.22	-0.032	-0.782	-0.665	0.715	0.244	-0.097	-0.179	0.051	0.367	0.544	0.243	-0.493	0.834	-	0.77
Ex. rate	0.522	-0.89	-0.782	0.912	-0.486	-0.539	0.554	-0.425	0.958	0.834	-0.743	-0.064	-0.29	0.738	0.582	-0.662	-0.83	-0.421	-0.024	-0.953	0.77	-

Figure 2. Correlation of Pearson.

Table 8. Principal Components.

Component	Variance	Proportion	Cumulative Proportion
1	11.396	0.518	0.518
2	5.743	0.261	0.779
3	2.095	0.095	0.874
4	1.222	0.056	0.930
5	0.827	0.038	0.967
6	0.411	0.019	0.986
7	0.195	0.009	0.995
8	0.111	0.005	1.000

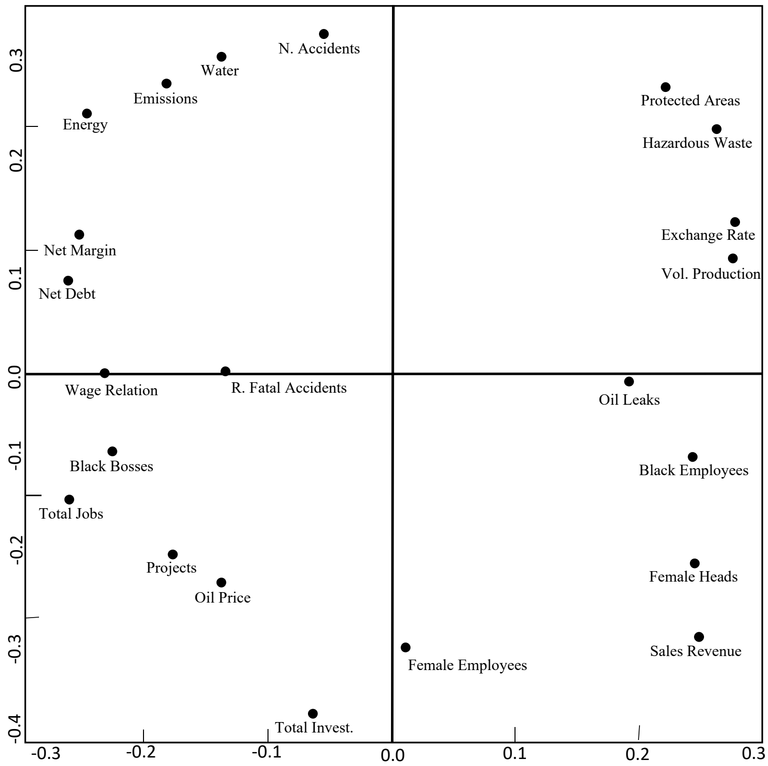

Figure 3. Principal Component Analysis (PCA) bi plot.

MLR data are shown in Table 9 and the multiple linear equation, shown in Figure 4, the future results of organizational sustainability can be estimated based on the values of the Oil Price and the exchange rate.

Table 9. Multiple Linear Regression Variables.

Years	Phi	Oil Price (USD)	Exchange Rate (Real/USD)
2009	0.0464	61.67	2.00
2010	0.0770	79.50	1.76
2011	0.1042	111.26	1.68
2012	0.0204	111.67	1.96
2013	0.0528	108.66	2.16
2014	−0.0334	98.90	2.35
2015	−0.1482	52.50	3.33
2016	−0.0762	46.00	3.49
2017	−0.0430	53.00	3.19

$$Phi = 0.3065 - 0.0003424OP - 0.1145ER \tag{6}$$

where: OP—Oil Price, E—Exchange rate

Calculated an estimate for the year 2019 with oil price of 70 dollars and exchange rate of 3.80 (Real/USD), we have the value of $Phi = -0.1525$.

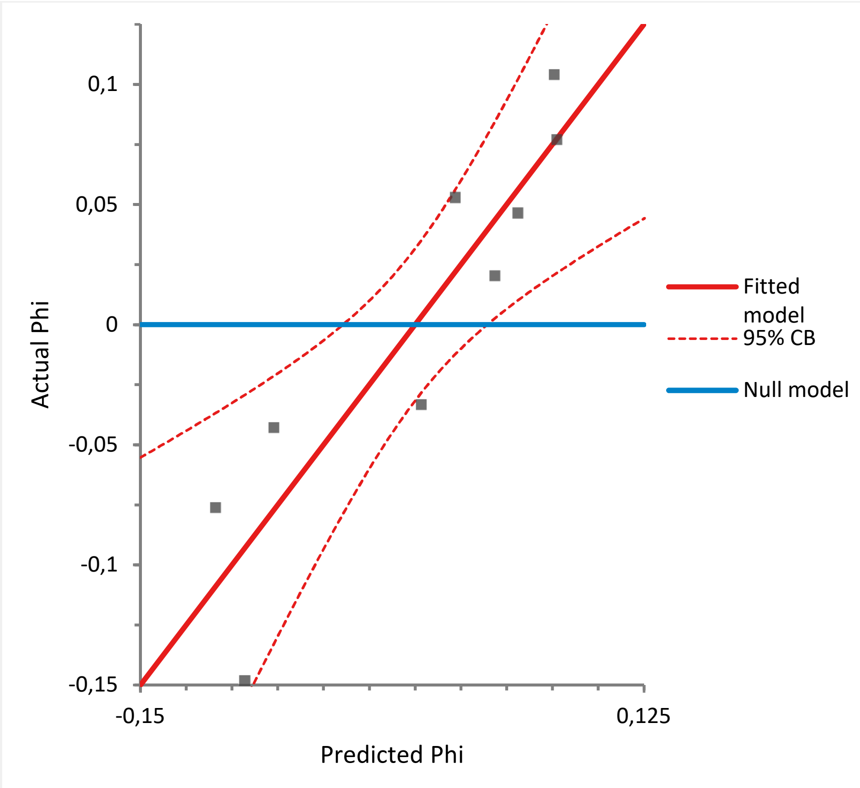

Figure 4. Multiple linear regression.

4. Conclusions

This paper presented a hybrid model using a multi-criteria decision analysis and statistical tools based on the principal component and a multiple linear regression model.

The hybrid model aimed to balance the dimensions of economic, social and environmental sustainability. The results of PROMETHEE showed that the company's best performance was in 2011 and 2010. The worst was in 2015 and 2016, the height of economic crisis in Brazil. The robustness of model was tested through the sensitivity test, changing the input data was verified small changes in the results. PROMETHEE as a multi-criteria model then proved to be an appropriate tool for sustainability performance analysis. The direction of variability of the indicators was highlighted by the principal component analysis. With the insertion of external indicators to the company, a multiple linear equation was proposed to be used as a forecasting tool.

The limitations of this research are through the collection and selection of indicators. Limited to publicly available corporate sustainability reports. The contribution and originality of this paper is the development of a hybrid model. PROMETHEE as a tool for evaluating corporate sustainability performance based on the comparison of years. PCA as a method for measuring indicator correlation and MLR as a forecasting mechanism for the future.

This hybrid model brings clear, objective decision-making results and can easily be replicated to other types and sizes of companies using publicly available sustainability reports. The technique employed offered a satisfactory result comparing the performance of organizational sustainability in the years 2009 to 2017. Assessment results provide information for business decision making. The company can identify which dimensions need improvement and allocate the necessary resources. Forecasting results can support more objective planning about the company's future.

Intelligent systems can be built for decision making based on the hybridization of models. Not only the combination of analytical and mathematical, but also with heuristic methods and simulation. A proposal for future work and for other researchers is the combination of multi-attribute and multi-objective models for assessing and optimizing corporate sustainability performance.

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