ENVIRONMENTAL SCIENCE & POLICY 37 (2014) 50–60

Available online at www.sciencedirect.com

SciVerse ScienceDirect

journal homepage: www.elsevier.com/locate/envsci

Efficiency in Brazil's industrial sectors in terms of energy and sustainable development

Flávia de Castro Camioto [a,*], *Enzo Barberio Mariano* [b], *Daisy Aparecida do Nascimento Rebelatto* [a]

[a] *Department of Production Engineering, University of São Paulo, Brazil*
[b] *Department of Production Engineering, University State of São Paulo, Brazil*

ARTICLE INFO

Available online 27 September 2013

Keywords:
Industrial sectors
Data envelopment analysis
Sustainable development
Energy

ABSTRACT

This article evaluates the efficiency of Brazil's industrial sectors from 1996 to 2009, taking into account energy consumption and respective contributions to the country's economic and social aspects. This analysis used a mathematical programming method called Data Envelopment Analysis (DEA), which enabled, from the SBM model and the window analysis, to evaluate the ability of industries to reduce energy consumption and fossil-fuel CO_2 emissions (inputs), as well as to increase the Gross Domestic Product (GDP) by sectors, the persons employed and personnel expenses (outputs). The results of this study indicated that the Textile sector is the most efficient industrial sector in Brazil, according to the variables used, followed by these sectors: Foods and Beverages, Chemical, Mining, Paper and Pulp, Nonmetallic and Metallurgical.

1. Introduction

Climate change poses major challenges to the planning and management policies of the domestic industrial sectors, as the complex interactions between the environment and the productive systems render difficult analyzing the reality by policymakers. This difficulty calls for more elaborate indicators that are conducive to an integrated assessment of the sustainability of productive sectors.

The term sustainable development owes its widespread usage to the Brundtland Commission Report (WCED, 1987), *Our Common Future*, which defined it as ''development that meets the needs of the present without compromising the ability of the future generations to meet their own meets''. With regard to production systems, Glavic and Lukman (2007) define the concept of ''sustainable production'' as the creation of goods using processes and systems that are non-polluting, that conserve energy and natural resources in economically viable, safe and healthy ways for employees, communities, and consumers and which are socially and creatively rewarding for all stakeholders for the short- and long-term future.

However, most of the current production processes that massively utilize nonrenewable natural and partially recyclable resources rarely fully meet all requirements related to sustainable production, particularly those related to mitigating global warming.

The data presented in the last Intergovernmental Panel on Climate Change (IPCC, 2007) indicate that global warming is largely due to human activity, especially human-caused CO_2 emissions. Thus, fossil fuel burning has been shown to be responsible for approximately 85% of all anthropogenic CO_2 emission produced yearly.

* *Corresponding author at*: Department of Production Engineering, University of São Paulo, Trabalhador São-Carlense, 400, São Carlos, SP 13566-590, Brazil. Tel.: +51 16 3373 9428; fax: +55 16 3373 9425.
E-mail addresses: flaviacamioto@yahoo.com.br (F.d.C. Camioto), enzo@feb.unesp.br (E.B. Mariano), daisy@sc.usp.br (D.A.d.N. Rebelatto).
1462-9011/$ – see front matter
http://dx.doi.org/10.1016/j.envsci.2013.08.007

Silva and Guerra (2009) explain that the use of fossil fuels has driven the world economy since the Industrial Revolution, with energy representing an essential component for the social and the economic development of a nation and its supply an essential pre-requisite to human activities.

Therefore, the environmental implications of the production and use of energy resources represent a major challenge for developed and developing countries, since the production, distribution, processing and consumption of energy should be directed to ensure development, without increasing it negative effects on society and the environment. As a result, the analysis of the relationship between energy consumption, economic growth and carbon emissions, has become the subject of several international studies in recent years.

Belke et al. (2011), for example, analyzed the long-term relationship between energy consumption and real Gross Domestic Product (GDP) of 25 OECD countries from 1981 to 2007. Ramanathan (2006) used DEA (Data Envelopment Analysis) to analyze the relationship between CO_2 emissions, GDP growth and energy consumption from 1980 to 2001. Moreover, Blancard and Hoarau (2013) used the DEA method to build a sustainability index for Small Island Developing States (SIDS), considering the carbon footprint, the GDP penalized by economic vulnerability, and also longevity and knowledge. Finally, the study by Niu et al. (2011) was conducted to evaluate the causality between energy consumption, GDP growth and carbon emissions for eight Asia-Pacific countries from 1971 to 2005, using panel data.

In their study, Niu et al. (2011) concluded that in developing countries the base carbon emissions, the per capita energy consumption and energy use efficiency are far lower than in developed countries, however, the CO_2 emissions per unit of energy use is higher. Although developing countries may reduce their CO_2 emissions per unit of energy use, total energy consumption will rise rapidly with economic development. Therefore, developing countries must determine how to undergo economic growth while conserving energy and reducing emissions.

Data from the National Energy Balance, BEN (2010), confirm this information for Brazil, from an ongoing series covering the period of 1970–2008, which shows that the overall trend has been the expansion of global energy consumption. From 1990 to 2008, for example, the cumulative growth was 77%, with total consumption increasing from 127.596 million toe to 226.393 million toe. The industrial sector is the largest energy consumer in Brazil, representing 34.6% of the country's total consumption (BEN, 2010).

Notwithstanding the study by Simões and La Rovere (2008), which analyzed the availability of renewable energy sources in Brazil, to conclude that Brazil's energy matrix is relatively clean, Brazil's internal use of renewable energy is of 43.7% (BEN, 2010), many of the activities of the industrial sector are still dependent on fossil fuels. The outcome is that the industry impacts the environment by emitting extremely high concentrations of greenhouse gases (GHG), increasing global warming, in addition to adding to the extensive mining in the form of fuel oil and coal. According to Freitas and Kaneko (2011), economic activities, together with demographic pressure, represent the leading forces that explain Brazil's emission increase. On the other hand, the main factors to mitigate emission are carbon intensity reductions and diversification of the energy mix toward cleaner sources.

Paz et al. (2007), who discussed the concepts of sustainability and ethics through the analysis of the Brazilian energy policy and its social and environmental implications, stresses that the dynamics of economic activities used to meet human needs should take into account the natural limiting factors, as for instance, energy production, transformation, distribution, and consumption conditions. In this context, according to Kolk and Pinkse (2004), companies currently face increasing pressure regarding the amount of fossil fuels used in their productive processes.

Considering that the industrial sector can significantly contribute to the challenge against climate change, several studies have been conducted focusing on environmental and economic aspects in the industry (Yellishetty et al., 2010; Oggioni et al., 2011; Scheneider et al., 2011; Tomasula and Nutter, 2011; Wernet et al., 2011; Hamzah et al., 2010; Berni et al., 2008; Narodoslawsky et al., 2008). However, most of these studies have focused on particular industrial sectors, processes or products.

Thus, notwithstanding the few works, such as Zhang et al. (2008), an eco-efficiency analysis for regional industrial systems in China by developing data envelopment analysis (DEA) based models, and Luken and Castellanos-Silveria (2011), which compared the changes in economic, environmental and social variables that occurred in the manufacturing industry in groups of developing countries, between 1990 and 2004, there are still ample opportunities for studies covering various industrial sectors and their contribution to promoting economic development with environmental respect and social improvement.

Since there is much discussion on how to define a multidimensional index of sustainability, combining economic, social and environmental aspects (Cracolici et al., 2010), and based on the definition by Glavic and Lukman (2007) of the sustainable production concept, the objective of this article is to analyze the efficiency of the main industrial sectors in Brazil, from 1996 to 2009, considering energy consumption and its contribution toward the economic and social aspects of the country.

Mao et al. (2011) conducted a similar study on multiple sustainability indicators using statistical data to analyze China's energy consumption and GHG emissions, by industrial subsystem and sector. Thus, compared to other works, this study stands out due to the fact it compares industrial sectors using an aggregate sustainable production index.

To reach this goal, a mathematical programming method called Data Envelopment Analysis (DEA) was used. This method, based on the SBM model and on the window analysis, enabled analyzing the efficiency of Brazil's industrial sectors to reduce energy consumption and CO_2 emissions from fossil fuels (inputs), while increasing the GDP by sectors, the persons employed and personnel expenses (outputs).

2. Methods

In this study the main Brazilian industrial sectors were selected, with data provided by the National Energy Balance

Table 1 – Contributions and limitations of the variables in the model for sustainable development.

Variables	Pillars of sustainability	Contributions and limitations for sustainable development	
		Contribution	Limitation
Sectorial GDP	Economic	Related to the generation of wealth to allow for new investments	Economic vulnerability was not regarded (EVI) in the sectors (Blancard and Hoarau, 2013)
	Social	Related to quality of life, life expectancy, education and health (Anand and Sen, 2000)	Social benefits depend on how income is distributed (Anand and Sen, 2000; Kuznetz, 1955)
	Environmental	Related to the generation of wealth to allow for new investments in cleaner technologies. When a country reaches a certain level of economic maturity, more attention is given to environmental issues (Arrow et al., 1995)	In the early stages of economic development there is increased pollution (Arrow et al., 1995)
Personnel expenses	Economic	Related to a country's internal consumption	Results in high operating costs in the industry
	Social	A population's income increase is an indicator of the work quality (Kalleberg et al., 2000)	This indicator depends on the existing wage gaps in the sector
	Environmental	The greater the perception of wages, the greater the demand for environmental quality (Smulders et al., 2011)	Controlling pollution will also depend on other factors such as, for example, regulatory measures (Smulders et al., 2011)
Persons employed	Economic	Related to a country's internal consumption	The more intensive the hand labor, the lower the sector's productivity
	Social	Fighting unemployment that results in the individual's loss of autonomy, self-trust and physical and psychological health (Sen, 1999)	Depends on the work conditions offered
	Environmental	–	–
CO_2 emissions from fossil fuels	Economic	Related to environmental legislation compliance, avoiding production taxes, and meet international requirements, enabling exports	Economic development is still very dependent on fossil fuel sources
	Social	Related to increase in pollution, causing health problems	–
	Environmental	Related to global warming	CO_2 emissions can be reduced by substituting fossil fuels with biofuel, emissions that can have serious drawbacks on nature preservation or biodiversity
Energy consumption	Economic	The decrease in energy consumption is related to lower production costs (energy efficiency)	Economic development is still directly related to high energy consumption
	Social	Reducing public investment in energy infrastructure to allocated it to other areas of social interest	Directly associated with Human Development Index – HDI (IEA, 2008), if not associated with increased efficiency
	Environmental	Related to air pollution emissions and fuel extraction such as oil or coal.	–

(BEN) and the Brazilian Institute of Geography and Statistics (IBGE), and some sectors were grouped due to the lack of available information from IBGE. Thus, for this work, the spatial delimitation of the Brazilian industry includes: (a) Nonmetallic, which corresponds to the cement and ceramics sectors, (b) Mining, which corresponds to the mining and pelletizing, excluding oil, natural gas and coal exploration, (c) Metallurgical, which corresponds to the sectors of pig-iron and steel, iron alloys and non-ferrous (d) Chemical, (e) Foods and Beverages, (f) Textiles, and (g) Paper and Pulp.

In addition to the energy consumption, the variables used in this analysis were: (1) sectorial GDP; (b) personnel expenses in the form of salaries, withdrawals and other remunerations; (c) persons employed in each sector; and (d) CO_2 emissions from fossil fuels. Table 1 lists some sustainable development contributions to each variable used in this model, and also some limitations of the variables that must be considered to perform the analysis in this study.

According to Table 1, although the concept of sustainable development cannot be linked to only these variables, they represent significant contributions to the pillars of sustainability. It should be emphasized that these were chosen due to the data availability for the sectors analyzed.

The data related to the variables ''personnel expenses'' and ''persons employed'' were collected from the website of the Brazilian Institute of Geography and Statistics (IBGE). The variables ''GDP sectorial'' and ''energy consumption'' were collected in the report of the National Energy Balance (BEN), available on the website of the Ministry of Mines and Energy (MME). The variable ''CO_2 emissions from fossil fuels'' was calculated using the top-down method, internationally recognized and recommended by the UN (United Nations).

The time interval analyzed in this study includes a period of 13 years (1996–2009), and the criterion used to define it was the data availability with the same calculation base.

2.1. Calculation of CO_2 emissions from fuel combustion: top-down method

In order to calculate the carbon emissions of the Brazilian energy system, the MCT (2006) adapted the top-down method for the specific characteristics of the Brazilian energy system, recommended by IPCC (1996). Thus, to calculate the CO_2 emissions, much of the data used in this work were drawn from this document. The application of the top-down method of the IPCC includes the following sequence of steps:

1. Estimate the apparent fuel consumption in the original units of measurement: in this work the direct consumption of the sectors under study was used to represent the specific emissions of the segments. Thus, the fuel consumption in industrial production and the total consumption of each industry sector were used. These data were found on the National Energy Balance (BEN).
2. Convert the apparent consumption into a common energy unit, terajoules (TJ): the amounts of fuels are expressed by BEN in tons of equivalent oil (toe), to obtain the consumption in TJ, the consumption in toe is multiplied by the conversion factor. It is known that the conversion factor is obtained by multiplying 45.217×10^{-3} by the correction factor. The correction factor is equal to 0.95 for solid and liquid fuels and 0.90 for gaseous fuel.
3. Transform the apparent consumption of each fuel carbon content by multiplying the fuel's emission carbon factor: in this study, the values used for the emission factor were collected from the MCT (2006), which uses the values recommended by the IPCC (1996), with a few exceptions.
4. Determine the carbon quantity in each fuel intended for non-energy purposes, deducting that amount from the carbon contained in the apparent consumption, to compute the actual carbon content that can be emitted. As the data used in this work refer to the final energy consumption of fuel, the amount of fuel intended for the non-energy sector was not determined. Thus, it was not necessary to use the share of carbon stored for each fuel in the CO_2 emission calculation.
5. Correct the values to consider the incomplete combustion of fuel, in order to compute only the amount of carbon actually oxidized during combustion. In this work, the oxidized carbon fraction was the values recommended by the IPCC (1996): 0.98 for coals, 0.99 for oils and its derivatives, 0.995 for natural gas. For the other energy sources the fraction of oxidized carbon was the same used by the MCT (2006).
6. Convert the oxidized carbon amount into CO_2 emissions, by multiplying the carbon content (after correction) by 44/12. Where 44 is the molecular weight of carbon dioxide (CO_2) and 12 is the molecular weight of carbon (C).

2.2. Data envelopment analysis

The Data Envelopment Analysis (DEA) technique has been successfully used to assess the relative performance of a set of firms, usually called Decision Making Units (DMUs), using the same inputs to produce the same outputs. The DEA has its origins in the works of Charnes et al. (1978) and Banker et al. (1984), who proposed an empirical model to measure relative efficiency. According to Farrell (1957), it is more advisable to determine the effectiveness of a firm, or an administrative unit, comparing it to the highest level of efficiency previously observed, than to compare it with some unattainable ideal.

DEA evaluates the relative efficiency of a set of DMUs, which in this article represents Brazil's main industrial sectors from 1996 to 2009. This approach has the advantage of considering both multiple inputs and outputs that characterize a particular production process. Additionally, DEA allows DMUs to have immediate information about their efficiency or inefficiency status, which in turn will depend on the DEA model adopted. Each model, depending on the type of returns to scale, form and frontier orientation chosen, will lead the efficiency to a different value, which must be interpreted in accordance with the assumptions of the model used.

Charnes et al. (1978), developed the first DEA mathematical model, referred to as CCR, which used the hypothesis of Constant Returns to Scale (CRS) along the production frontier. The extension proposed by Banker, Charnes and Cooper in 1984, formulated the BCC model, which presents Variable Returns to Scale (VRS).

According to Coelli et al. (1998), CCR and BCC models may follow two directions: to maximize the outputs or to minimize the inputs. On the other hand, when working with additive models, which were developed by Charnes et al. (1985), it is not necessary to choose a direction, because the original model already considers, simultaneously, the maximizing of outputs and the minimizing of inputs. It should be noted that the additive models can belong to the variant type, with Variable Returns to Scale, or to the invariant type, with Constant Returns to Scale.

One of the disadvantages of the additive model is that it does not determine the efficiency index of the DMUs being compared; it only indicates the efficient DMUs and goals for the inefficient DMUs. Thus, the interpretation of the results of the additive model should be performed somewhat different to the BCC and CCR models, where the result of 100% indicates an efficient DMU. For the additive model, the value of the objective function represents the sum of the distances, also called slacks, of the DMU to the efficient frontier, for each variable.

Due to this limitation of the additive model, some enhancements were proposed, of which the SBM (Slacks-Based Measure) model stands out. This model, introduced by Tone (2001), is quite similar to the additive model, since it also considers a simultaneous orientation to the inputs and outputs, but as a result it provides an efficiency value that ranges from 0% to 100%. Thus, the results of this model, though from the same assumptions of the additive model, can be interpreted similarly to the results of CCR and BCC models. Expressions (1)–(6) show the variant SBM DEA model (Tone, 2001):

$$\min \tau = t - \frac{1}{n}\sum_{j=1}^{n}\frac{S_j}{x_{j0}} \tag{1}$$

Subject to:

$$1 = t + \frac{1}{m}\sum_{i=1}^{m}\frac{S_i}{y_{i0}} \tag{2}$$

$$\sum_{k=1}^{z} x_{jk}\cdot\lambda_k + S_j = t\cdot x_{j0},\ \text{for } j = 1, 2, \ldots, n \tag{3}$$

$$\sum_{k=1}^{z} y_{jk}\cdot\lambda_k - S_i = t\cdot y_{j0},\ \text{for } i = 1, 2, \ldots, m \tag{4}$$

$$\sum_{k=1}^{z}\lambda_k = t \tag{5}$$

$$\lambda_{k,} S_j \ \ \textit{and}\, S_i \geq 0 \ \ \textit{and} \ \ t > 0 \tag{6}$$

where λ_k, participation of the DMU k for the goal of the DMU under analysis; x_{jk}, amount of *input* j of DMU k; y_{ik}, amount of *output* i of DMU k; x_{j0}, amount of *input* j of DMU under analysis; y_{i0}, amount of *output* i of DMU under analysis; z, number of unit assessed; m, number of *outputs*; n, number of *inputs*; S_i, slack of output i; S_j, slack of input j; t, linear fit variable.

It was observed in this work that the orientation to minimize inputs and maximize outputs, simultaneously, is most appropriate, since from a sustainability point of view the objective is to reduce energy consumption and CO_2 emissions from fossil fuels and, at the same time, to increase the number of persons employed, personnel expenses and GDP by sector, i.e., reduce environmental impacts and increase social benefits and economic growth. The SBM model variant was chosen for this study because it allows comparing sectors that operate on different scales, implying that reductions or increases in inputs do not necessarily cause changes in the output in the same proportion.

2.3. *Window analysis*

One way to include the time factor within the DEA technique is by performing the window analysis, whose details can be found in Cooper et al. (2000). The window analysis consists of a structured method to blend in a single application, data of DMUs in a variety of different years, and this is done by performing multiple applications of DEA, considering different combinations of years (window). Thus, it is possible to conclude that the window analysis is also an important means to circumvent the problem of low number of DMUs, which according to Cooper et al. (2000), must be at least three times the sum of the amount of inputs to the amount of outputs.

The window analysis covers the separation of the years analyzed in different groups (windows), this way, from the available data, the first step in such analysis is to determine the size of each window and the number of windows to be built. This information can be obtained in Expressions (7) and (8), where k represents the number of periods and p the window size, which should be rounded up when necessary.

$$\text{Window size}(p) = \frac{k+1}{2} \tag{7}$$

$$\text{Number of windows} = k - p + 1 \tag{8}$$

To illustrate the use of these formulas and the subsequent construction of windows, in this analysis, which evaluates data available from 1996 to 2009 ($k = 14$), the window size should be 8 and the amount of windows should be 7, comprising, respectively, data from: (a) 1996 to 2003 (b) 1997 to 2004, (c) 1998 to 2005, (d) 1999 to 2006, (e) 2000 to 2007, (f) 2001 to 2008, (g) 2002 to 2009.

After building all the windows, the DEA should be applied to each one so that a table that incorporates the results for each unit in each window can later be prepared. It should be noticed that in this approach, the end result of each DMU's efficiency should be the average of the efficiencies obtained in all years and in all the windows, and the standard deviation of each DMU can also be calculated to test the stability of its efficiency in time.

3. Results and discussion

3.1. *Input and output analysis*

First, in order to verify if the "CO_2 emissions from fossil fuels" and "energy consumption" contributed to the formation of the output variables, we performed an econometric analysis in order to capture the statistical significance of each explanatory variable (input) in relation to each output. The statistical significance of the independent variable related to the dependent variable is reflected by the *p*-value. For the variable to be considered statistically significant, its *p*-value should be as close to zero as possible, if the null hypothesis is to be rejected. Then, at the confidence level of 90%, which was adopted in this work, it can be stated that a variable is statistically significant if the *p*-value is less than 0.1, exceeding this value, the variable can be considered negligible. The software used to perform this analysis was Stata 9.2.

After conducting some tests, we detected the presence of autocorrelation and heteroscedasticity among the variables, which meant that the equations had to be estimated by the method of generalized least squares, with the variables expressed in natural logarithms, in order to not cause bias and inconsistency in the parameters.

The first estimate was of the function that considered the inputs "CO_2 emissions from fossil fuels" and "energy consumption" and the output "GDP by sector", from 1996 to 2009, according to Expression (9). After, the equations were estimated considering as output, instead of "GDP by sector",

Table 2 – Results of econometric analysis to *p*-value.

	GDP by sector	Persons employed	Personnel expenses
Ln_emission	0.049	0.168	0.697
Ln_consumption	0.000	0.000	0.045
_cons	0.000	0.000	0.000

the variables "persons employed" and "personnel expenses", respectively according to Expressions (10) and (11).

$$\ln(\text{GDP by sector}) = \alpha + \beta_1 \cdot \ln(\text{CO}_2\,\text{emissions}) + \beta_2 \cdot \ln(\text{Energy consumption}) \qquad (9)$$

$$\ln(\text{Persons employed}) = \alpha + \beta_1 \cdot \ln(\text{CO}_2\,\text{emissions}) + \beta_2 \cdot \ln(\text{Energy consumption}) \qquad (10)$$

$$\ln(\text{Personnel expenses}) = \alpha + \beta_1 \cdot \ln(\text{CO}_2\,\text{emissions}) + \beta_2 \cdot \ln(\text{Energy consumption}) \qquad (11)$$

Table 2 includes the *p*-value results, obtained by the generalized least squares estimation of the parameters in Expressions (9)–(11).

As shown in Table 2, for Expression (9), the estimated coefficients are significant for both variables analyzed. For Expression (10), it was found that only the "energy consumption" variable was significant. Finally, for Expression (11), the results show that only the "energy consumption" variable was significant.

Note that though the *p*-value of the variable "CO_2 emissions from fossil fuels" was quite high for the variables "employed persons" and "personnel expenses", it was considered interesting to include it in the DEA, in order to incorporate the three pillars of the triple bottom line in the analysis, as it is an environmental variable.

Furthermore, the fact that the input variables are not fully independent was taken into account, since the consumption of fossil fuels is considered as information for the variable "Energy Consumption", as well as for the variable "CO_2 emissions from fossil fuels". Therefore, there is a bias for the sectors in which the energetic consumption of fossil fuels is high, since for them any reduction in energy consumption suggested by DEA will also automatically generate a reduction in CO_2, and this cannot be considered in the analysis. This bias will ultimately penalize the sectors that have an energy matrix that is more dependent on fossil energy sources, and its distance to the frontier estimated by DEA would be greater than the real one.

However, tests were performed with DEA, considering the exclusion of each of these variables in the analysis, and it was found that both variables provide important and complementary information to the study object of this work. The variable "CO_2 emissions from fossil fuels" takes into account the composition of the energy matrix of the sector, since in its calculation different weights are assigned to the energy from each source, based on how much each fossil source pollutes, not taking into account the energy generated by renewable sources. Therefore, the main reason this variable was included in the analysis is because it can measure the impact of replacing fossil fuels for cleaner ones. The variable "energy consumption", on the other hand, sums up all energy consumption, including from renewable sources, without differentiating the source. Thus, considering that so-called clean sources also have some sort of environmental impact, it is equally important that, in addition to replacing fossil fuels for cleaner sources, energy consumption as a whole should be reduced, hence it is interesting to also include this variable in the analysis.

3.2. *Efficiency analysis*

After applying the SBM model of DEA, the window analysis was performed to evaluate the efficiency of industrial sectors from 1996 to 2009, considering both the reduction of inputs "energy consumption" and "CO_2 emissions from fossil fuels", such as the increase of outputs "GDP by sector", "persons employed" and "personnel expenses". The results of this study indicated that the Textile sector was the one with the highest average efficiency, with the variables used, and according to Table 3, by the sectors: Foods and Beverages, Chemical, Mining, Paper and Pulp, Nonmetallic, and Metallurgical.

As for the standard deviation of efficiency, in Table 3, the Mining sector had the highest value, followed by the sectors: Chemicals, Foods and Beverages, Mining, Textile, Nonmetallic, Paper and Pulp and Metallurgical. To better understand the reasons for the high standard deviation shown by the mineral, chemical and food and drinks industries, the results of all windows built for these sectors will be shown. Next, each sector is examined with respect to the results obtained.

The Metallurgical sector, considering the variables analyzed in this work, are the least efficient, and with the lowest standard deviation, equal to 1.3%. These results corroborate those obtained by Mao et al. (2011) for China, which found that the ferrous sector accounts for only 3.5% of the national industry, but consumes 20% of the country's total energy. Table 3 shows that despite being very inefficient, there is no great variation, indicating that this Brazilian sector showed no significant improvement and no worsening over the years analyzed.

Then, in Brazil's second to last efficiency ranking of industrial sectors, there is the Nonmetallic sector, which according to Table 3, this sector was becoming more efficient as the oldest years were being excluded and the most recent ones used in the windows, and efficiency increased from 13.17% in the first window (1996–2003) to 16.16% in the last one (2002–2009). However, it was observed that compared to the other sectors analyzed, the variability was not very high, with the standard deviation equal to 3.42%.

Table 3 – Efficiency of Industrial Sectors.

Ranking efficiency	Sector	Windows (%)							Mean (%)	Standard deviation (%)
		1 (1996–2003)	2 (1997–2004)	3 (1998–2005)	4 (1999–2006)	5 (2000–2007)	6 (2001–2008)	7 (2001–2009)		
1	Textile	94.21	93.31	94.52	95.95	95.95	95.72	93.55	94.75	6.92
2	Foods and Beverages	92.36	81.28	77.80	80.49	85.39	83.95	88.63	84.27	14.69
3	Chemical	77.83	61.68	64.12	64.64	65.93	62.27	59.57	65.15	25.28
4	Mining	14.72	14.83	15.08	25.48	36.07	42.73	43.46	27.48	30.07
5	Paper and Pulp	15.09	14.87	14.97	15.88	17.11	16.96	17.49	16.05	3.01
6	Nonmetallic	13.17	13.00	13.31	13.92	14.66	14.86	16.16	14.15	3.42
7	Metallurgical	10.70	9.72	9.63	10.05	10.52	10.11	10.72	10.21	1.30

Table 4 – Window analysis – Mining sector.

Sector_Year	Windows (%)						
	1	2	3	4	5	6	7
Mining_1996	16.89						
Mining_1997	16.01	15.79					
Mining_1998	14.47	14.27	14.10				
Mining_1999	14.00	13.82	13.61	13.30			
Mining_2000	13.28	13.14	12.93	12.63	12.63		
Mining_2001	13.80	13.66	13.48	13.18	13.18	12.19	
Mining_2002	14.41	14.29	14.11	13.81	13.81	12.80	12.19
Mining_2003	14.91	14.81	14.65	14.36	14.36	13.35	12.74
Mining_2004		18.89	18.59	17.99	16.97	14.58	14.58
Mining_2005			19.16	18.58	17.61	15.28	15.28
Mining_2006				100.00	100.00	100.00	100.00
Mining_2007					100.00	73.61	73.61
Mining_2008						100.00	100.00
Mining_2009							19.30
Mining_Mean	14.72	14.83	15.08	25.48	36.07	42.73	43.46
Total mean	27.48						
Standard deviation	30.07						

Table 5 – Growth of the variables between 2005 and 2006.

Sectors	Energy consumption (%)	CO_2 emissions (%)	Sectoral GDP (%)	Persons employed (%)	Personnel expenses (%)
Foods and Beverages	12.25	−8.27	2.01	6.26	16.16
Mining	3.73	3.59	5.27	7.30	18.47
Metallurgical	−0.86	−2.49	−1.09	6.73	10.51
Nonmetallic	6.05	8.35	3.31	9.35	15.13
Paper and Pulp	4.32	−15.50	3.48	3.41	9.53
Chemical	2.73	3.87	0.51	2.39	8.97
Textile	0.87	−0.37	−3.57	1.74	7.02
Average growth	4.45	−0.40	1.43	5.54	12.48

Source: BEN (2010) and IBGE (2011).

The third place in the inefficiency ranking is the Paper and Pulp sector, similar to the Nonmetallic sector, in which its efficiency generally increased as the oldest years were excluded from the analysis and the most recent ones were used in the windows. It should be noted, however, that the variability of this sector was also relatively small when compared with the other industrial sectors, with the standard deviation equal to 3.01%.

The fourth place, both in efficiency and inefficiency, is the Mineral Extraction sector, especially in the last four windows analyzed, with increased efficiency as the oldest years were excluded and the youngest ones were included in the analysis. Thus, it can be said that the Mining industry has shown improvement in recent years, in terms of their contribution to social, economic and environmental aspects. In Table 4, which shows the results of the windows for this sector, it can be clearly identified that this sector's leap in quality began in 2006, between windows 3 and 4, when the average efficiency increased from 15.08% to 25.48%. Interestingly, the exception to this fact was the year of 2009, in the last window, when the sector showed significant worsening.

It should be mentioned that the performance leap of the mineral extraction sector in 2006 was primarily due to the higher growth rate of this sector's output variables when compared to the other sectors, as illustrated in Table 5.

Notwithstanding the good efficiency level of the Chemical sector, third place in the ranking, it also showed a great variability over the years, which can be confirmed by Table 3. When analyzing the results of this sector it is important to consider that although it has, in general, worsened from window to window, the last year of each window was always efficient, as shown in Table 6, which presents the window analysis for this sector. This aspect demonstrates that the sector has shown significant and rapid improvement, with the most recent year of the window always more efficient than the previous ones. It should be mentioned that the exceptions to this fact were the years of 2008 and 2009, when the sector showed significant worsening due to a sharp GDP drop in the sector, a result of the global economic crisis. Interestingly, the years this sector stood out most, efficient in all the windows, were 2004 and 2007.

Similar to the Chemical sector, shown in Table 3, the Foods and Beverages sector also showed high variability in terms of efficiencies. This sector, as well as the Chemical sector, showed significant and rapid improvement in recent years, which can be corroborated by the fact that the last year of each window, without exception, was efficient in relation to the others. According to Table 7, the years the Foods and Beverages sector most stood out, efficient in multiple windows, were 2004, 2006 and 2008.

Table 6 – Window Analysis – Chemical sector.

Sector_Year	Windows (%)						
	1	2	3	4	5	6	7
Chemical_1996	87.86						
Chemical_1997	67.29	42.11					
Chemical_1998	83.16	51.97	51.97				
Chemical_1999	100.00	75.84	75.84	64.14			
Chemical_2000	52.27	40.15	36.71	35.05	33.31		
Chemical_2001	66.10	51.86	41.19	39.37	37.78	32.76	
Chemical_2002	65.95	51.72	41.18	38.37	36.96	32.12	31.04
Chemical_2003	100.00	79.83	66.10	57.15	51.76	39.58	38.29
Chemical_2004		100.00	100.00	100.00	100.00	100.00	100.00
Chemical_2005			100.00	83.05	75.99	66.00	48.95
Chemical_2006				100.00	91.61	88.19	83.55
Chemical_2007					100.00	100.00	100.00
Chemical_2008						39.49	37.56
Chemical_2009							37.14
Chemical_Mean	77.83	61.68	64.12	64.64	65.93	62.27	59.57
Total mean	65.15						
Standard deviation	25.28						

Table 7 – Window analysis – Foods and Beverages sector.

Sector_Year	Windows (%)						
	1	2	3	4	5	6	7
Foods and Beverages_1996	100.00						
Foods and Beverages_1997	92.04	72.59					
Foods and Beverages_1998	76.94	67.27	62.66				
Foods and Beverages_1999	80.85	68.31	63.80	60.21			
Foods and Beverages_2000	100.00	100.00	69.94	67.38	66.93		
Foods and Beverages_2001	100.00	77.26	72.27	71.76	71.61	61.74	
Foods and Beverages_2002	89.08	77.55	72.43	68.35	68.35	62.21	61.90
Foods and Beverages_2003	100.00	87.24	81.29	76.26	76.26	69.87	69.49
Foods and Beverages_2004		100.00	100.00	100.00	100.00	100.00	100.00
Foods and Beverages_2005			100.00	100.00	100.00	86.34	86.26
Foods and Beverages_2006				100.00	100.00	100.00	100.00
Foods and Beverages_2007					100.00	91.47	91.42
Foods and Beverages_2008						100.00	100.00
Foods and Beverages_2009							100.00
Foods and Beverages_Mean	92.36	81.28	77.80	80.49	85.39	83.95	88.63
Total mean	84.27						
Standard deviation	14.69						

Finally, the sector that was most efficient by reducing inputs and increasing outputs, in this work, was the Textile sector. This sector, according to Table 3, showed high average efficiency in all windows. The years this sector most stood out, effective in multiple windows, were 1999, 2001, 2003, 2007 and 2008.

4. Final discussion

Much time and many resources have been lavished on the issue of sustainability in its economic, social and environmental pillars, especially through comparative analyzes between countries, regions, districts or sectors. In these analyzes, although far from a consensus on the variables to be used, there has been much emphasis on CO_2 emissions and energy consumption, given their major contribution to global warming. It is noteworthy that one of the major causes for the sharp increase in CO_2 emissions and energy consumption was the economic development of emerging countries, among them Brazil.

Compared to developed countries, the large share of renewable sources in the Brazilian energy matrix ensures the country's low GHG emissions in absolute terms. Nevertheless, energy consumption and CO_2 emissions per capita in Brazil have increased as fossil fuel sources have a significant share in the Brazilian industrial consumption. Given that much of the responsibility for energy consumption and CO_2 emissions falls on the industries, sustainability should be studied under that focus.

Accordingly, many studies have performed comparative analyzes aimed at the industry, but most target specific industrial sectors (intra-sectorial analyzes), ensuring the comparison of homogeneous units. Moreover, the work of Mao et al. (2011), which conducts a comparison of China's industrial sectors (intersectorial analysis) through a series of indexes statistically built, was included.

In this paper the Brazilian industrial sectors were compared by constructing a sustainable production aggregate index, using the DEA methodology, which measured the efficiency of industrial sectors to transform their energy consumption and CO_2 emissions into economic and social benefits.

It should be noted that the index proposed in this study has limitations, mainly with regards to the heterogeneity of the units compared, which causes the efficiency index obtained to incorporate the sectors' structural characteristics, which are difficult to control. Thus, the interpretation of this index requires taking into account the peculiarities of each production system in their interactions with society, economy and the environment.

Although its use requires attention, the index measured is important in terms of being useful for public policies and sectorial actions related to industry, with the following potentials:

- Contribute to the discussions related to evaluating the industrial sectors' sustainability, helping to identify those with the best practices with regard to social, economic and energy consumption aspects.
- Guide policy decisions regarding government incentives to promote the development of industries in search of more sustainable production.

There is for example, albeit limited, the possibility for technology transfer between industrial sectors, and these transfers essentially relate to the generation and use of energy from cleaner and more efficient energy sources. According to the results presented herein, while the textile sector can be a reference of good sustainable practices that should be further examined, the Metallurgical sector can be worthy of more attention, with regard to improvements. Another important reference regards the efficiency leaps, such as that achieved by the mineral extraction sector between 2005 and 2006, which if well understood and analyzed can serve as an improvement parameter in other sectors.

The aggregated index presented in this work and the ranking of industrial sectors also helps to allocate the attention and government resources to incentive or protection policies against foreign competition, focusing on strategic sectors such as Brazil's textile sector.

A question for future studies is whether the same ranking of industrial sectors would be achieved if the same methodological procedure was repeated for other countries. Another interesting analysis would be to compare the performance of one sector among different countries, which could give rise to public policies on technology transfer, at an international level.

REFERENCES

Anand, S., Sen, A., 2000. Human development and economic sustainability. World Dev. 28 (12) 2029–2049.

Arrow, K., et al., 1995. Economic growth, carrying capacity and the environment. Science 268, 520–521.

Banker, R.D., Charnes, A., Cooper, W.W., 1984. Some models for estimating technical and scale inefficiencies in data envelopment analysis. Manage. Sci. 30, 1078–1092.

Belke, A., Dobnik, F., Dreger, C., 2011. Energy consumption and economic growth: new insights into the cointegration relationship. Energy Econ. 33, 782–789.

BEN – Balanço Energético Nacional, 2010. Divulga informações relativas ao binômio oferta consumo de fontes de energia. BEN Available at: https://ben.epe.gov.br (accessed 04.11.10).

Berni, M.D., Bajay, S.V., Jannuzzi, G.M., Gomes, R., 2008. Brazilian and other countries' pulp and paper industry: an assessment between emission levels and energy efficiency indexes. O Papel (Brazil) 69 (11) 87–96.

Blancard, S., Hoarau, J.F., 2013. A new sustainable human development indicator for small island development states: a reappraisal from data envelopment analysis. Econ. Model. 30, 623–635.

Charnes, A., Cooper, W.W., Golany, B., Seiford, L., 1985. Foundation of data envelopment analysis for Pareto-Koopmans efficient empirical production functions. J. Econom. 30, 91–107.

Charnes, A., Cooper, W.W., Rhodes, E., 1978. Measuring the efficiency of decision making units. Eur. J. Oper. Res. 2, 429–444.

Coelli, T., Prazada Rao, D.S., Battese, G.E., 1998. Introduction to Efficiency and Productivity Analysis. Kluwer Academic Publishers, Massachusetts.

Cooper, W.W., Seiford, L.M., Tone, K., 2000. Date Envelopment Analysis: A Comprehensive Text with Models, Applications, Reference and DEA-Solver Software, first ed. Kluwer Academic Publishers, Norwell.

Cracolici, M.F., Cuffaro, M., Nijkamp, P., 2010. The measurement of economic, social and environmental performance of countries: a novel approach. Soc. Indic. Res. 95 (2) 339–356.

Farrell, M.J., 1957. The measurement of productive efficiency. J. R. Stat. Soc. A 120 (3) 253–281.

Freitas, L.C., Kaneko, S., 2011. Decomposition of CO_2 emissions change from energy consumption in Brazil: challenges and policy implications. Energy Policy 39, 1495–1504.

Glavic, P., Lukman, R., 2007. Review of sustainability terms and their definitions. J. Clean. Prod. 15, 1875–1885.

Hamzah, M.O., Jamshidi, A., Shahadan, Z., 2010. Evaluation of the potential of Sasobit® to reduce required heat energy and CO_2 emission in the asphalt industry. J. Clean. Prod. 18, 1859–1865.

IBGE – Instituto Brasileiro de Geografia e Estatística, 2011. Pesquisa Industrial Anual – Empresa. IBGE Available at: http://www.sidra.ibge.gov.br (accessed 04.05.11).

IEA – International Energy Agency, 2008. World Energy Outlook: Energy and Development. IEA Available at: http://www.iea.org/weo (accessed 10.07.12).

IPCC – Intergovernmental Panel on Climate Change, 1996. Greenhouse gas inventory reporting instructions – revised IPCC Guidelines for national greenhouse gas inventories. In: United Nations Environment Program, The Organization for Economic Co-operation and Development and the International Energy Agency, London.

IPCC – Intergovernmental Panel on Climate Change, 2007. Climate Change 2007: Mitigation. In: Metz, B., Davidson, O.R., Bosch, P.R., Dave, R., Meyer, L.A. (Eds.), Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Kalleberg, A.L., Reskin, B.F., Hudson, K., 2000. Bad jobs in America: standard and nonstandard employment relations and job quality in the United States. Am. Sociol. Rev. 65, 256–278.

Kolk, A., Pinkse, J., 2004. Market strategies for climate change. Eur. Manage. J. 22, 304–314.

Kuznetz, S., 1955. Economic growth and income inequality. Am. Econ. Rev. 45 (1.) .

Luken, R., Castellanos-Silveria, F., 2011. Industrial transformation and sustainable development in developing countries. Sustain. Dev. 19, 167–175.

Mao, J., Du, Y., Xu, L., Zeng, Y., 2011. Quantification of energy related industrial eco-efficiency of China. Front. Environ. Sci. Eng. China, http://dx.doi.org/10.1007/s11783-010-0289-8.

MCT – Ministério da Ciência e Tecnologia, 2006. Emissões de dióxido de carbono por queima de combustíveis: abordagem top-down. Available at: http://www.mct.gov.br (accessed 05.11.10)MCT.

Narodoslawsky, M., Niederl-Schmidinger, A., Halasz, L., 2008. Utilising renewable resources economically: new challenges and chances for process development. J. Clean. Prod. 16, 164–170.

Niu, S., Ding, Y., Niu, Y., Li, Y., Luo, G., 2011. Economic growth, energy conservation and emissions reduction: a comparative analysis based on panel data for 8 Asian-Pacific countries. Energy Policy 39 (4) 2121–2131.

Oggioni, G., Riccardi, R., Toninelli, T., 2011. Eco-efficiency of the world cement industry: a data envelopment analysis. Energy Policy 39, 2842–2854.

Paz, L.R.L., Silva, N.F., Rosa, L.P., 2007. The paradigm of sustainability in the Brazilian energy sector. Renew. Sustain. Energy Rev. 11, 1558–1570.

Ramanathan, R., 2006. A multi-factor efficiency perspective to the relationships among world GDP, energy consumption and carbon dioxide emissions. Technol. Forecast. Soc. Change 73, 483–494.

Scheneider, M., Romer, M., Tschudin, M., Bolio, H., 2011. Sustainable cement production – present and future. Cement Concrete Res. 41 (7) 642–650.

Sen, A., 1999. Development as a Freedom, first ed. Oxford University Press.

Silva, F.I.A., Guerra, S.M.G., 2009. Analysis of the energy intensity evolution in the Brazilian industrial sector – 1995 to 2005. Renew. Sustain. Energy Rev. 13 (9) 2589–2596.

Simões, A., La Rovere, E.L., 2008. Energy sources and global climate change: the Brazilian case. Energy Sources A: Recovery Util. Environ. Eff. 30, 1327–1344.

Smulders, S., Bretschger, L., Egli, H., 2011. Economic growth and the diffusion of clean technologies: explaining environmental Kuznets curves. Environ. Resour. Econ. 49, 79–99.

Tomasula, P.M., Nutter, D.W., 2011. Mitigation of greenhouse gas emissions in the production of fluid milk. Adv. Food Nutr. Res. 62, 41–88.

Tone, K., 2001. A slacks-based measure of efficiency in data envelopment analysis. Eur. J. Oper. Res. 130, 498–509.

Wernet, G., Mutel, C., Hellweg, S., Hungerbühler, K., 2011. The environmental importance of energy use in chemical production. J. Ind. Ecol. 15 (1) 96–107.

World Commission on Environment Development – WCED, 1987. Our Common Future. WCED, Oxford University Press, Oxford.

Yellishetty, M., Ranjith, P.G., Tharumarajah, A., 2010. Iron ore and steel production trends and material flows in the world: is this really sustainable? Resour. Conserv. Recycl. 54 (12) 1084–1094.

Zhang, B., Bi, J., Fan, Z., Yuan, Z., Ge, J., 2008. Eco-efficiency analysis of industrial system in China: a data envelopment analysis approach. Ecol. Econ. 68, 306–316.

Flávia de Castro Camioto is a Production Engineering PHD student at São Carlos' Engineering School, University of São Paulo.

Enzo Barbeiro Mariano is an assistant professor at the Production Engineering Department in Engineering School in Bauru, São Paulo State University. He holds PhD in Production Engineering from the Engineering School of São Carlos, University of São Paulo.

Daisy Aparecida do Nascimento Rebelatto is a Professor of Production Engineering at São Carlos' Engineering School, University of São Paulo.