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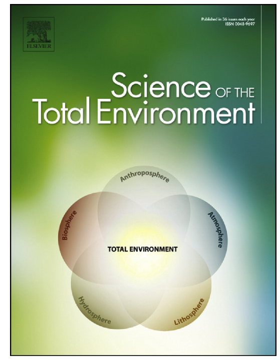

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Combined use of Data Envelopment Analysis and Life Cycle Assessment for operational and environmental benchmarking in the service sector: a case study of grocery stores

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Abstract

Ensuring sustainable production patterns doing more and better with less is a key sustainable development goal. In this sense, the joint use of Life Cycle Assessment and Data Envelopment Analysis (i.e., the LCA + DEA methodology) arises as a quantitative tool for the eco-efficiency assessment of multiple similar entities. To date, the LCA + DEA methodology has been widely applied to case studies within the primary and secondary sectors. However, the applicability of this combined methodology to case studies within the tertiary (service) sector is still unexplored, which constitutes a current knowledge gap in this field. This work contributes to filling this gap by benchmarking the operational and environmental performance of a sample of 30 groceries located in Spain. All the evaluated groceries were found to involve relative efficiency scores above 0.60, with one third of the groceries deemed fully efficient. Average reductions of 3-26% in the consumption of operational inputs were calculated, leading to average reductions of 9% in the carbon footprint and 10% in the energy footprint. Furthermore, economic savings of up to 3% of the annual turnover were estimated. These results were further enriched through the application of a super-efficiency DEA model for a refined identification of the best-performers, as well as through the novel use of a specific model for the gradual operational and environmental benchmarking of the sample. Overall, a high applicability of the LCA + DEA methodology for eco-efficiency assessment within the service sector is concluded, facilitating the identification and quantification of sustainable operational patterns.

Keywords: data envelopment analysis; efficiency; grocery; life cycle assessment; service sector; tertiary sector

1. Introduction

Global warming and its visible effects such as floods, droughts and heat waves are associated with growing social concerns. However, global energy-related CO_2 emissions increased in 2017 (+1.4%) after three years of stability, reaching a historic peak of 32.5 Gt (IEA, 2018). This trend was not global but some regions such as the European Union raised their emissions while others such as the United States of America and Japan were able to reduce them (Eurostat, 2018; IEA, 2018). In the case of Spain, the estimated emission of 338.8 Mt CO_2 eq for the year 2017 represents an increase of +4.4% with respect to the previous year, or +17.8% compared to 1990 (MITECO, 2018). Although the main rise with respect to 1990 is due to power generation, all major emitting sectors have experienced an increase in their emissions.

Within the greenhouse gas (GHG) emitting sectors in Spain, the commercial sector belongs to the SNAP (Selected Nomenclature for Air Pollution) category 02 of the Spanish inventory of GHG. The contribution of this sector to the national CO_2 emissions increased from 1.8% in 1990 to 4.8% in 2016, meaning the release of 10,794.8 kt CO_2 to the atmosphere in 2016. This trend is similar for other GHG emissions such as methane, with an increasing contribution of the commercial sector to the national CH_4 emissions (from 0.8% in 1990 to 5.9% in 2016) (MAPAMA, 2018). Thus, the commercial sector in Spain arises as a relevant source of GHG emissions, significantly contributing to the so-called diffuse emissions.

Within the commercial sector in Spain, grocery stores are among the most energy-intensive classes of buildings, thus being associated with high GHG emissions (Iyer et al., 2015). In this regard, the environmental performance of groceries should be thoroughly assessed. In particular, Life Cycle Assessment (LCA) is a standardised methodology to evaluate the environmental aspects and potential impacts of a product system (ISO, 2006a, 2006b). A high variability in the environmental impacts of grocery stores is expected because of the significant number of these facilities at the national level (Ríos and Roqueñí, 2018). Additionally, this variability may increase due to differences in the operational practices across the stores. In this sense, the link between operational and environmental performances is often measured through the concept of eco-efficiency, which refers to the delivery of competitively priced goods and services that satisfy human needs while progressively reducing environmental impacts and resource intensity throughout the entire life cycle to a level at least in line with the Earth's estimated carrying capacity (Schmidheiny, 1992).

Despite the relevance of life cycle-based methods to identify and evaluate the sources of environmental impact in a system, their utility as single approaches to eco-efficiency verification and operational performance analysis is weak. In fact, the combination of LCA with appropriate operational research tools is recommended to quantitatively verify the eco-efficiency of entities (Vázquez-Rowe and Iribarren, 2015). In particular, Data Envelopment Analysis (DEA) arises as a linear programming methodology that quantifies in an empirical manner the comparative productive efficiency of multiple similar entities (Cooper et al., 2007; Tone, 2017). For instance, DEA alone has been widely applied to evaluate the relative efficiency of multiple resembling entities within the service sector (Westermann, 1999; Avkiran, 2011). Furthermore, in the last years the combined use of LCA and DEA for the identification and quantification of the potential environmental consequences of operational inefficiencies has become a growing trend in the primary (e.g., agriculture) and secondary (e.g., construction and power generation) sectors (Vázquez-Rowe and Iribarren, 2015; Martín-Gamboa et al., 2017). However, there is a lack in the current LCA + DEA literature regarding its application to case studies in the tertiary sector.

Within this context, to the best of our knowledge, this article constitutes the first application of the LCA + DEA methodology to a case study in the service sector. This is done by addressing the eco-efficiency assessment and operational and environmental benchmarking of a set of Spanish groceries. When compared to other approaches, the use of LCA + DEA for eco-efficiency assessment is justified by its potential to (i) address a number of operational parameters affecting eco-efficiency (Lijó et al., 2017) as well as a multiple number of entities (Vázquez-Rowe et al., 2010), and (ii) quantify targets leading to sustainable operational patterns for those entities identified as currently inefficient (Vázquez-Rowe and Iribarren, 2015). Besides addressing the first case study within the tertiary sector, this article aims to provide new insights into the potential use of DEA models currently unexplored in the LCA + DEA field (Berlin and Iribarren, 2018).

2. Material and methods

2.1. Definition of the case study

The retail trade is set as a strategic area for economic growth and employment generation in Spain. In fact, the commercial sector represents 12% of the total gross domestic product of the Spanish economy, with the retail trade sub-sector meaning 5%. This sub-sector –excluding vehicles– accounted for 31% of the turnover and 56% of the personnel occupied in the commercial sector in 2017. In addition, 60% of the companies in the sector were retail stores (SEPE, 2018). Within this group, grocery stores are widely present in Spain as retail stores that primarily sell food. They can operate either as a single traditional grocery or as facilities belonging to a common company, the latter being the most widespread option at present.

Grocery stores within a company typically operate as a chain, being groceries the central element with tens to hundreds of facilities distributed across various locations. Given the relevance of groceries as a central element of the supply chain, they were selected herein as the decision making unit (DMU), i.e. the homogenous entity whose input/output conversion undergoes assessment (Cooper et al., 2007). A sample of 30 groceries was used in this study. These DMUs belong to the same company and are all located in the northwest of Spain. The reference year of the study is 2017.

Grocery stores typically are energy-intensive buildings since they involve many processes that require long operating times (e.g., heating, cooling, and lighting). Additionally, groceries are intensive in terms of material flows such as paper, plastic, and waste. Therefore, a laborious task of primary data collection was required in this study to include the main material and energy flows of each individual store. The LCA + DEA methodology, detailed later in Section 2.2, requires the quantification of a large number of input and output data for each DMU (Vázquez-Rowe and Iribarren, 2015; Martín-Gamboa et al., 2017). Fig. 1 shows the LCA and DEA elements taken into account in this work. The LCA study was limited to the operation of each grocery due to the environmental relevance of this specific phase. Accordingly, the selected LCA inputs include: electricity, paper (both ticket paper and wax paper), and plastic bags. The LCA output includes waste to treatment (mainly based on animal waste to incineration), while the system's function was set to be represented by the annual turnover of each grocery.

[Fig. 1. Representation of the unit of assessment: the grocery]

The DEA elements under assessment were selected based on their suitability within the methodological framework (Iribarren et al., 2016) and their expected environmental, economic and/or social relevance (Iribarren et al., 2011, 2013). In this respect, the direct communication with the managers of the groceries' company facilitated an appropriate selection of the relevant DEA elements. Thus, the selected DEA elements include all the above-mentioned LCA inputs and outputs (i.e., electricity, ticket paper, wax paper, plastic bags, waste, and turnover) and, additionally, labour. It should be noted that the inclusion of labour –expressed in terms of working hours– enriches the analysis by providing a socio-economic perspective (Iribarren and Vázquez-Rowe, 2013). Finally, the choice of annual turnover as the DEA output is widely supported by the scientific literature (Westermann, 1999; Avkiran, 2011).

2.2. LCA + DEA framework

The goal of the study is to determine the relative operational efficiency of 30 groceries and quantify operational and environmental benchmarks based on the optimisation of their operational performance. In this regard, the application of the combined LCA + DEA methodology allows analysts to systematically assess the operational performance across stores and identify those with a higher potential for material and energy savings. To date, two main LCA + DEA strategies have been defined: the three- and the five-step LCA + DEA method (Martín-Gamboa et al., 2017). For the case study of groceries, the five-step LCA + DEA approach was selected due to advantages in terms of methodological robustness (Iribarren et al., 2013; Vázquez-Rowe and Iribarren, 2015). This method processes information on material and energy flows and socio-economic aspects to a sustainability outcome via the computation of consistent operational, socio-economic and environmental benchmarks associated with the optimised performance of the DMUs (Iribarren et al., 2016).

Fig. 2 shows the five-step LCA + DEA method applied to the case study of groceries. The first step refers to the collection of data regarding material and energy flows and socio-economic aspects. This step results in the life cycle inventories (LCIs) of each of the groceries. In a second step, these LCIs were used to carry out the life cycle impact assessment (LCIA), thus obtaining the current environmental profile of each grocery.

In the third step, the DEA computation of the sample of DMUs was carried out. This was done using the most relevant data from the first step. This DEA step provides relative efficiency scores (Φ) as well as quantitative operational and socio-economic benchmarks for the entities deemed inefficient. Efficiency scores allow distinguishing comparatively efficient facilities ($\Phi = 1$) from inefficient entities ($\Phi < 1$), while benchmarks are defined as target values that turn inefficient DMUs into efficient entities. In this sense, target groceries were defined by operational reduction percentages that show the desired reduction in current input levels while performing the same economic function (i.e., maintaining the annual turnover). Efficiency scores and target DMUs were calculated by solving an optimisation model with a set of key features regarding orientation, and display of the production possibility set. The specific DEA model and the key features selected are detailed later in Section 3.3.

The operational benchmarks calculated in the third step to define the target groceries involve a modification of the LCI of each inefficient entity. Hence, the fourth step addresses the LCIA of the DMUs modified according to the new inventory data. Thus, this step means the computation of environmental benchmarks for the inefficient groceries.

The final step involves the interpretation of the results from the previous steps. In this respect, the presence of two LCIA blocks (steps 2 and 4) is linked to the use of the method for eco-efficiency verification, i.e. proving that minimising resource intensity leads to environmental impact reductions while performing the same service (Iribarren et al., 2010). Furthermore, the operational benchmarks obtained in step 3 were translated into economic savings as another outcome of the study (Iribarren and Martín-Gamboa, 2014). As recommended in Iribarren et al. (2013), it should be noted that the interpretation of the socio-economic benchmarks (i.e., reduced working hours) needs to be carefully addressed. In this regard, the analysis facilitates the identification of useless hours that should be reallocated to activities such as training, which would indirectly result in future socio-economic benefits. Overall, the calculation of socio-economic benchmarks along with the operational and environmental ones enables a joint interpretation of the results from a sustainability perspective (Iribarren et al., 2016).

[Fig. 2. Representation of the five-step LCA +DEA method followed for the analysis of groceries]

3. Results

This section presents the results from the application of the proposed LCA + DEA method to the case study of grocery stores. For the sake of clarity, the section was structured following the methodological steps defined in Section 2.2.

3.1. Step 1: inventory data

Data availability is a critical point in LCA + DEA studies (Iribarren et al., 2016). In this work, a specific survey was prepared to collect data directly from the managers of the groceries' company. The use of primary data from this survey reduces the uncertainty associated with the results and thereby increases the reliability of the study. Regarding the LCA component, inventory data for background processes were retrieved from the ecoinvent database (Weidema et al., 2013). Table 1 presents the data collected through the survey, which refer to one year of operation of the groceries (year 2017).

[Table 1. Annual data collected for the sample of groceries]

For the reference year, the average turnover of the sample of groceries was 407 k€, with a maximum turnover of 760 k€ (found for Grocery11). The coefficient of variation (or relative standard deviation, RSD) associated with the inputs of the sample ranges between 20% and 46%. The observed data variability hinders the direct identification of the most efficient entities in terms of operational performance. Therefore, the use of DEA becomes an appropriate solution for such a purpose (Section 3.3).

3.2. Step 2: current environmental characterisation

The LCIA of each grocery was carried out through the implementation of the inventories in SimaPro 8 (Goedkoop et al., 2016). Four environmental impact potentials were evaluated: global warming (GWP), cumulative non-renewable energy demand (CED_{nr}), acidification (AP), and eutrophication (EP). GWP and CED_{nr} were evaluated according to the Intergovernmental Panel on Climate Change (IPCC, 2013) and Verein Deutscher Ingenieure (VDI, 2012), respectively. On the other hand, acidification and eutrophication were evaluated using the CML method (Guinée et al., 2001). Since GWP and CED_{nr} are life-cycle indicators of special interest when addressing the operational stage of groceries (Iyer et al., 2015; Seebauer et al., 2016), and according to the managers' preferences, the focus was placed on these two indicators throughout the main manuscript, while the results for AP and EP are included in the appendix .

Fig. 3 shows the environmental characterisation results of each grocery. The average GWP and CED_{nr} values for the reference year were 26 t CO_2 eq and 600 GJ, respectively. As shown in Fig. 3, similar trends were found for GWP and CED_{nr} due to the high correlation usually found between these life-cycle indicators (Valente et al., 2018).

[Fig. 3. Current environmental characterisation of the sample of groceries (annual impacts)]

3.3. Step 3: DEA performance

DEA was performed using the most relevant inputs and outputs of the DMUs according to the managers' preferences. The DEA matrix corresponds to Table 1. In order to compute the efficiency scores and the operational benchmarks, the DEA matrix was implemented in an optimisation model solved through the software DEA-Solver Pro (Saitech, 2019). The specific DEA model used in this work is an input-oriented slacks-based measure of efficiency (SBM-I) model with variable returns to scale (VRS) (Tone et al., 2001). The choice of non-radial metrics and input orientation is in accordance with the objectives of the study, and further supported by previous studies (Martín-Gamboa et al., 2017).

Table 2 presents the efficiency scores computed for the groceries under assessment, as well as their operational and socio-economic benchmarks (expressed as target reduction percentages relative to current values in Table 1). The DEA output (i.e., turnover) is not included in Table 2 since it was kept unaltered (input-oriented model). One third of the sample (i.e., 10 out of 30 grocery stores) was found to operate efficiently ($\Phi = 1$). In fact, efficiency scores above 0.6 were found for all the evaluated groceries. Hence, the analysis suggests a relatively good performance of the whole sample for the reference year. Nevertheless, while efficient groceries involve by definition 0% reduction targets, the groceries deemed inefficient ($\Phi < 1$) were found to be associated with significant reduction targets. The average reduction percentages for the reference year range between 3% (for electricity) and 26% (for wax paper). Concerning the reduction in working hours, it should be interpreted as a virtual means towards the redefinition of tasks (Iribarren and Vázquez-Rowe, 2013; Iribarren et al., 2013).

[Table 2. Efficiency scores (Φ) and operational and socio-economic reduction targets (%) for the sample of groceries]

3.4. Step 4: target environmental characterisation

The operational benchmarks defined in the previous step entail modifications in the LCIs of the inefficient groceries. Table 3 presents the characterisation results (environmental benchmarks) of the target groceries expressed as impact reduction percentages relative to the values in Fig. 3. It should be noted that currently-efficient groceries involve 0% impact reductions since their target and current operating points are identical. On the other hand, the highest impact reductions (33% for both GWP and CED_{nr}) were found for Grocery23. The average environmental impact reduction percentages are 9% for GWP and 10% for CED_{nr}. Similar reduction percentages were found for each grocery in terms of GWP and CED_{nr} due to the high correlation between these indicators (Valente et al., 2019).

[Table 3. Impact reduction targets (%) for the sample of groceries]

3.5. Step 5: interpretation

According to the eco-efficiency concept (Schmidheiny, 1992), reductions in resource consumption should lead to environmental impact reductions. The LCA + DEA methodology has often been used to quantitatively verify this hypothesis (Iribarren et al., 2013). In this sense, the link between the average reductions in the DEA inputs (from 3% for electricity to 26% for wax paper) and the resultant average reduction in the environmental impacts (9% for GWP and 10% for CED_{nr}) proves the eco-efficiency concept in a quantitative way.

Furthermore, Table 4 presents the estimation of the potential economic savings linked to the attainment of the operational benchmarks set for each grocery. These values were calculated for the reference year taking into account the economic prices of the operational inputs directly provided by the company's managers. No economic saving was attributed to the socio-economic benchmark since working hours are not reduced, but reallocated in areas such as training (Iribarren and Vázquez-Rowe, 2013; Iribarren et al., 2013). The total annual savings for the inefficient DMUs were found to range from 777 € to 8.3 k€, with an average annual saving of 2.7 k€ for the whole sample. In other words, economic savings up to 3% of the grocery's turnover were found for the reference year.

[Table 4. Annual economic savings (€) linked to the accomplishment of operational targets]

4. Further interpretation of the results

The results from the novel application of the LCA + DEA methodology to the case study of grocery stores was enriched through the use of additional DEA models (Martín-Gamboa et al., 2017). In particular, Section 4 addresses the use of specific models for the gradual benchmarking of the grocery stores in terms of continuous improvement (Section 4.1) and the refined identification of the best-performers (Section 4.2).

4.1. Application of the SBM-Max model

The SBM model used so far in this study evaluates the efficiency of DMUs referring to the furthest efficient frontier point within a range (Tone, 2001). This results in DMU projections that may be excessively ambitious as target values. In this regard, the SBM-Max model (Tone, 2016) has recently been proposed as an alternative approach to the conventional SBM model (also named SBM-Min). The SBM-Max model uses a standard linear programming code to find approximate solutions for the closest reference point on the efficient frontiers so that slacks are minimised and scores are maximised (Tone, 2017). Thus, when compared to the application of the SBM-Min model, inefficient DMUs would turn efficient under lower input reduction targets.

While the use of the SBM-Min model arises as a common choice in current LCA + DEA literature (Vázquez-Rowe and Iribarren, 2015; Martín-Gamboa et al., 2017), the use of the SBM-Max model is still unexplored (Berlin and Iribarren, 2018). Hence, this section presents a novel LCA + DEA potential based on the additional use of the SBM-Max model: the computation of progressive operational and environmental benchmarks for continuous improvement. For this purpose, the third step of the five-step LCA + DEA method detailed in Section 2.2 was redone by implementing the DEA matrix (Table 1) in an input-oriented SBM-Max model with VRS solved through DEA-Solver Pro (Saitech, 2019).

Fig. 4 shows the efficiency scores obtained when applying the SBM-Max model (the scores from the previous application of the SBM-Min are also included for comparative purposes). As a result, 12 out of 30 grocery stores were identified as efficient DMUs. In fact, all the evaluated groceries were found to score above 0.7, with more than half of the sample (17 groceries) accounting for efficiency scores above 0.9. The average efficiency score of the sample is 0.91.

[Fig. 4. Efficiency scores from the application of SBM-Min and SBM-Max models]

As expected, all the efficiency scores calculated under the SBM-Max model are equal or greater than those calculated under the SBM-Min model (Fig. 4), while the average reduction in DEA inputs is generally lower when using the SBM-Max model (Fig. 5). In this regard, the application of the SBM-Max model leads to average operational reductions ranging from 3% (waste) to 13% (wax paper). Therefore, inefficient groceries could turn efficient with lower input reduction targets than those from the application of the SBM-Min model. The combination of the reduction targets from both SBM models leads to set ranges of operational (and subsequently environmental) benchmarks for continuous improvement by using the lowest reduction values as short-term benchmarks and the highest (i.e., most ambitious) values as mid/long-term benchmarks. Overall, this novel approach was found to be feasible and useful for the gradual benchmarking of multiple resembling entities. At the company level, this would facilitate environmental management by providing a robust framework for the quantification of continuous improvement targets (Berlin and Iribarren, 2018).

[Fig. 5. Average reduction in DEA inputs from the application of SBM-Min and SBM-Max models]

4.2. Super-efficiency analysis

Given the relatively high number of groceries deemed efficient (Section 3.3), a super-efficiency analysis was also carried out in order to refine the identification of the best-performing grocery stores (Iribarren et al., 2010). The implementation of super-efficiency DEA models is highly recommended within this context, ranking efficient DMUs by assigning an efficiency score greater than 1. In particular, an input-oriented slacks-based measure of super-efficiency (Super-SBM-I) model with VRS was used herein for the discrimination between efficient entities (Tone, 2002).

Table 5 presents the super-efficiency scores calculated for the efficient DMUs through DEA-Solver Pro (Saitech, 2019). Two outstanding efficient groceries were identified: Grocery15 and Grocery8, with super-efficiency scores above 1.35. These specific groceries are associated with relatively low operational consumption and relatively high annual turnover. These best-performers could be taken as reference groceries in order to propose benchmarks for the performance of similar entities (Iribarren et al., 2010). In this sense, these results might complement those from the SBM-Max model when it comes to setting long-term targets.

[Table 5. Super-efficiency scores (Φ_S) for the sample of efficient groceries]

Overall, the results in Sections 3 and 4 show the high applicability of the LCA + DEA methodology to case studies within the tertiary sector. This was found to be in line with the sustainable development goals (SDGs) defined by the United Nations (2015). In particular, this type of methodological approach highly contributes to SDG 12, which refers to ensuring sustainable production patterns by “doing more and better with less”, i.e. achieving net welfare gains from economic activities by reducing resource use, degradation and pollution along the whole life cycle. Moreover, other SDGs are positively affected, e.g. SDG 13 on climate change mitigation.

Regarding policy implications, the application of this type of methodological approach to case studies within the tertiary sector is expected to play a significant role in plans and policies at the company level, especially when it comes to defining performance benchmarks. This is particularly relevant to the SDG target 12.6, which encourages companies to adopt sustainable practices and integrate sustainability information into their reporting cycle. Nevertheless, national policy-makers could also benefit from this type of methodological solution to set threshold values for the sustainable management and efficient use of resources in the service sector.

5. Conclusions

The LCA + DEA methodology proved to be a useful tool to evaluate and benchmark the operational and environmental performance of groceries as an illustrative case study within the tertiary sector. Overall, a high applicability of the LCA + DEA methodology to the service sector is concluded. Regarding the specific case study, a relatively good operational and environmental performance of the set of groceries is concluded, with all of them involving efficiency scores above 0.6 and a third of them being deemed efficient. Average reductions of 3-26% in the consumption of operational inputs were benchmarked, leading to average impact reductions of 9% in terms of carbon footprint and 10% in terms of non-renewable energy footprint, thus quantitatively verifying the eco-efficiency concept.

This study also proved the feasibility of using the SBM-Max model within the LCA + DEA framework as a useful tool for gradual multi-dimensional benchmarking of resembling entities for the sake of continuous improvement. This led to the complementary benchmarking of less ambitious reduction targets regarding the consumption of operational inputs in the evaluated grocery stores (3-13%). This outcome was further enriched through the identification of two best-performing groceries through a super-efficiency analysis. Overall, the LCA + DEA methodology showed high potential in supporting decision-makers such as company managers when it comes to setting robust targets for the operational and environmental improvement of grocery stores within the service sector.

Appendix

Table A.1 presents the LCA + DEA results for each grocery store in terms of current and target acidification and eutrophication impacts.

[Table A.1. Current and target acidification (kg SO_2 eq) and eutrophication (kg PO_4^{3-} eq) annual impacts for the sample of groceries]

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Fig. 4. Efficiency scores from the application of SBM-Min or SBM-Max models.

Fig. 5. Average reduction in DEA inputs from the application of SBM-Min and SBM-Max models.

Table 1. Annual data collected for the sample of groceries.

DMU code	Electricity (kWh)	Ticket paper (kg)	Wax paper (kg)	Plastic bags (kg)	Waste (kg)	Working hours (h)	Turnover (€)
Grocery1	43,373	18	1040	572	4650	4800	173,900
Grocery2	43,373	27	1560	853	7750	5760	293,000
Grocery3	65,060	36	1560	1196	10,850	5760	360,000
Grocery4	66,506	37	2080	1146	13,020	6720	435,000
Grocery5	70,843	54	2600	2325	19,220	7680	582,500
Grocery6	52,048	55	1664	2192	12,710	7680	406,000
Grocery7	43,373	26	1040	1415	8060	3840	257,000
Grocery8	57,831	20	1560	598	9300	7680	328,300
Grocery9	46,265	36	1820	1145	10,850	5760	376,300
Grocery10	66,506	37	2600	1529	18,600	8640	626,300
Grocery11	60,000	38	2600	1938	26,350	9600	759,800
Grocery12	61,446	36	1560	1550	15,500	6720	509,000
Grocery13	45,542	22	624	763	4650	3840	214,000
Grocery14	60,723	36	1300	912	9300	5760	382,000
Grocery15	75,181	29	1404	1240	7440	6720	554,800
Grocery16	59,277	36	1560	1240	18,600	6720	653,000
Grocery17	75,181	40	2080	1647	18,600	9600	662,000
Grocery18	65,060	54	2080	2418	10,540	6720	409,000
Grocery19	75,181	54	2080	1938	13,640	6720	526,000
Grocery20	72,289	63	2600	2116	12,400	7680	478,000
Grocery21	60,723	72	3120	2325	14,260	8640	553,000
Grocery22	43,373	36	1560	1116	9920	6720	319,500
Grocery23	62,169	27	2080	858	5580	4800	202,900
Grocery24	46,988	22	1040	687	4650	3840	177,500
Grocery25	57,831	45	2080	1516	9920	6720	371,400
Grocery26	59,277	54	3120	2325	9920	5760	358,200

Grocery27	40,482	18	780	572	3720	3840	166,400
Grocery28	40,482	45	2080	1860	8680	5760	336,400
Grocery29	43,373	27	1040	954	8990	5760	343,000
Grocery30	54,940	45	2080	1824	10,230	6720	398,600

Table 2. Efficiency scores (Φ) and operational and socio-economic reduction targets (%) for the sample of groceries.

DMU code	Φ	Electricity (%)	Ticket paper (%)	Wax paper (%)	Plastic bag (%)	Waste (%)	Working hours (%)
Grocery1	1.00	0.00	0.00	0.00	0.00	0.00	0.00
Grocery2	0.89	0.00	11.34	37.74	4.19	2.90	12.60
Grocery3	0.74	11.19	35.05	30.06	24.30	48.62	8.41
Grocery4	0.75	3.05	30.64	41.75	9.78	51.67	13.22
Grocery5	0.68	0.21	42.91	44.31	46.67	44.91	12.50
Grocery6	0.68	0.00	49.38	37.81	55.55	17.08	33.38
Grocery7	1.00	0.00	0.00	0.00	0.00	0.00	0.00
Grocery8	1.00	0.00	0.00	0.00	0.00	0.00	0.00
Grocery9	0.85	0.00	25.13	39.41	17.64	7.27	2.78
Grocery10	0.81	4.37	9.08	41.63	18.92	16.31	22.22
Grocery11	1.00	0.00	0.00	0.00	0.00	0.00	0.00
Grocery12	0.83	0.00	17.01	18.48	27.67	27.76	10.69
Grocery13	1.00	0.00	0.00	0.00	0.00	0.00	0.00
Grocery14	0.87	9.12	31.05	13.38	0.00	17.50	7.91
Grocery15	1.00	0.00	0.00	0.00	0.00	0.00	0.00
Grocery16	1.00	0.00	0.00	0.00	0.00	0.00	0.00
Grocery17	0.87	17.51	10.87	14.56	14.83	0.00	23.01
Grocery18	0.63	3.93	52.37	48.54	57.16	40.74	18.34
Grocery19	0.71	3.33	47.79	35.67	38.08	47.18	3.62
Grocery20	0.62	5.49	57.68	50.75	47.63	45.93	19.92
Grocery21	0.67	0.00	56.47	55.13	51.01	6.43	27.26
Grocery22	0.80	0.00	29.00	35.41	20.30	16.32	19.36
Grocery23	0.69	29.64	29.57	59.68	26.02	27.07	14.36
Grocery24	0.87	11.34	12.78	28.50	10.19	15.34	0.00
Grocery25	0.68	0.00	46.94	46.67	39.42	38.68	20.66

Grocery26	0.60	2.80	56.79	65.12	61.20	43.98	8.64
Grocery27	1.00	0.00	0.00	0.00	0.00	0.00	0.00
Grocery28	1.00	0.00	0.00	0.00	0.00	0.00	0.00
Grocery29	1.00	0.00	0.00	0.00	0.00	0.00	0.00
Grocery30	0.71	0.00	43.12	44.59	49.08	16.45	20.00

Table 3. Impact reduction targets (%) for the sample of groceries.

DMU code	GWP	CED_{nr}
Grocery1	0.00	0.00
Grocery2	5.31	4.69
Grocery3	14.65	14.72
Grocery4	8.92	7.97
Grocery5	13.16	15.39
Grocery6	14.15	18.56
Grocery7	0.00	0.00
Grocery8	0.00	0.00
Grocery9	7.44	7.62
Grocery10	11.17	11.08
Grocery11	0.00	0.00
Grocery12	5.52	6.81
Grocery13	0.00	0.00
Grocery14	8.95	8.34
Grocery15	0.00	0.00
Grocery16	0.00	0.00
Grocery17	16.56	16.69
Grocery18	17.78	21.32
Grocery19	11.39	12.85
Grocery20	17.14	18.97
Grocery21	16.89	19.67
Grocery22	7.09	7.53
Grocery23	33.15	32.39
Grocery24	12.77	12.44
Grocery25	11.06	12.45
Grocery26	22.75	25.67

Grocery27	0.00	0.00
Grocery28	0.00	0.00
Grocery29	0.00	0.00
Grocery30	12.93	15.81

Table 4. Annual economic savings (€) linked to the accomplishment of operational targets.

DMU code	Electricity	Ticket paper	Wax paper	Plastic bag	Waste management	Total savings
Grocery1	0.00	0.00	0.00	0.00	0.00	0.00
Grocery2	0.00	35.63	588.80	129.74	22.49	776.67
Grocery3	1281.72	146.82	468.96	1052.60	527.57	3477.68
Grocery4	356.92	130.93	868.47	405.53	672.74	2434.59
Grocery5	26.17	269.62	1152.00	3934.96	863.20	6245.95
Grocery6	0.00	315.44	629.23	4410.67	217.02	5572.37
Grocery7	0.00	0.00	0.00	0.00	0.00	0.00
Grocery8	0.00	0.00	0.00	0.00	0.00	0.00
Grocery9	0.00	106.32	717.19	729.52	78.85	1631.88
Grocery10	511.25	39.54	1082.42	1047.86	303.43	2984.50
Grocery11	0.00	0.00	0.00	0.00	0.00	0.00
Grocery12	0.00	71.25	288.25	1552.68	430.34	2342.52
Grocery13	0.00	0.00	0.00	0.00	0.00	0.00
Grocery14	974.54	130.10	173.95	0.00	162.76	1441.34
Grocery15	0.00	0.00	0.00	0.00	0.00	0.00
Grocery16	0.00	0.00	0.00	0.00	0.00	0.00
Grocery17	2316.23	50.09	302.80	885.87	0.00	3554.98
Grocery18	450.45	329.10	1009.70	5017.84	429.36	7236.45
Grocery19	440.82	300.33	741.92	2675.75	643.58	4802.40
Grocery20	698.65	422.84	1319.39	3658.99	569.56	6669.42
Grocery21	0.00	473.17	1719.92	4300.91	91.63	6585.63
Grocery22	0.00	121.48	552.34	818.13	161.85	1653.80
Grocery23	3242.96	92.92	1241.36	807.05	151.04	5535.34
Grocery24	937.38	32.12	296.38	252.78	71.31	1589.98
Grocery25	0.00	245.83	970.72	2161.62	383.70	3761.87

Grocery26	292.19	356.87	2031.86	5160.64	436.30	8277.86
Grocery27	0.00	0.00	0.00	0.00	0.00	0.00
Grocery28	0.00	0.00	0.00	0.00	0.00	0.00
Grocery29	0.00	0.00	0.00	0.00	0.00	0.00
Grocery30	0.00	225.81	927.40	3231.17	168.26	4552.65

Table 5. Super-efficiency scores (Φ_S) for the sample of efficient groceries.

DMU code	$\mathbf{\Phi_S}$
Grocery15	1.47
Grocery8	1.36
Grocery7	1.18
Grocery16	1.17
Grocery27	1.13
Grocery13	1.10
Grocery11	1.09
Grocery28	1.06
Grocery29	1.05
Grocery1	1.04

Table A.1. Current and target acidification (kg SO_2 eq) and eutrophication (kg PO_4^{3-} eq) annual impacts for the sample of groceries.

DMU code	Acidification			Eutrophication		
	Current	**Target**	**Reduction (%)**	**Current**	**Target**	**Reduction (%)**
Grocery1	108.88	108.88	0.00	23.89	23.89	0.00
Grocery2	115.94	110.57	4.63	26.81	24.50	8.63
Grocery3	166.46	143.40	13.85	37.02	30.65	17.21
Grocery4	174.15	160.16	8.03	40.09	34.21	14.68
Grocery5	197.62	178.07	9.90	46.22	38.93	15.77
Grocery6	146.30	131.80	9.91	33.04	29.26	11.43
Grocery7	115.47	115.47	0.00	25.28	25.28	0.00
Grocery8	146.06	146.06	0.00	33.14	33.14	0.00
Grocery9	127.18	119.41	6.11	29.99	26.93	10.21
Grocery10	182.34	164.07	10.02	43.67	37.40	14.34
Grocery11	172.39	172.39	0.00	43.05	43.05	0.00
Grocery12	161.89	155.57	3.90	36.84	34.41	6.60
Grocery13	111.42	111.42	0.00	23.37	23.37	0.00
Grocery14	152.45	138.47	9.17	33.63	30.20	10.21
Grocery15	186.92	186.92	0.00	39.90	39.90	0.00
Grocery16	155.54	155.54	0.00	36.47	36.47	0.00
Grocery17	197.70	164.55	16.77	45.46	38.56	15.18
Grocery18	179.54	154.62	13.88	39.75	32.83	17.43
Grocery19	198.91	180.54	9.23	44.49	38.50	13.45
Grocery20	198.11	169.76	14.31	45.07	36.25	19.57
Grocery21	179.11	155.62	13.11	42.74	35.12	17.83
Grocery22	118.24	111.55	5.66	27.54	24.88	9.66
Grocery23	161.20	108.30	32.82	36.23	23.18	36.01
Grocery24	117.62	102.78	12.62	25.50	21.90	14.14
Grocery25	157.22	143.86	8.49	35.93	30.87	14.07
Grocery26	175.05	143.00	18.31	41.03	30.56	25.51
Grocery27	100.15	100.15	0.00	21.45	21.45	0.00
Grocery28	121.41	121.41	0.00	28.49	28.49	0.00
Grocery29	112.41	112.41	0.00	25.21	25.21	0.00
Grocery30	153.10	138.44	9.58	34.97	30.42	13.03
Average	153.03	140.17	7.68	34.88	30.99	10.17

Combined use of Data Envelopment Analysis and Life Cycle Assessment for operational and environmental benchmarking in the service sector: a case study of grocery stores

Cristina Álvarez-Rodríguez, Mario Martín-Gamboa, Diego Iribarren

Research highlights

- ✓ Joint Life Cycle Assessment and Data Envelopment Analysis of 30 groceries in Spain
- ✓ Efficiency scores suggest a relatively good performance of the sample
- ✓ Refined identification of best-performers though super-efficiency analysis
- ✓ Novel use for the calculation of gradual operational and environmental benchmarks
- ✓ Proven applicability of the combined methodology to the service sector

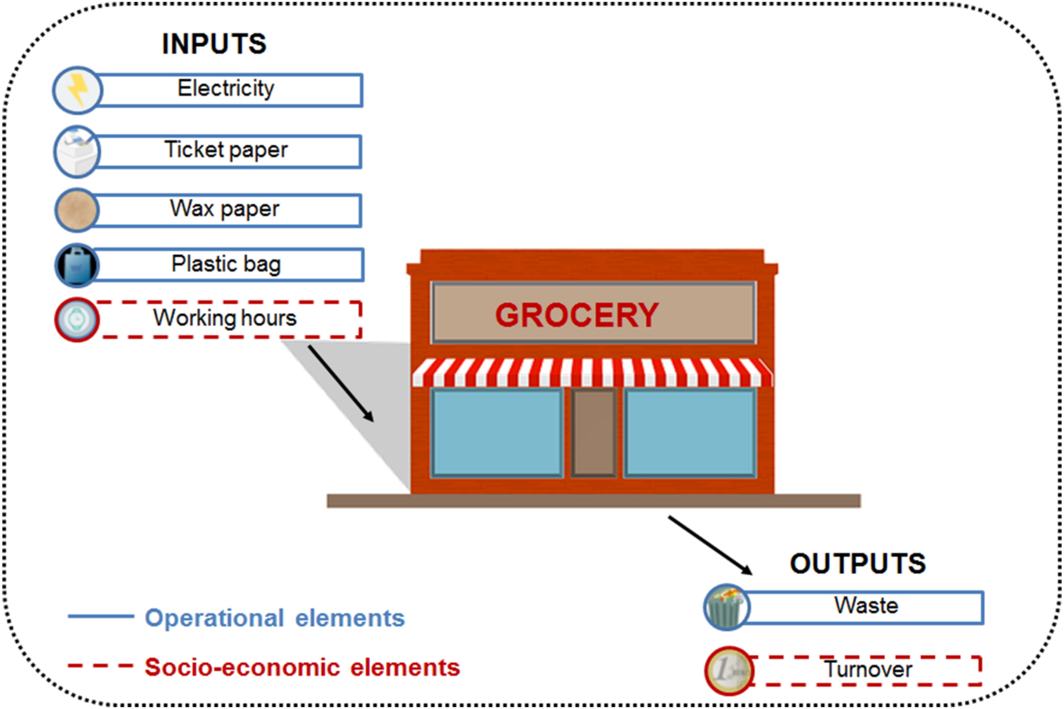

INPUTS
Electricity
Ticket paper
Wax paper
Plastic bag
Working hours
GROCERY
OUTPUTS
Waste
Turnover
Operational elements
Socio-economic elements

Figure 1

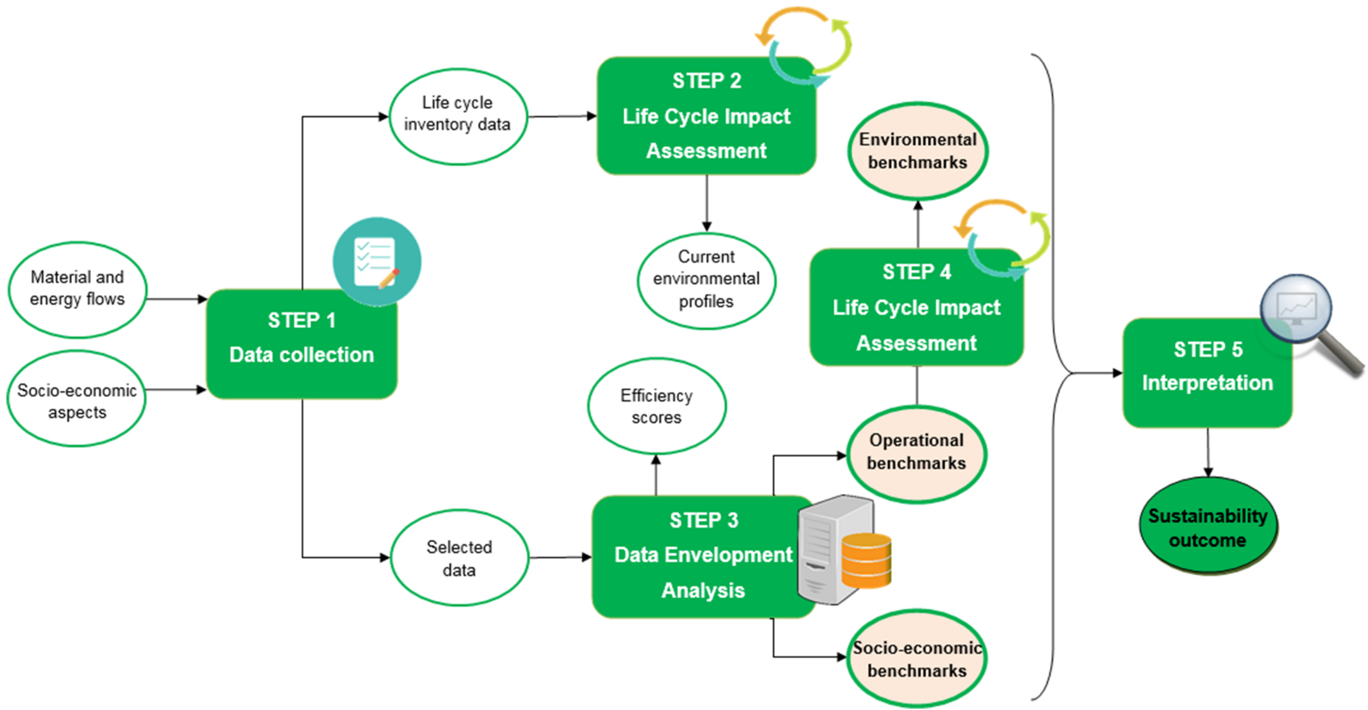
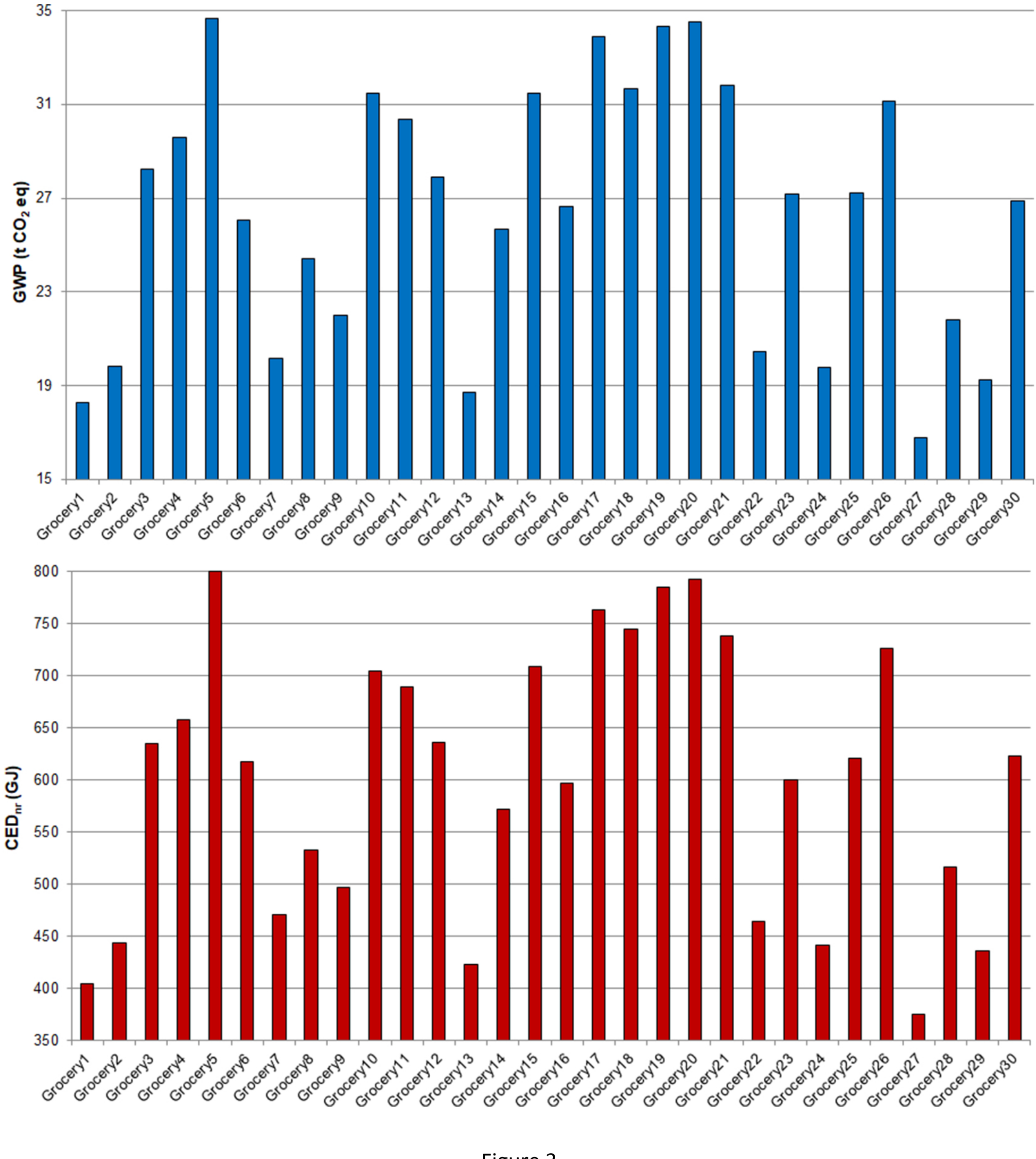

Material and energy flows
Socio-economic aspects
STEP 1
Data collection
Life cycle inventory data
STEP 2
Life Cycle Impact Assessment
Current environmental profiles
Selected data
STEP 3
Data Envelopment Analysis
Efficiency scores
Environmental benchmarks
STEP 4
Life Cycle Impact Assessment
Operational benchmarks
Socio-economic benchmarks
STEP 5
Interpretation
Sustainability outcome

Figure 2


GWP (t CO2 eq)
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23
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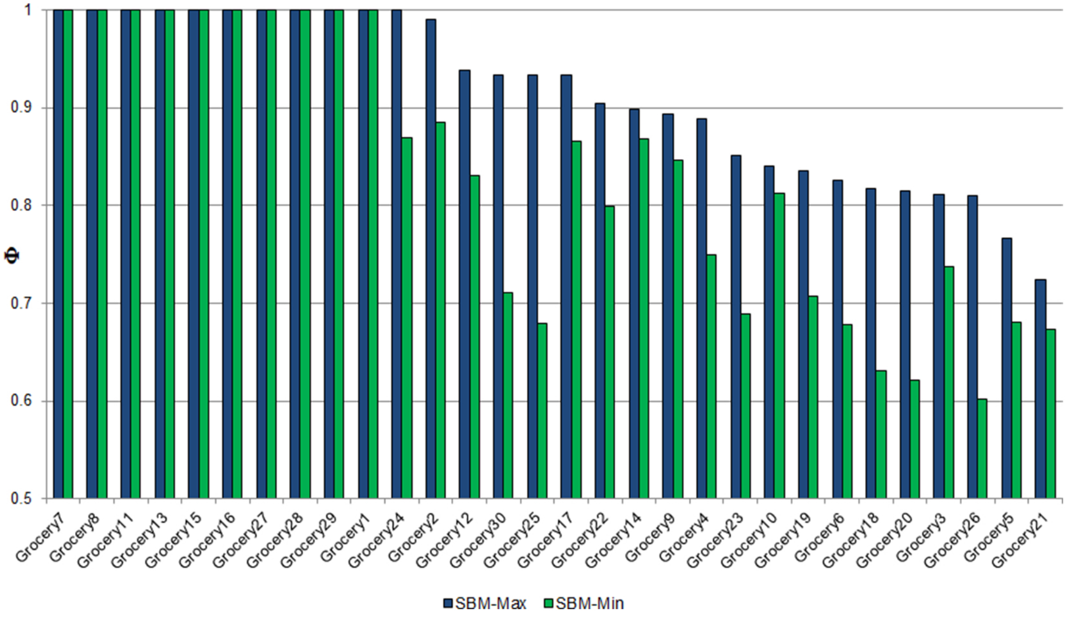
15
Grocery1 Grocery2 Grocery3 Grocery4 Grocery5 Grocery6 Grocery7 Grocery8 Grocery9 Grocery10 Grocery11 Grocery12 Grocery13 Grocery14 Grocery15 Grocery16 Grocery17 Grocery18 Grocery19 Grocery20 Grocery21 Grocery22 Grocery23 Grocery24 Grocery25 Grocery26 Grocery27 Grocery28 Grocery29 Grocery30
CEDnr (GJ)
800
750
700
650
600
550
500
450
400
350
Grocery1 Grocery2 Grocery3 Grocery4 Grocery5 Grocery6 Grocery7 Grocery8 Grocery9 Grocery10 Grocery11 Grocery12 Grocery13 Grocery14 Grocery15 Grocery16 Grocery17 Grocery18 Grocery19 Grocery20 Grocery21 Grocery22 Grocery23 Grocery24 Grocery25 Grocery26 Grocery27 Grocery28 Grocery29 Grocery30

Figure 3



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0.8
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Φ
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Grocery13
Grocery15
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Grocery23
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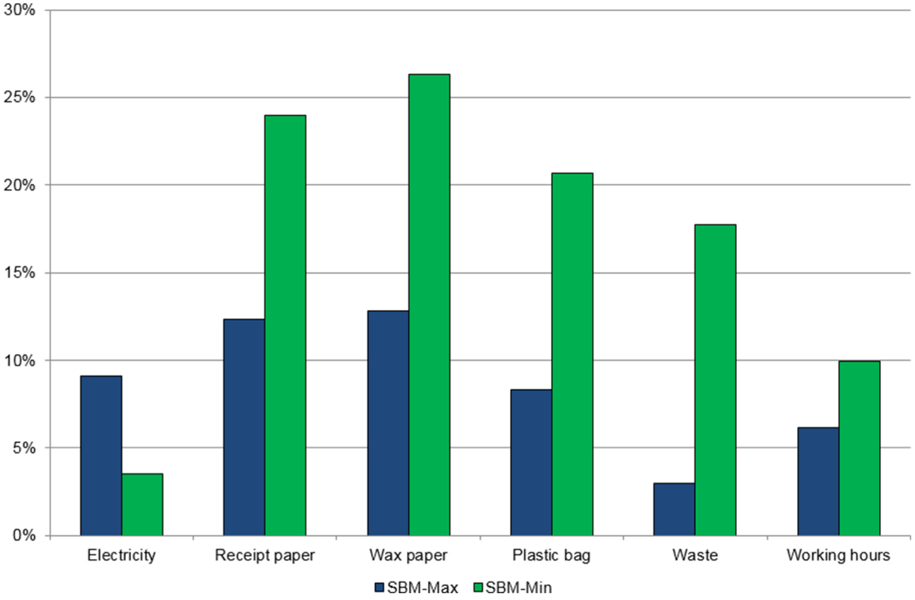
Grocery21
SBM-Max
SBM-Min

Figure 4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25%
20%
15%
10%
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Electricity
Receipt paper
Wax paper
Plastic bag
Waste
Working hours
SBM-Max
SBM-Min

Figure 5