METHODOLOGY FOR SETTING CORPORATE SUSTAINABILITY TARGETS

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METODOLOGIA PARA A DEFINIÇÃO DE METAS DE SUSTENTABILIDADE EMPRESARIAL

Rodrigo Gomes Távora Maia

Março/2022

Orientadores: Amaro Olimpio Pereira Junior
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Estabelecer metas de sustentabilidade realistas e desafiadoras é um passo importante para motivar mudanças e orientar empresas a contribuírem significativamente para o desenvolvimento sustentável e para sucesso dos Objetivos de Desenvolvimento Sustentável (ODS) definidos na Agenda 2030. No entanto, além de barreiras acerca do conceito de sustentabilidade e sua universalização e materialização, existem poucas ferramentas para estabelecer tais metas e, as disponíveis, geralmente são sobre temas específicos. Portanto, essa dissertação desenvolve uma metodologia para estabelecer metas de sustentabilidade empresarial, sem restrição temática, baseada na integração de métodos de Pesquisa Operacional de Análise Envoltória de Dados, Análise de Agrupamentos, previsão de séries temporais e Programação por Metas. É apresentada a aplicação da metodologia para uma empresa do setor elétrico brasileiro e as suas nove unidades de negócio na definição metas de consumo de energia e água, relacionadas com os ODS 6, 7, 8 e 12.

Abstract of Dissertation presented to COPPE/UFRJ as a partial fulfillment of the requirements for the degree of Master of Science (M.Sc.)

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Setting realistic but challenging sustainability targets is critical for motivating business plan changes and guiding corporations toward meaningful contributions to sustainable development and the 2030 Agenda for Sustainable Development Goals (SDGs). However, aside from the conceptual barriers to sustainability, as well as its universalization and materialization, which make defining sustainability targets difficult, there are few tools for setting such targets, and those that do exist are usually theme-specific. Therefore, this dissertation proposes a methodology for setting corporate sustainability targets that is free of thematic constraints and based on the integration of Operational Research methods Data Envelopment Analysis, clustering analysis, time series forecasting, and Goal Programming. An application for defining energy and water consumption targets related to SDGs 6, 7, 8, and 12 is presented for a Brazilian electricity company and its nine business units.

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1 INTRODUCTION

Corporate sustainability practices are known as a corporation's leadership and management approach to promote profitable growth while also delivering social, environmental, and economic outcomes (KANTABUTRA, KETPRAPAKORN, 2020). These practices are the result of an integrated sustainability management approach, transforming organizations in such a way that they contribute to the long-term development of the economy and society while remaining within the ecosystem's constraints (SCHALTEGGER, HANSEN, *et al.*, 2016).

Environmental, Social, and Governance (ESG) and Corporate Social Responsibility (CSR) are terms frequently used to describe such practices. Both, in general, refer to how companies integrate social and environmental concerns into their business operations and interactions with stakeholders (EUROPEAN UNION: EUROPEAN COMMISSION, 2011, UNIDO, 2021). However, while ESG addresses governance issues directly, CSR does so indirectly through environmental and social concerns (GILLAN, KOCH, *et al.*, 2021). Furthermore, the terms appeared at different times.

Although sustainable development only came to the forefront with the Brundtland Report (WCED, 1987), with the technological and scientific advancement and a better understanding of how humans and their activities interact with nature, the period following World War II raised strong doubts about economic growth, kicking off the discussion and construction of the concept of sustainability linked to the idea of environmental preservation in a global context. Concurrently, this and the 1950s can be viewed as a period of adaptation and changing attitudes toward the discussion of CSR, but also as a period in which few corporate actions went beyond philanthropic activities (CARROLL, 2009).

BOWEN (1953) believed that large corporations concentrated great power and that their actions had a tangible impact on society, and that as a result, there was a need to change their decision-making to include considerations of their impact (LATAPÍ AGUDELO, JÓHANNSDÓTTIR, *et al.*, 2019). As consequence, BOWEN (1953) proposed defining a specific set of principles for corporations to fulfill their social responsibilities. Bowen's approach is relevant as it was the first academic work specifically focused on the doctrine of social responsibility, making him known as the "Father of Corporate Social Responsibility" (CARROLL, 1999, LATAPÍ AGUDELO, JÓHANNSDÓTTIR, *et al.*, 2019).

The term ESG, on the other hand, first appeared more than 50 years later in the UNITED NATIONS GLOBAL COMPACT (2004) report "Who Cares Wins: Connecting Financial Markets to a Changing World", a guideline developed by the financial industry to better integrate environmental, social, and governance issues in analysis, asset management, and securities brokerage (ECCLES, LEE, *et al.*, 2020). Since then, ESG practices have gained a lot of traction in the market, with global ESG assets on track to exceed $53 trillion by 2025, accounting for more than a third of the projected total assets under management of $140.5 trillion (BLOOMBERG INTELLIGENCE, 2021).

Regardless of the approach or terminology used, when corporate sustainability practices are effectively integrated into business plans, they create a "win-win-win" environment for the company, its suppliers, and customers, ensuring the company's competitive edge in the twenty-first century (ELKINGTON, 1994). Globally, these practices are becoming increasingly important to corporate financial performance (OECD, 2021), with research findings supporting this affirmation.

XIE, NOZAWA, *et al.* (2019) investigated the relationship between corporate efficiency and corporate sustainability to determine whether firms concerned about ESG can also be efficient and profitable. At the moderate disclosure level, the authors discovered a positive relationship between corporate transparency and ESG information and corporate efficiency. Furthermore, the authors evaluated the association between specific ESG activities and corporate financial performance (CFP) and discovered that the majority of ESG activities have a nonnegative relationship with CFP.

ZHAO, GUO, *et al.* (2018) analyzed the relationship between ESG performance and financial indicators in the energy power market by assessing China's listed power generation groups. The findings indicated that good ESG performance can indeed improve financial performance, which has important implications for investors, company management, decision-makers, and industry regulators.

ISLAM, ISLAM, *et al.* (2021) assessed CSR influences on customer loyalty by taking into account corporate reputation, customer satisfaction, customer trust, and corporate abilities as mediators and moderators. CSR initiatives, according to the authors, were significantly and positively associated with corporate reputation, customer satisfaction, and customer trust. The study emphasizes the importance of CSR actions for organizational success and serves as a guide for policymakers, managers, and academics.

The market's movement in response to the demand for information about corporate sustainability also demonstrates the importance of such practices. The extraordinary growth of tools such as corporate sustainability indexes, socially responsible investment (SRI) funds, and ESG reporting frameworks are just a few examples.

The sustainability indexes aim to provide investors with a "theoretical portfolio" of stocks from companies that have demonstrated a well-known commitment to social and environmental responsibility (ORSATO, GARCIA, *et al.*, 2015). Several indices linked to financial markets have emerged to assist investors in evaluating the sustainability performance of corporations (SEARCY, ELKHAWAS, 2012). According to SUSTAINABLE STOCK EXCHANGES INITIATIVE (2019), 45 exchanges worldwide had a market covered by a sustainability-related index in 2019.

The New York Stock Exchange was the first to have a sustainability index, launched in 1999 under the name Dow Jones Sustainability Indices (DJSI). The DJSI was created to track the financial performance of the world's leading sustainability-driven companies, based on an analysis of financially material ESG factors (S&P GLOBAL, 2022). The first Latin American sustainability index was the Corporate Sustainability Index (ISE) in São Paulo, Brazil, which includes 40 companies (B3, 2021a). ISE was established to assist investors in making investment decisions and to persuade companies to adopt the best sustainability practices (B3, 2022).

SRI funds are offered by financial institutions looking to raise funds from investors, with the main feature being the incorporation of social and environmental criteria in the selection of companies that will comprise the fund's portfolio (ORSATO, GARCIA, *et al.*, 2015). Although social screening of investments has been around for more than a century, the PAX World Fund, a fund launched in 1971 that avoided investments in military-related stocks, is generally acknowledged as the first SRI fund (FOWLER, HOPE, 2007). Several studies on SRIs and their performance have been conducted since then, with mixed results (JONES, VAN DER LAAN, *et al.*, 2008).

LEAN, ANG, *et al.* (2015) used a sample of 500 European and 248 North American SRI funds from January 2001 to December 2011 to analyze and compare the performance persistence of SRI funds. Over this period, the authors discovered that SRI funds outperformed the market benchmark in Europe and North America. JONES, VAN DER LAAN, *et al.* (2008) on the other hand, found no statistically significant differences in the performance of 89 Australian ethical funds relative to market benchmarks and/or a matched sample of conventional funds from 1986 to 2005. However, this study was conducted in 2008, when sustainability was not as prominent and, as a result, was not in high demand by stakeholders.

As a proxy for sustainability performance, both SRI and sustainability indexes require metrics, and thus data, on corporate sustainability practices. However, there are two major issues with such metrics that jeopardize their reliability: a lack of transparency and convergence (WIDYAWATI, 2020). The use of ESG frameworks is one solution to these issues.

ESG frameworks are systems for standardizing ESG metric reporting and disclosure. They typically determine the metrics and qualitative elements that a company should disclose, as well as the format and frequency with which that reporting is done. Carbon Disclosure Project (CDP), Global Reporting Initiative (GRI), and Sustainability Accounting Standards Board (SASB) are three of the major frameworks. According to the 2020 KPMG Survey of Sustainability Reporting (KPMG, 2020), 96% of the world's largest 250 companies report on their sustainability performance, with nearly three-quarters (73%) using the GRI framework.

Aside from financial implications, corporate sustainability practices are critical to the consolidation of sustainable development and, in particular, to the Sustainable Development Goals (SDGs) of the 2030 Agenda (SCHEYVENS, BANKS, *et al.*, 2016). The 2030 Agenda, a global action plan launched in 2015, redefined organizations' roles and ESG/CSR practices by establishing 17 SDGs to align governments, civil society, universities, and United Nations (UN) agencies toward global sustainable development (UN, 2015).

Following on from the work begun by the Millennium Development Goals (MDGs), the SDGs have received widespread business support (UNITED NATIONS GLOBAL COMPACT, 2020). GRI and SUPPORT THE GOALS (2022) analyzed a sample of 206 companies around the world that produced a GRI report in 2020 and found that 83% of companies support the SDGs and recognize the value of aligning their reports with the Goals of the 2030 Agenda.

Some examples of support are the internalization of the concepts of sustainable development and the triple bottom line (ELKINGTON, 1997), as well as the definition of key performance indicators (KPIs) of sustainability, monitoring procedures against pre-determined goals, and communication of results to strategic stakeholders. Furthermore, businesses' interest in developing new solutions that enable sustainable consumption and production patterns has grown over time, with strategies aimed at identifying hotspots with the greatest potential to improve the system's environmental and social impact (UNITED NATIONS, 2020).

However, the participation of corporate sustainability practices must be effective and objective, as the SDGs establish specific goals and targets that must be monitored through indicators to be met by 2030. Despite corporate support for the SDGs, quantitative findings indicate that corporate involvement remains limited in general (VAN DER WAAL, THIJSSENS, 2020). Additionally, a qualitative examination of individual reports reveals that the company's involvement is more symbolic and deliberate than substantive (VAN DER WAAL, THIJSSENS, 2020).

According to a survey conducted by the United Nations Global Compact (2020), while 84% of companies report taking action to support the SDGs, their targets are typically not sufficiently ambitious. Only 39% of companies believe their targets are sufficiently ambitious to accomplish the 2030 Agenda's goals, are scientifically valid, and/or are aligned with societal needs (UNITED NATIONS GLOBAL COMPACT, 2020). In the aforementioned GRI and SUPPORT THE GOALS (2022) analyses, 40% of companies set measurable commitments to help achieve the SDGs, while 20% include evidence to assess their positive impacts. These low percentage raises questions about the effectiveness of corporate engagement, requiring a deeper examination of whether companies' ESG/CSR practices are truly aligned with sustainable development or are merely used for practices such as greenwashing[1].

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[1]Introduced by Jay Westerveld in 1986, greenwashing is the practice of promoting the dissemination of false or misleading information about an organization's environmental strategies, goals, motivations, and actions in order to profit financially.

Two challenging conditions can partially justify this generally limited business contribution: universalizing concepts of sustainability and unsustainability and defining metrics and indicators for concrete targets (SUSTAINABLE DEVELOPMENT GOALS FUND, 2016). Despite its widespread use, the concept of sustainability is difficult to express concretely and operationally (LABUSCHAGNE, BRENT, *et al.*, 2005), as it is a paradigm absent of reference values that represent indisputable sustainability. This is especially difficult for the social dimension of corporate sustainability, which has been dealt with inefficiently due to the difficulties in assessing and valuing social actions (SCHRIPPE, RIBEIRO, 2019). Additionally, diverse norms, political systems, levels of corruption, legislation, climate, and geography of countries and societies may all pose obstacles to achieving universal goals (SUSTAINABLE DEVELOPMENT GOALS FUND, 2016). As a result, in the absence of a clear and quantifiable line separating sustainable and unsustainable behavior, corporate assessment of their actions becomes limited.

To assist corporations in maximizing their contribution to the SDGs, the Global Reporting Initiative (GRI), the United Nations Global Compact, and the World Business Council for Sustainable Development developed the SDG Compass. This methodology consists of the following five steps: (1) understanding the SDGs; (2) defining priorities; (3) setting goals; (4) integrating; and (5) reporting and communicating (GRI, UNITED NATIONS GLOBAL COMPACT, *et al.*, 2015). The steps (1), (2), and (5) concentrate the most tools available to assist corporations, with the GRI framework (GLOBAL REPORTING INITIATIVE, 2006) and CDP (CARBON DISCLOSURE PROJECT, 2000) for sustainability reporting and communicating being the most emblematic examples. However, few tools exist to assist in aligning the early stages of strategic management, such as 'problem definition' and 'goal setting' (GRAINGER-BROWN, MALEKPOUR, 2019), i.e., step (3) of setting companies goals aligned with the SDGs and step (4) of integrating companies targets across all functions within the company to achieve set goals, respectively.

Thus, the research question is: **How to define corporate targets that are realistic in operational terms and incorporate societal demands?**

To begin answering this question, it is necessary to define the difference between target and goal. A target is a specific and measurable short-term goal whose outcome will significantly contribute to the achievement of one or more goals. As such, sustainability targets are intended to guide an organization toward a goal consistent with sustainable development concepts. Because targets are measurable, indicators are required to monitor the organization's progress. These indicators, which can be individual or composite, are frequently used to assess sustainability (SARTORI, 2016).

Two methodologies for setting sustainability targets in the corporate environment are presented, both of which are well-established in the market and accepted by the scientific community: Science-Based Targets initiative (SBTi) (SBTI, 2020) and LIFE Methodology (LIFE, 2018). The first uses individual indicators of greenhouse gas (GHG) emissions, whereas the second uses individual indicators to create a composite indicator (index) of biodiversity.

Along with the tools presented, one well-known method of establishing a company's target is through benchmarking, which is the process of comparing the performance of a company's products, services, or processes to that of other similar companies. Sustainability indices such as the DJSI and ISE, for example, use benchmarking analysis to assess corporate sustainability.

The efficiency with which inputs are converted to outputs is one way to measure performance in a manufacturing process. When an inefficient company is compared to a benchmark, the distance between it and the relative efficiency frontier can be determined, and this distance can be set as a target. Linear regression (Corrected Ordinary Least Squares – COLS), Stochastic Frontier Analysis (SFA), and Data Envelopment Analysis (DEA) are three of the most frequently used techniques for measuring this efficiency.

DEA has grown to be one of the most widely used methodologies for environmental efficiency (MATSUMOTO, MAKRIDOU, *et al.*, 2020, ZHOU, YANG, *et al.*, 2018). It provides an assessment of relative sustainability levels, which aids in determining the most cost-effective path to reduce environmental degradation (ZHOU, YANG, *et al.*, 2018) and serves as a methodological bridge between engineering, natural, and social sciences (SUEYOSHI, YUAN, *et al.*, 2017).

In the context of sustainability assessment, DEA empirically quantifies the so-called environmental, sustainability, or ecological efficiency of mutually comparable decision-making units (DMUs) by converting inputs, i.e., what one wishes to minimize, to outputs, i.e., what one wishes to maximize. The efficient DMUs serve as a benchmark against which all inefficient DMUs can be measured, and each inefficient DMU can be assigned a potential performance target, providing policymakers with critical information for operating more efficiently in a dynamic business environment where competitive rivalry is increasing exponentially (RABAR, 2017). Additionally, this method has been used to evaluate countries, states, and various sectors and companies throughout the world, establishing a scientific foundation for it.

IRAM *et al*. (2020) used DEA to evaluate the efficiency of energy usage and its role in CO_2 emissions and economic-environmental efficiency (EEE) in some OECD countries from 2013 to 2017. The authors used primary energy consumption and population as inputs and population gross domestic products (GDP) and CO_2 emissions as desirable and undesirable outputs, respectively. MATSUMOTO *et al*. (2020) assessed the environmental performance of European Union countries using the DEA approach and the global Malmquist-Luenberger index. As the article stated, the financial crisis of 2007–2008 had a negative impact on the evaluated nations' environmental performance, particularly in eastern European countries. These findings assist countries and policymakers in identifying both positive and negative aspects of their environmental performance and in setting targets for future improvement based on comparable peers' best (MATSUMOTO, MAKRIDOU, *et al.*, 2020).

In the manufacturing sector, EGILMEZ *et al.* (2013) used DEA to assess the sustainability of 53 DMUs in the manufacturing sector of the United States, using GHG emissions, energy use, water withdrawals, and hazardous waste generation as inputs and total economic activity as outputs. CHAI *et al.* (2020) evaluated the technical efficiency of 17 listed companies in China's thermal power sector in 2017 and 2018, using employees, clean energy installed capacity, and coal power installed capacity as inputs, total power generation as desirable output, and sulfur dioxide, nitrogen oxides, and soot emissions as undesirable outputs. The authors concluded that, although clean-energy power generation has better environmental benefits, it is still lacking in efficiency. SARTORI (2016) proposed an assessment of the sustainability of electricity generation sector companies using a DEA model with Directional Distance Function (DDF) and the Global Reporting Indicator (GRI) as reference for collecting input and output indicators of 29 companies from the countries with the highest GDP in the world in 2012. In the building sector, ALBERTINI *et al*. (2021) investigated environmental efficiency during building construction in terms of waste generation, water, and energy consumption using the DEA and Tobit models. The mean efficiency was 83.5%, with five of the sixteen construction sites proving to be 100% efficient.

The mean efficiency and the number of efficient DMUs found by ALBERTINI *et al*. (2021) are what one wants from a DEA result, i.e., a good fit to the frontier (high mean efficiency) while maintaining good model discrimination (few DMUs on the frontier) (MEZA, MELLO, *et al.*, 2005). However, this is not always the case, as DEA frequently includes unrealistic efficiency scores and a large distance to the efficiency frontier (REZAEI, HAERI, 2019), resulting in unattainable targets. One explanation for this is the use of DMUs from the same sector but with distinct business models, a distinction that can be emphasized depending on the inputs and outputs used in DEA.

A possible solution is to use clustering to improve the selection of DMUs, which maximizes within-group homogeneity and between-group heterogeneity and generates clusters and dendrograms to aid in identifying homogeneous groups (SARKIS, 2007). NAJADAT *et al*. (2020) assessed the performance of Jordanian public hospitals using a methodology that combined DEA and clustering and discovered that a hospital's efficiency can be more meaningfully assessed when compared to a group of hospitals that share some characteristics. REZAEI and HAERI (2019) used DEA with hierarchical clustering to identify the optimal virtual DMUs and minimize the possibility of inappropriate efficiency scores. This clustering prior to DEA enables the selection of more similar DMUs based on the analyzed characteristics, resulting in higher mean efficiency and, consequently, more realistic targets.

Another limitation of using DEA to define corporate sustainability targets is the granulometry of the available data to include in the model. Companies, especially large and multinational ones, are divided into distinct business units. As a result, the DEA model's inputs and outputs at the business unit level should be included. However, companies rarely disclose such de-identified data, resulting in the incorporation of aggregate data at the company level into the DEA model and the establishment of a unique target for the entire company, which may be difficult to distribute and apply across its business units. As a result of this limitation, step (4) of the SDG Compass, in which companies integrate their targets across all organization functions, is not implemented.

To address this issue and ensure that the target set in the DEA model applies to all business units, this paper proposes using the DEA target as a constraint on Goal Programming (GP) (CHARNES, COOPER, 1977), a linear programming model that enables the solution of decision problems by determining the solution that is closest to all initially established goals (DALMÁCIO, SANT'ANNA, *et al.*, 2008, HUSSAIN, KIM, 2020). The integration of DEA and GP, introduced by ATHANASSOPOULOS (1995), was originally developed as an aid to the reorganization of the allocation of central funds to local authorities in Greece, with the objective of applying DEA principles to the global organizational level without losing its attractive features. Additionally, this integration enables the incorporation of the decision maker's opinion, which is typically ignored in DEA because the model is solely determined by the observed data (DI CAPRIO, EBRAHIMNEJAD, *et al.*, 2020).

ALI *et al.* (2021) proposed a multi-objective optimization model integrating economic growth, electricity consumption, GHG emission, and the number of employees across the primary, secondary and tertiary sectors of the Indian economy using the concept of GP with a satisfaction function. The findings provided a quantitative justification for achieving economic growth, electricity consumption, with optimal employment strength across the sectors.

OGLETHORPE (2010) used GP in a case study for alternative food supply chain strategies at local, regional, and national levels, considering interdependencies between businesses and stakeholders with total environmental or social impact. The findings demonstrated how a priori beliefs can be challenged and how operational and resource efficiency can be improved using such a model, which enables broad stakeholder acceptance and the opportunity to explore and test new environmental or social challenges. The author concluded that GP can simplify a complex simultaneous decision situation into a useful and constructive decision and planning framework.

In addition to DEA-GP integration, forecasting is critical in each of the major functional areas of business management (MAKRIDAKIS, WHEELWRIGHT, 1977), and forecasting consumption is a critical factor affecting the optimal allocation of resources (MEIDUTE-KAVALIAUSKIENE, DAVIDAVICIENE, *et al.*, 2021). YUAN *et al.* (2016) used the univariate models Autoregressive Integrated Moving Average (ARIMA) and grey model (GM) to forecast China's primary energy consumption. The authors concluded that those models are suitable for China's primary energy consumption forecasting. RAZALI *et al.* (2018) forecasted the water consumption expenditure of University Tun Hussein Onn Malaysia using Holt-Winter's and ARIMA models and found that ARIMA provided a reasonable forecasting tool for university campus water usage. In a review of energy models for demand forecasting, SUGANTHI and SAMUEL (2012), traditional methods such as time series, regression, econometric, ARIMA as well as soft computing techniques such as fuzzy logic, genetic algorithm, and neural networks were being extensively used for demand-side management.

Understanding the trend in the demand behavior of a particular indicator across the company's units enables the definition of the company's perspective on defined targets, i.e., whether they are achievable or not, particularly in the short term. As a result, this work proposes, in addition to the target set in DEA, the use of time series forecasting of business units as constraints in GP to define sustainability targets for a company's business units. The use of GP, a method for organizing and analyzing complex decisions, allows for the incorporation of quantitative (business unit forecasts and company-level target) and qualitative (decision makers' opinion) information, allowing for the definition of more customized targets for each business unit while still addressing the company-level target defined in DEA. Additionally, links between the indicator used to set the target and the SDGs targets are highlighted, based on GRI (2021), to specify which SDGs the corporate sustainability target contributed to.

With the proposed methodology, individual sustainability targets for each business unit that converge with the company's target, taking as reference a benchmarking with the main companies of the sector around the world, is defined and meeting with step (3) of the SDG Compass methodology. Additionally, more realistic and appropriate targets are set for each business model, making them more practical to integrate into their strategic planning, which is critical for motivating effective actions to achieve such targets, as stated in step (4) of the SDG Compass. The allocation of individual targets maximizes the global achievements of the system (effectiveness), the contribution of individual units to global targets (efficiency), and the share of each unit to the allocated resources (equity) (ATHANASSOPOULOS, 1995).

By integrating different methods in a way that makes them complementary and enables the establishment of compelling sustainability targets that are generally missing in corporate business plans, this paper aims to guide corporations to produce positive impacts on the SDGs by motivating innovation, responsiveness, efficiency, and the provision of specific skills and resources. Thus, this work seeks to assist companies that are looking for ways to effectively link their ESG/CSR practices to sustainable development but have as one of their challenges the definition of concrete targets to guide them.

To the author's knowledge, no such methodology exists for setting corporate targets for various sustainability topics. Additionally, no methodology for integrating the company's targets into the business plans of its operating units was identified in the literature, which is frequently a significant barrier to the adoption of such targets.

To illustrate the proposed methodology, a real example of setting energy and water consumption targets for an electricity company in Brazil and its nine business units is presented. The electricity sector is critical to the current and future development of society, as it generates the second most commonly used form of energy by final consumers worldwide (IEA, 2020) and it is a growing sector whose negative impacts must be avoided or mitigated and the positive ones must be promoted.

In turn, the consumption of energy and water resources are exhaustively used by the sector. In Brazil, according to the Environmental Water Economic Accounts 2013-2017 (IBGE, 2020), the electricity and gas sector has the highest water use intensity (ratio between the volume of water used and the gross value added generated). The indicator of energy consumption has a significant relationship with financial performance (MOON, MIN, 2020) and is linked to targets of SDG 7 (Affordable and Clean Energy), SDG 8 (Decent Work and Economic Growth), and SDG 12 (Responsible Consumption and Production) (GRI, 2021). The indicator of water consumption is directly linked to SDG 6 (Clean Water and Sanitation) (GRI, 2021). Additionally, the assessed company prioritizes water and energy consumption efficiency in its ESG practices.

This work is divided into four chapters. Chapter 1 described the context of the main problems and motivations for this study, the general and specific objectives, and research questions. Additionally, Chapter 1 addressed the evolution of sustainability in the global and business context, the concept of efficiency and its various interpretations and applications in the sustainability context, and existing methodologies to quantitatively assess corporate sustainability.

Chapter 2 presents the proposed methodological structure, with the individual explanation of each method used as well as how they are integrated to achieve the research objectives.

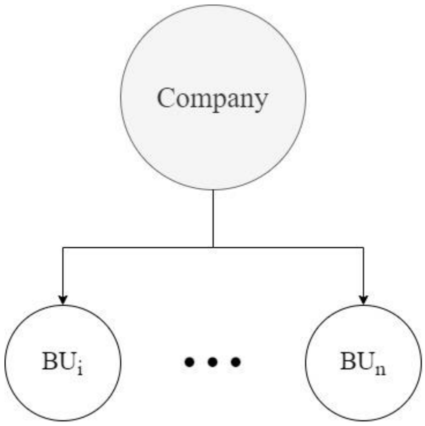
Chapter 3 presents the application of the methodology, describing the procedures used to define water and energy consumption targets for a company in the Brazilian electricity sector and its business units

Chapter 4 discusses the main results obtained and highlights the main conclusions and findings of this research, including the innovations, limitations, recommendations, and proposition of future related studies.

2 MATERIAL AND METHODS

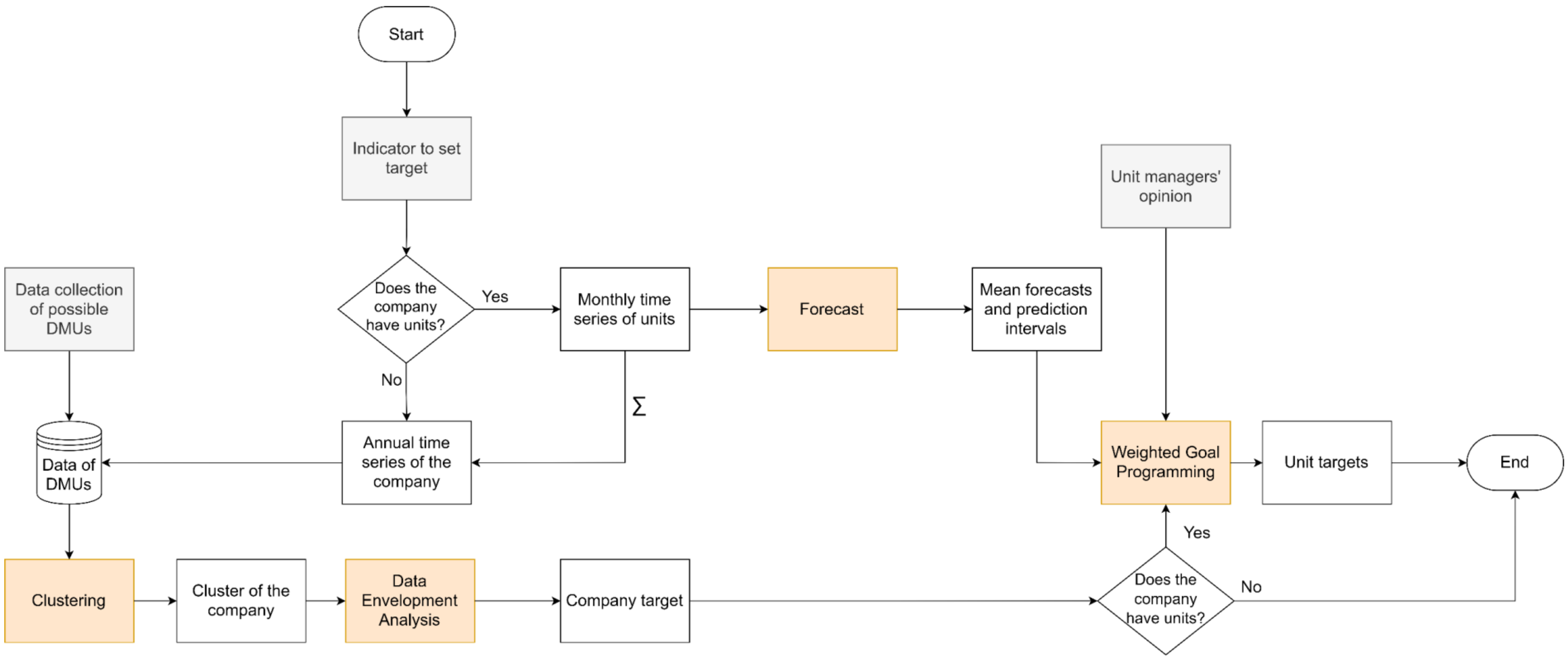
Considering a company composed of different business units (BU_i) (Figure 1), the proposed methodology for target setting is presented in Figure 2.

Figure 1 - General structure of a company composed of different business units



Source: Author.

Figure 2 - Flowchart of the proposed methodology



Source: Author.

Legend: Rectangles represent processes, with those in orange being the key methods and those in gray being external to the methodology. Decisions are represented by parallelograms.

In Figure 2, the methodology begins with the selection of an “Indicator to set target” for the company analyzed. This can be accomplished by selecting a company's sustainability KPI and linking it to SDG targets based on GRI (2021). GRI (2021) establishes this link exclusively through the use of GRI indicators, however, the use of a non-GRI KPI can be associated with similarity. Although is outside the scope of the proposed methodology as it corresponds to step (2) of SDG Compass, choosing a KPI that accurately captures the company's significant impact is critical for defining targets that contribute to preventing and/or mitigating such impact.

There are no theme restrictions, however a quantitative indicator with a historical series is required, i.e., observations made over time and registered periodically. Such periodicity must be monthly at the business unit level for forecasting purposes. Additionally, it must be a widely used and reported indicator within the company's sector to have enough DMUs for benchmarking.

If the company has no business units or only wants to define a group-level target, the "Annual time series of the company" must be collected. With this information and after surveying comparable companies in the market, as well as indicators that will be used as outputs in the benchmarking step, a database of "Data of DMUs" is created. Using the indicator of interest to the company and comparable companies, a "Clustering" is applied to the data collected to group the most similar companies to the company analyzed ("Cluster of the company"). With this cluster, the "Data Envelopment Analysis" is used, now including the output indicators, which returns the eco-efficiency of the company analyzed, as well as the "Company target" for the chosen indicator, bringing the methodology to an end.

However, there are cases in which the company is composed of different business units (Figure 1), making it interesting to set customized targets for each BU in compliance with the "Company target". For this, two methods are used in addition to the path mentioned above. First, the "Monthly time series" of the indicator are collected for each business unit, representing the company's series as a whole. The "Forecast" of this indicator is made for the period of interest using ARIMA and Exponential Smoothing (ETS) methods, resulting in "Mean forecasts and prediction intervals" for each business unit. These findings, along with the previously defined "Unit managers' opinion" and

"Company target," are added into "Weighted Goal Programming" (WGP), providing individual targets for each business unit ("Unit targets").

The entire methodology was developed in RStudio version 1.4 (RSTUDIO, 2019), an integrated development environment for R (R CORE TEAM, 2020), a free software environment for statistical computing and graphics. R packages, which extend the software functionality, were also used.

For benchmarking with DEA and clustering, the packages 'benchmarking' (BOGETOF, OTTO, 2019), 'factoextra' (KASSAMBARA, MUNDT, 2020), and 'scales' (WICKHAM, SEIDEL, 2020) were used. For time series treatment and forecasting, the 'forecast' package (HYNDMAN, R, ATHANASOPOULOS, *et al.*, 2020). Finally, for the distribution of individual targets, the WGP was formulated using 'lpsolve' (BERKELAAR, 2020).

Additionally, a tool with a user interface was created to facilitate the application of the methodology. For this, 'Shiny' (RSTUDIO, 2020), an R package to build interactive web apps, was used and the result is presented in Appendix II.

2.1 Clustering

The DEA application is preceded by cluster analysis, the purpose of which is to identify DMUs that are most similar to the evaluated company. Clustering is the process of identifying natural groupings within multidimensional data based on some similarity measure (OMRAN, ENGELBRECHT, *et al.*, 2007). This enables the DEA model to be improved by categorizing DMUs based on their characteristics, leading to increased mean efficiency and, as a result, more feasible targets.

The differences between a DMU i and a DMU j can be evaluated by the Euclidean distance of their n outputs y presented in Eq. (1), where S_y denotes the sample standard deviation.

$$D(DMU_i; DMU_j) = \sqrt{\sum_{r=1}^{n} \left(\frac{y_{r_{DMU_i}} - y_{r_{DMU_j}}}{S_{y_r}} \right)^2} \qquad \text{Eq. (1)}$$

The average linkage approach, a hierarchical agglomerative method (JOHNSON, WICHERN, 2007), was used to define the clusters. Initially, each cluster contains one DMU, but with each iteration of the algorithm, two clusters are aggregated until only one group with all DMUs exists.

The initial distances between clusters correspond to the Euclidean distances between two DMUs, calculated by Eq. (1), since each cluster has only one DMU. The closest clusters are the most similar and therefore the first to be clustered. The order of the distance matrix drops by one unit as the clusters are grouped, and the distances between two clusters are updated by the averages of the distances between the DMUs in the two clusters.

In the end, the complete chaining method successively groups the N objects (DMUs) into *N*-1, *N*-2,....,2, 1 clusters, resulting in a tree structure known as a dendrogram, which allows the identification of the natural grouping structure of the DMUs. The number of clusters can be visually determined, with a minimum value to meet the ratio of having at least three times more DMUs than inputs and outputs in DEA (BOWLIN, 1998).

It is important to note that not all outputs used in clustering must be used in DEA, and vice versa. This is up to the decision-maker, as discussed in Chapter 3.

2.2 Data Envelopment Analysis

Introduced by CHARNES *et al*. (1978), DEA is a non-parametric technique used to evaluate the efficiency of comparable production units (DMUs), i.e., units that employ similar technological processes in the transformation of multiple inputs into multiple outputs. The method uses linear programming to construct a production frontier based on observations of the quantities of inputs and outputs of the DMUs evaluated, without requiring any prior knowledge of any importance (weights) relationship between the variables considered. The production frontier serves as a benchmark against which the performances of DMU can be compared, with those that are efficient (equal to 1) are located on the frontier and those that are inefficient are located below the frontier. DMU deviations from the frontier measure inefficiencies and can be used to set targets for each DMU. As DEA measures relative efficiency, the choice of companies that are representative of the sector in terms of production and ESG/CSR practices should be prioritized for inclusion in the benchmarking.

DEA was originally established to assess production efficiency; however, in the context of ecological sustainability evaluation, it can be adapted, and the measured productive efficiency can be interpreted as ecological efficiency (eco-efficiency) (KUOSMANEN, KORTELAINEN, 2005). Ecological sustainability is recognized as the main reflection of the synergy between social development, economic growth, and environmental protection, whereas eco-efficiency is an index used to reflect the sustainable development of the ecological environment (LI, CAI, *et al.*, 2020) and an aspect of sustainability that relates the environmental performance of a product system to the system value of that product (ABNT, 2014).

There are several types of DEA models to calculate this efficiency, but two stand out as pioneering and most widely used in the literature: constant returns to scale (CRS) (CHARNES, COOPER, *et al.*, 1978) and variable returns to scale (VRS) (BANKER, CHARNES, *et al.*, 1984). In general, both can be input-oriented, i.e., identify inefficiency as reducing input usage with output levels held constant, or output-oriented i.e., identify inefficiency as increasing output production with input levels held constant.

In the VRS model a DMU that has a minimum input value for any input item or a maximum output value for any output item is always efficient (COOPER, SEIFORD, *et al.*, 2002). This can lead to a wrong interpretation of the analyzed company's efficiency and, consequently, of its target setting.

Therefore, the DEA CRS model was used in this work. Furthermore, because the goal is to set targets for companies' resource use (e.g., water, material, or energy), an input-oriented model was adopted. Additionally, as previously mentioned, it is recommended that the number of DMUs should be at least three times the number of variables (COOPER, SEIFORD, *et al.*, 2002) to maintain its discriminatory power.

Using the input-oriented CRS model, the eco-efficiency (E_o) of the evaluated DMU (DMU_o) corresponds to the solution of the linear programming model in Eq. (2) with n+1 constraints (each constraint corresponds to a DMU) and *s*+*r* decision variables, among them the weights assigned to the variables that characterize the DMUs.

$$E_o = Max \sum_{j=1}^{s} u_j y_{jo} \qquad \text{Eq. (2)}$$

s.t.

$$\sum_{j=1}^{s} u_j y_{jk} - \sum_{i=1}^{r} v_i x_{ik} \leq 0 \qquad \forall k = 1, n$$

$$\sum_{i=1}^{r} v_i x_{io} = 1$$

$$v_i, u_j \geq 0$$

In Eq. (2), the decision variables v_i and u_j are the weights of inputs i (i = 1,..., r) and outputs j (j = 1,..., s); x_{ik} and y_{jk} are the values of the inputs i and outputs j of DMU k (k = 1,…, n); and x_{io} and y_{jo} are the inputs i and outputs j of the evaluated DMU.

The model identifies weights that would be best for each DMU in the sense of maximizing its efficiency rating. If any DMU other than DMU_o attain a better ratio of the sum of weighted inputs to outputs, then DMU_o has room for improvement, relative to 'benchmark' units attaining top efficiency with the weights favoring the unit being assessed.

Therefore, if E_o is equal to 1, DMU_o is considered eco-efficient and its target can be to maintain the use of inputs. If E_o is less than 1, DMU_o is not eco-efficient, and it is possible to obtain the value of input *i* that DMU_o must have to become eco-efficient, i.e., its target, given by:

$$T_{io}^{*} = x_{io} E_o \qquad \text{Eq. (3)}$$

In DEA, inputs are understood as what one wants to reduce and outputs as what one wants to increase. As a result, the social or environmental indicator to be minimized is entered as an input, while indicators defining the company's main products, such as sales and revenue generated, are used as outputs. However, DEA has a prerequisite of isotonicity relationship, i.e., positive correlation, between inputs and outputs (WANG, LIN, *et al.*, 2016). Therefore, to test if the data matches this prerequisite, the correlation analysis is calculated between the selected inputs and outputs. If there are negative coefficient variables, the input or output variables need to be changed.

2.3 Forecast

The time series forecast is based on the premise that factors that have influenced past data behavior continue to influence future data. Thus, by analyzing the past behavior of the time series, the elements can be obtained to predict its future behavior. The purpose of the forecasting methods is to distinguish the evolution pattern of the series (the signal) from any noise that may be contained in the observations and then use this pattern (the signal) to predict future values of the series (RAGSDALE, 2008).

The accuracy of forecasts can only be determined by considering how well a model performs on new data that were not used when fitting the model (HYNDMAN, R. J., ATHANASOPOULOS, 2018). To evaluate the forecasting models, the time series is separated into a training set and a test set, an intact part of the series, is used to compare the forecast with the real data.

Treating the time series is an important step in forecasting. The eventual existence of outliers, i.e., data that differs from the other historical observations or missing data, may impair the model's adjustments and their predictive capabilities. The method used to carry out the treatment of the time series, more specifically, the training set, is the one used by the 'tsclean' function of the 'forecast' R package (HYNDMAN, R, ATHANASOPOULOS, *et al.*, 2020). This function uses Friedman's super smoother for non-seasonal series (FRIEDMAN, 1984) and a robust STL decomposition for seasonal series (DOKUMENTOV, HYNDMAN, 2015). Linear interpolation is used to replace outliers or to estimate missing values (HYNDMAN, R, ATHANASOPOULOS, *et al.*, 2020).

This methodology proposes the use of ETS and ARIMA, typically used for time series forecasts related to environmental resources (GOEL, RANJAN, *et al.*, 2017, RAZALI, RUSIMAN, *et al.*, 2018, YUAN, LIU, *et al.*, 2016) and as benchmarks for other methods (MAKRIDAKIS, SPILIOTIS, *et al.*, 2018, 2020). To select the best model (smallest forecast error), the time series is divided into training and test set, where the first is used to estimate any parameters of a forecasting method and the last is used to evaluate its accuracy. The Mean Absolute Scaled Error (MASE) (HYNDMAN, Rob J., KOEHLER, 2006), used in the M4 Competition (MAKRIDAKIS, SPILIOTIS, *et al.*, 2020), was the metric chosen to measure this accuracy. Therefore, the model with the smallest MASE is the one used.

In general, the ETS model can be represented by the additive Holt-Winters. This method involves a forecasting equation and three smoothing equations (level, trend, and seasonality) and is presented by R. J. Hyndman and Athanasopoulos (2021) as:

$$\hat{y}_{t+h|t} = l_t + hb_t + s_{t+h-m(k+1)} \qquad \text{Eq. (4)}$$

Where:

$$l_t = \alpha(y_t - s_{t-m}) + (1-\alpha)(l_{t-1} + b_{t-1})$$
$$b_t = \beta^*(l_t - l_{t-1}) + (1-\beta^*)b_{t-1}$$
$$s_t = \gamma(y_t - l_{t-1} - b_{t-1}) + (1-\gamma)s_{t-m}$$

For a period t, Eq. (4) represents the forecast y for $t+h$, with h being the forecast period (horizon) based on the estimates of level (l_t), slope (b_t), and seasonality (s_t), with α, β^* and γ being their respective smoothing parameters. The variable m corresponds to the seasonal period, being equal to 12 for monthly data. The variable k is the integer part of $(h-1)/m$, which ensures that the estimates of the seasonal indices used for the forecast come from the last year of the sample. Additionally, $0 \leq \gamma \leq 1-\alpha$.

The seasonal ARIMA $(p, d, q)(P, D, Q)_s$ model is presented as:

$$y_t = \frac{\theta(B)\Theta(B^s)}{\varphi(B)\Phi(B^s)(1-B^s)^D(1-B)^d} a_t \qquad \text{Eq. (5)}$$

Where:

$$\varphi(B) = 1 - \varphi_1 B - \cdots - \varphi_p B^p$$
$$\theta(B) = 1 - \theta_1 B - \cdots - \theta_q B^q$$
$$\Phi(B^s) = 1 - \Phi_1 B^s - \cdots - \Phi_P B^{sP}$$
$$\Theta(B^s) = 1 - \Theta_1 B^s - \cdots - \Theta_Q B^{sQ}$$

In Eq. (5), *p* and *q* are the polynomial degrees of the autoregressive and moving average parts of the non-seasonal component, respectively; P and Q are the polynomial degrees of the autoregressive and moving average parts of the seasonal component, respectively; *d* is the number of non-seasonal differences needed for stationarity; *D* is the number of seasonal differences needed for stationarity; *s* is the seasonal period; *B* is the backward shift operator; and a_t is the white noise.

In addition to the mean forecast, the prediction intervals can assist the distribution of the company target defined in Eq. (3) among its business units. Since the proposed methodology utilizes monthly time series to generate annual forecasts, prediction intervals cannot be aggregated due to forecast error correlations. To overcome this, the bootstrapped prediction interval proposed by HYNDMAN and ATHANASOPOULOS (2021) is used, in which the prediction intervals are defined by calculating the percentiles of future sample paths for each forecast horizon.

2.4 Weighted Goal Programming

The Goal Programming (GP) (CHARNES, COOPER, 1957) makes it possible to solve decision problems in which the objective is to determine the solution that most closely matches all the goals initially established (DALMÁCIO, SANT'ANNA, *et al.*, 2008).

Most of the linear programming techniques assume that the model constraints cannot be violated (hard constraints) (RAGSDALE, 2008). However, GP involves both hard and soft constraints. Soft constraints are weighted relative to each other and then approximately weighted relative to the hard constraints (KENDALL, 1975). The decision-maker decides which gives the most appropriate solution, allowing more flexible and achievable goals.

GP has different approaches. The most used models are Weighted GP (WGP), Lexicographic GP, and Minmax GP (SILVA, MARINS, 2013). However, only WGP is used in this methodology due to its practical integration with forecasts and DEA, while also allowing the insertion of weights, such as the managers' opinion, in the distribution of the targets.

The WGP model for *n* business units of a company is given by:

$$\underset{d_i^+ d_i^-}{Min} \sum_{i=1}^{n} W_i^+ d_i^+ / R_i \; + W_i^- d_i^- / R_i \qquad \text{Eq. (6)}$$

s.t.

$$T_i = R_i + d_i^+ - d_i^-$$

$$\sum_{i=1}^{n} T_i = T^*$$

$$\alpha_i \le T_i \le \beta_i$$

$$d_i^+, d_i^- \ge 0$$

Eq. (6) is the objective function that aims to minimize the weighted sum of the slack variables d_i^+ and d_i^-, i.e., the deviations between the reference values R_i and the targets. If $d_i^+ > 0$, then the target for the i-th unit is above the R_i, whole is $d_i^- > 0$, the target for the i-th unit is below the R_i. The R_i is the reference value for each unit: if the model has a good predictive ability, is the predicted value ($\hat{y}_{t+h}$) in Eq. (4) or Eq. (5); if not, the value of the indicator in the baseline year. The unit's targets are T_i and becomes flexible thanks to the slack variables d_i^+ and d_i^-.

The sum of T_i must be equal to the target of the company T^*, defined in Eq. (3). Additionally, T_i must be between α_i and β_i: if R_i is the predicted value, α_i and β_i are the prediction intervals; if not, α_i and β_i are the R_i times 1 $\pm$ maximum absolute percent change that ever occurred in the time series of unit i.

The weights W_i^+ and W_i^- are applied to determine the most important objectives since in the WGP the slack variables initially have the same importance. For the least important targets, for which the minimization of the respective slack variables is irrelevant, the weight is assigned as zero or close to zero; otherwise, a higher value must be assigned (ULIANA, 2010). This step highly depends on the decision-makers and is particular to each application of the methodology. A proposal of criteria for the definition of weights is the inclusion of the managers' opinion about the indicator trend and the use of the MASE, which will be detailed in the example of the methodology. Another option is to integrate with multi-criteria decision analysis such as Analytic Hierarchy Process (AHP) (BADRI, 1999, YU, 2002).

3 CASE STUDY

To demonstrate the application of the proposed methodology, annual corporate sustainability targets will be set for a company (Holding) in the Brazilian electricity sector with nine business units (BU) engaged in the generation, transmission, and business activities. The targets will be set for 2021, with 2020 serving as the reference year.

3.1 Indicators to set targets

For this case study, the total water consumption (TWC) and energy consumption (EC) indicators were chosen. TWC is equivalent to GRI 303-5 (Water consumption) and EC to GRI 302-1 (Energy consumption within the organization) and GRI 302-2 (Energy consumption outside of the organization). These indicators were chosen because they are commonly reported by companies of the electricity sector, which allows benchmarking, as seen in SARTORI (2016).

As previously mentioned, it is possible to relate the chosen indicators to SDG targets from GRI (2021)**.** The links of these indicators to the SDGs and their specific targets are presented in Table 1.

Table 1 - Indicators links to SDGs

Indicator to set a target	GRI equivalent		Link with SDG		
	Disclosure	Version	SDG	Target	Description
Energy consumption (EC)	302	2016	7 AFFORDABLE AND CLEAN ENERGY	7.3	By 2030, double the global rate of improvement in energy efficiency
			8 DECENT WORK AND ECONOMIC GROWTH	8.4	Improve progressively, through 2030, global resource efficiency in consumption and production and endeavor to decouple economic growth from environmental degradation, in accordance with the 10-year framework of programs on sustainable consumption and production, with developed countries taking the lead
			12 RESPONSIBLE CONSUMPTION AND PRODUCTION	12.2	By 2030, achieve the sustainable management and efficient use of natural resources
Total water consumption (TWC)	303-5	2018	6 CLEAN WATER AND SANITATION	6.4	By 2030, substantially increase water-use efficiency across all sectors and ensure sustainable withdrawals and supply of freshwater to address water scarcity and substantially reduce the number of people suffering from water scarcity

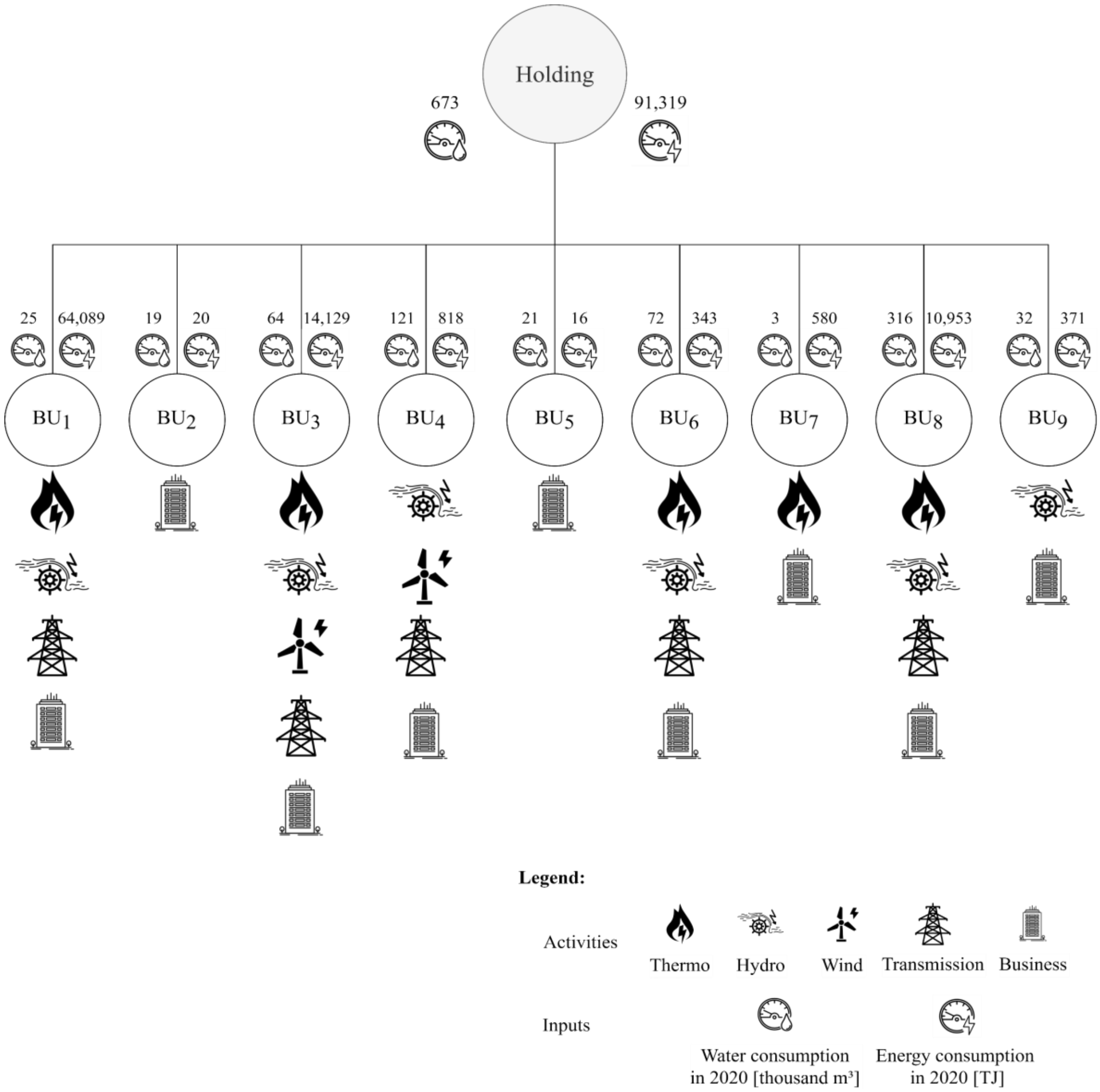
Source: Based on GRI (2021).

According to Table 1, EC is related to SDG 7 (Affordable and Clean Energy), SDG 8 (Decent Work and Economic Growth), and SDG 12 (Responsible Consumption and Production) targets, while TWC is related to SDG 6 (Clean Water and Sanitation) target. It is interesting to note that there are targets for increasing efficiency in the use of both resources, which is precisely the aim of the targets defined by the proposed methodology.

3.2 Time series of the Business Units and the Company

The following step is to gather the company's business units' monthly historical series from 2015 to 2020, which when combined represent the company's historical series. This survey was conducted using information from the company's database. We obtain the annual water and energy consumption of the company by adding the months of the series, which will be used as inputs in separate DEA models. Figure 3 presents the results, as well as a description of the Holding's structure and operational activities.

Figure 3 - Operational activities and water and energy consumption of the Holding and its BUs in 2020



Source: Author.

Holding is composed of nine BUs with different operating activities. All have business activities, 5 have energy transmission, and 7 have energy generation activities. Among the generation activities, there is thermoelectric, hydroelectric, and wind generation. In terms of water, BU_7 has the lowest consumption (3 thousand m³) and BU_8 the highest consumption of this resource (316 thousand m³). Regarding energy, BU_5 had the lowest consumption (16 TJ), while BU_1 had the highest energy consumption (64,089

TJ). Adding together the water and energy usage of each BU results in Holding consuming 673 thousand m³ of water and 91,319 TJ of energy in 2020.

In general, it is possible to conclude that generation activities have a higher demand for these resources. The company's heterogeneity is important for the case study application because it demonstrates a complex situation of corporate target setting, with business groups with very different activities but with the same goal of energy supply.

3.3 Data Collection of DMUs

Apart from the inputs (indicators to set target), it is necessary to define the outputs to be collected from the Holding and DMUs. Renewable Energy Generation (REG) and Earnings Before Interest, Taxes, Depreciation and Amortization (EBITDA) were chosen as outputs because they generally represent the main products of a company in the electricity sector and are commonly used in similar studies (CAIADO, HEYMANN, *et al.*, 2020, CHAI, FAN, *et al.*, 2020, MARADIN, CEROVIĆ, *et al.*, 2021).

Additionally, prior clustering analysis is performed using the percentage of non-renewable in the company's generation portfolio (NRGP). This decision was made because Holding generates nearly 90% of its energy from renewable sources, which distinguishes it from companies that generate a large portion of their energy from non-renewable sources, resulting in a different use of inputs compared to companies with a mostly non-renewable matrix, especially water (SPANG, MOOMAW, *et al.*, 2014) and energy.

The data was gathered from companies in the electricity and heat sectors worldwide based on their annual reports. Certain search criteria against which the company should be evaluated were previously established in order to standardize and improve the analysis's reliability.

To begin, companies listed in the GRI Disclosure Database (deactivated in the second half of 2021), the Dow Jones Sustainability Index (DJSI) in 2020 (S&P GLOBAL, 2020), and/or the WBA's SDG2000 (WORLD BENCHMARKING ALLIANCE, 2021) were surveyed. This was done in an attempt to gather the sector's leading corporations in terms of ESG/CSR practices.

Following that, information about each company's business activities was gathered. If the business is not a generator of electricity, it was disregarded. This was done to resemble Holding, which generates electricity through hydroelectric, wind, solar, thermoelectric, and nuclear sources. As a result, 50 distinct companies from more than 25 countries met these criteria, and data for TWC, EC, REG, EBITDA, and NRGP were surveyed for each of these companies from 2017 to 2020.

Companies that lacked at least one output were eliminated. The lack of input data was not liable to exclusion because, as a database is built, it may be worthwhile to apply the methodology to other inputs such as waste and GHG emissions, which are not dependent on whether companies report water or energy consumption but are dependent on whether they report renewable and non-renewable generation and EBITDA. This resulted in 135 DMUs because the company enters the database as a distinct DMU each year that it matches the set criteria. Appendix I contains the 135 DMUs and their indicators used in this work.

The descriptive analysis of the indicators raised for the initial set of DMUs is presented in Table 2.

Table 2 - Descriptive analysis of the inputs and outputs of the initial set of 135 DMUs

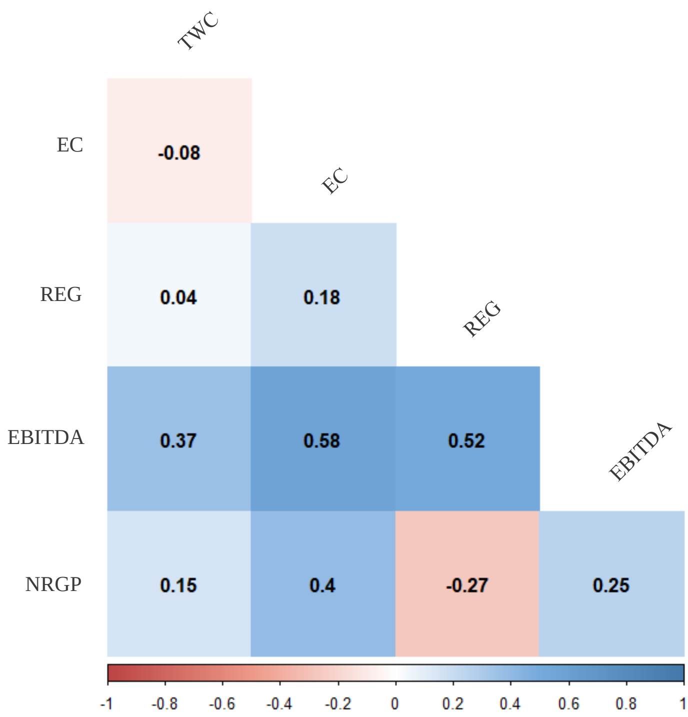
Indicator	Min.	1st Quartile	Median	Mean	3rd Quartile	Max.
TWC [10^3 m^3]	89	6,550	20,000	90,395	88,463	1,047,850
EC [TJ]	101	20,195	89,968	267,498	415,604	1,674,503
EBITDA [M. EUR]	150	486	2,430	3,453	3,950	17,940
REG [GWh]	1	4,410	10,393	23,362	28,885	175,479
NRGP [%]	0	17	65	54	87	100

Source: Author.

As illustrated in Table 2, the database created contains businesses of various sizes and energy generation sources. For instance, the minimum EBITDA is 150 million euros, while the maximum is 17,940 million euros, a value 120 times greater; renewable energy generation ranges from 0% to 100%. Thus, even though they operate in the same sector, comparing them is inappropriate since their business models are distinct, particularly when using the DEA model assuming constant returns to scale. For this reason, before DEA, a clustering step is performed, allowing for more realistic benchmarking.

Another important analysis before applying DEA is to check any statistical association, whether causal or not, between the selected inputs and outputs, i.e., correlation. Additionally, as previously stated, DEA requires an isotonic relationship. (WANG, LIN, *et al.*, 2016). Therefore, Figure 4 presents the correlation matrix that illustrates the correlation between variables to gain a better understanding of the data before proceeding to more advanced analyses.

Figure 4 - Correlation matrix of inputs and outputs used in DEA



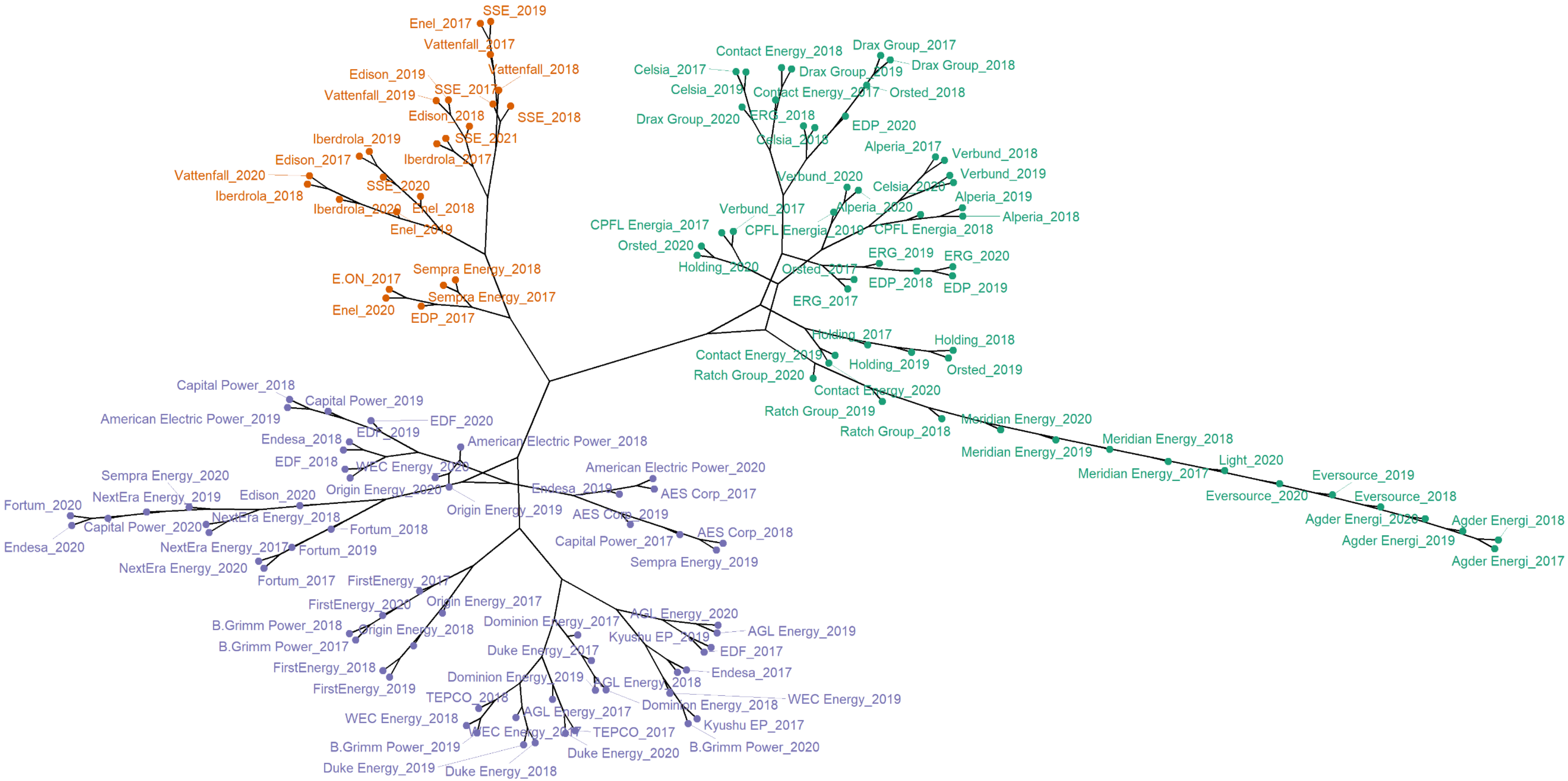
Source: Author.

From Figure 4, both inputs have a positive correlation with outputs. At the same time, there is little correlation between the outputs, and each one can be maintained independently. Thus, not only do these outputs make sense in terms of the study's analysis, but their selection is also statistically justified.

3.4 Clustering

DMUs are then clustered according to their NRGP. The dendrogram in Figure 5 illustrates the result, while Table 3 shows and compares the range analysis of the inputs and outputs of the Holding_2020's cluster.

Figure 5 - Clustering results based on Nonrenewable Energy Generation (NRGP)



Source: Author.

Table 3 - Comparison of the range of values of the indicators in the initial sample and cluster 3

Indicator	Initial sample		Cluster 3	
	Max	**Min**	**Max**	**Min**
TWC [10^3 m^3]	1,047,850	89	403,330	282
EC [TJ]	1,674,503	101	234,747	4,149
EBITDA [M. EUR]	17,940	150	4,429	257
REG [GWh]	175,479	1	175,479	4,340
NRGP [%]	100	0	36	5

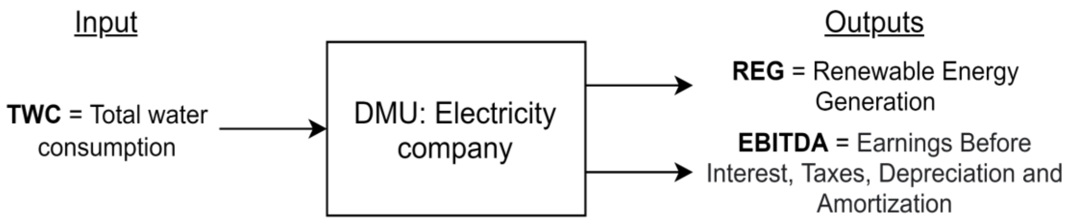
Source: Author.

In Figure 5, Holding_2020's cluster is the green one, named as cluster 3, composed of 53 DMUs, including Holding in all four years. As shown in Table 3, there was a standardization of the data, both inputs and outputs, which resulted in a reduction in the range of all indicators. Thus, clustering accomplished its objective of defining a group of companies that are more similar to the analyzed company, thereby enabling more reliable benchmarking.

3.5 Data Envelopment Analysis

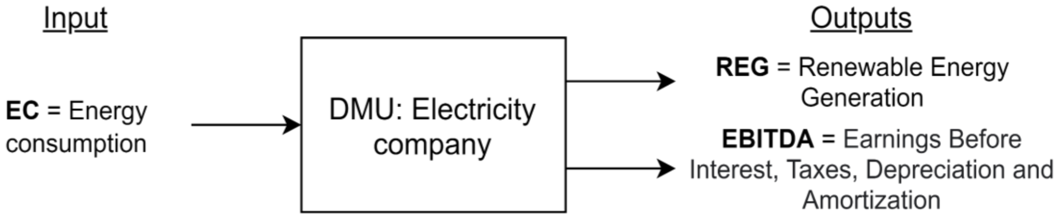
Two distinct DEAs are performed using only the DMUs in cluster 3: one with TWC as the input (Figure 6) and another with EC as the input (Figure 7), both using the same outputs. This was done to set different targets for energy and water consumption.

Figure 6 - DMU and its input and outputs for the first DEA model



Source: Author.

Figure 7 - DMU and its input and outputs for the second DEA model



Source: Author.

Due to the lack of information on the water and/or energy consumption of some DMUs in this cluster, the two DEA models have distinct DMUs. Both models were constructed using the vertical dimension approach, i.e., one frontier was constructed for each model that contained DMUs during the four-year analysis period.

Table 4 summarizes the eco-efficiency and target results for the model based on TWC.

Table 4 - DEA results for TWC model

DMU	Eco-Efficiency	Target for 2021	Absolute target [10^3 m^3]	Relative target [m^3/GWh of REG]
Celsia_2017	0.02	-98%	37.14	7.54
Celsia_2018	0.02	-98%	37.58	7.95
Celsia_2019	0.02	-98%	37.16	8.50
Celsia_2020	0.07	-93%	31.77	7.32
Contact Energy_2017	0.00	-100%	34.21	5.03
Contact Energy_2018	0.00	-100%	30.56	4.49
Contact Energy_2019	0.00	-100%	33.05	4.41
Contact Energy_2020	0.00	-100%	27.87	3.93
EDP_2018	0.02	-98%	358.98	7.35
EDP_2019	0.02	-98%	400.83	8.87
EDP_2020	0.03	-97%	427.26	8.88
Holding_2017	0.89	-11%	424.29	2.67
Holding_2018	1.00	0%	481.10	3.04
Holding_2019	1.00	0%	419.18	2.62
Holding_2020	**0.68**	**-32%**	**458.83**	**2.62**
Orsted_2017	0.56	-44%	326.98	19.85

Orsted_2018	1.00	0%	435.00	22.30
Orsted_2019	0.90	-10%	253.15	10.35
Orsted_2020	0.23	-77%	262.88	9.10
Verbund_2017	0.16	-84%	100.15	3.27
Verbund_2018	0.24	-76%	93.86	3.18
Verbund_2019	0.29	-71%	128.36	4.06
Verbund_2020	0.63	-37%	140.17	4.32

Source: Author.

Holding_2020 had an eco-efficiency of 0.68, i.e., at least one DMU could produce the same products with less water consumption. Hence, its target for 2021 is to reduce its water consumption by 32% compared to its consumption in 2020, setting an absolute target of 458 thousand m³ of water.

In 2020, Holding consumed 3.84 m³ of water for each GWh of renewable energy generated. As an alternative to an absolute target, a relative target of 2.62 m³/GWh of REG can also be established, which is critical in the case of company-wide renewable energy expansion, as the company's REG increased by 11% over the last four years. This is aligned with target 6.4 of SDG 6 of "substantially increase water-use efficiency across all sectors".

Table 5 summarizes the results for the EC model.

Table 5 - DEA results for EC model

DMU	Eco-Efficiency	Target for 2021	Absolute target [TJ]	Relative target [TJ/GWh of REG]
Alperia_2017	0.74	-26%	2,478	0.67
Alperia_2018	1.00	0%	3,099	0.73
Alperia_2019	0.93	-7%	3,311	0.75
Alperia_2020	1.00	0%	3,630	0.71
Celsia_2017	0.53	-47%	4,851	0.98
Celsia_2018	0.47	-53%	4,909	1.04
Celsia_2019	0.52	-48%	4,855	1.11
Celsia_2020	1.00	0%	4,149	0.96
Contact Energy_2017	0.29	-71%	4,922	0.72
Contact Energy_2018	0.26	-74%	4,606	0.68

Contact Energy_2019	0.36	-64%	5,019	0.67
Contact Energy_2020	0.35	-65%	4,453	0.63
Drax Group_2018	0.04	-96%	7,386	0.54
Drax Group_2019	0.05	-95%	8,327	0.61
Drax Group_2020	0.05	-95%	8,520	0.59
EDP_2018	0.20	-80%	46,882	0.96
EDP_2019	0.26	-74%	52,372	1.16
Holding_2017	0.67	-33%	84,651	0.53
Holding_2018	1.00	0%	87,092	0.55
Holding_2019	1.00	0%	84,983	0.53
Holding_2020	**1.00**	**0%**	**91,319**	**0.52**
ERG_2017	0.34	-66%	6,671	1.40
ERG_2018	0.34	-66%	6,939	1.30
ERG_2019	0.35	-65%	7,123	1.31
ERG_2020	0.38	-62%	6,798	1.30
Orsted_2017	0.47	-53%	42,775	2.60
Orsted_2018	0.70	-30%	56,913	2.92
Orsted_2019	0.52	-48%	33,087	1.35
Orsted_2020	0.60	-40%	34,350	1.19
Verbund_2017	0.58	-42%	17,483	0.57

Source: Author.

In this model, Holding_2020 was eco-efficient (1.00), i.e., no DMU had a better ratio of the sum of weighted inputs to outputs. Hence, its target for energy consumption is to maintain the company's performance for the year 2021 based on its consumption in the year 2020. Therefore, the company has an absolute target to consume 91,319 TJ.

It is important to highlight that a maintenance goal also requires efficiency in energy consumption without limiting the expansion of the company's generation, especially in a scenario where there is a projected growth of electricity demand of 3.5% per year in the period 2021-2031 in Brazil (ENERGY RESEARCH OFFICE, 2021).

Additionally, a relative target of 0.52 TJ/GWh of REG can also be set. When compared to the year 2018, this relative target makes the company maintain a 5.5% improvement in energy efficiency, being aligned with SDG 8.4 "Improve progressively, through 2030, global resource efficiency in consumption and production".

3.6 Forecasting

Having the company's targets for both indicators, the next step is to distribute them among its nine BUs. For this, the time series from 2015 to 2020 of water and energy consumption of each BU were collected from the company's sustainability management database.

As it is desired to evaluate the forecast for the 12 months of 2021, the time series were divided into a training set from 2015 to 2019 and a test set in 2020 to obtain the MASE for each BU. The model with the lowest MASE is the best-adjusted model and is used to forecast the consumption of water and energy for 2021. It is important to note that 2020 was marked by remote work due to the COVID-19 pandemic, which impacts the water and energy consumption of the BUs' business activities and, consequently, forecasts.

Table 6 presents the results for water consumption.

Table 6 - Forecast results for BU's water consumption

Business unit	**Lowest MASE**	**Best adjusted model**	**TWC in 2020 [10^3 m^3]**	**TWC forecast for 2021 [10^3 m^3]**
BU_1	746.1	ETS	25	9
BU_2	3.2	ARIMA	19	22
BU_3	1.1	ARIMA	64	59
BU_4	1.0	ARIMA	121	128
BU_5	3.3	ARIMA	21	14
BU_6	1.1	ETS	72	72
BU_7	9.2	ARIMA	3	3
BU_8	0.9	ARIMA	316	362
BU_9	1.1	ETS	32	37
Holding	**-**	**-**	**673**	**697**

Source: Author.

Table 6 shows that ARIMA models had better results in 6 of the 9 BUs. This converges with results found by RAZALI *et al.* (2018). In general, the models had low

MASE, except for BU_1 and BU_7. The MASE of BU_1 was very high because since 2015 it has undergone restructuring and methodology changes in water consumption reporting, which made its time series variable. Additionally, Holding is forecast to increase its water consumption in 2021 compared to 2020. This makes the task of defining a target for reducing water consumption more difficult, which will be shown later in the step of distributing targets with WGP.

Table 7 presents the results for energy consumption.

Table 7 - Forecast results for BU's energy consumption

Business unit	**Lowest MASE**	**Best adjusted model**	**EC in 2020 [TJ]**	**EC forecast for 2021 [TJ]**
BU_1	1.15	ETS	64,089	67,656
BU_2	4.37	ETS	20	24
BU_3	2.9	ETS	14,129	18,691
BU_4	19.16	ETS	818	1,088
BU_5	2.81	ETS	16	17
BU_6	1.44	ARIMA	343	3,771
BU_7	2.05	ARIMA	580	267
BU_8	2.29	ETS	10,953	14,704
BU_9	11.39	ETS	371	376
Holding	**-**	**-**	**91,319**	**106,594**

Source: Author.

Table 7 shows that ETS models had better results in 7 of the 9 BUs. In general, the models had low MASE, but with a higher average than TWC forecasts. The exception is BU_4 and BU_9. One possible explanation is the improved reporting of energy consumption by BU_4 over the series analyzed. Additionally, BU_4 has a thermoelectric activity which makes its energy consumption (coal) for electricity generation quite variable, since its increase and decrease in generation depends on the country's hydroelectric generation, making its time series forecast challenging. On the other hand, no features called attention to justify BU_9's high MASE.

As well as water consumption, Holding is forecast to have an increase in energy consumption for 2021 compared to 2020. Although it may initially seem easy to achieve, this makes the maintenance target set in the DEA model challenging.

3.7 Weighted Goal Programming

With the forecasts, the last step before distributing the company's target among its BUs with WGP is the definition of the reference values (R_i) and weights (W_i) in Eq. (6). In this step enters the opinion of the managers of each BU regarding the behavior of their unit in relation to the indicator evaluated. For the case study, the manager of each BU was asked his/her opinion about the trend of water and energy consumption for 2021 compared to 2020.

With the answers, the following criterion was defined: if the manager's opinion of a BU_i equals with the forecasted trend for that BU_i and its MASE is less than the median of the MASEs of the nine BUs, the forecasted value for 2021 is the reference value for the target distribution. Therefore, in this case, the WGP will seek to minimize deviations from the forecast since this, from the defined criteria, is considered reliable. Otherwise, if the manager's opinion diverges from the forecast and/or BU_i's MASE is greater than the median, R_i is the indicator (water or energy consumption) value in 2020. Therefore, in this case, WGP will seek to minimize deviations from the previous year, since the forecast for BU_i, based on the defined criteria, is not considered reliable. The results of R_i are presented in Table 8.

Table 8 - Reference value for each BU based on established criteria. Forecast and MASE were collected from Table 6 and Table 7.

BU	Water consumption				Energy consumption			
	Manager's Opinion	**Forecast**	**MASE (Med.)**	**R_i**	**Manager's Opinion**	**Forecast**	**MASE (Med.)**	**R_i**
BU_1	D	D	746 (1.12)	P	D	I	1.15	P
BU_2	D	I	3.2 (1.12)	P	I	I	4.37	P

BU_3	D	D	1.07 (1.12)	F	D	I	2.9	P
BU_4	D	I	1.02 (1.12)	P	I	I	19.16	P
BU_5	I	D	3.28 (1.12)	P	D	I	2.81	P
BU_6	D	D	1.06 (1.12)	F	D	I	1.44	P
BU_7	I	D	9.25 (1.12)	P	I	D	2.05	P
BU_8	D	I	0.95 (1.12)	P	I	I	2.29	F
BU_9	I	I	1.12 (1.12)	P	I	I	11.39	P

Source: Author.

Legend: I = Increase; D = Decrease; P = Past consumption as reference; F = Forecast consumption as reference.

For the allocation of the weights of each BU in the WGP, the higher the weight the more importance is given to keeping the reference value R_i, i.e., less deviation is desired. Therefore, the more confidence in the behavior that the BU will have regarding water and energy consumption in the future, the lower the weight that directs towards this expected behavior. Thus, in cases where more is known about the consumption behavior, i.e., where both the forecast and the manager's opinion converge, and at the same time there is a low MASE, the weight given to this BU will be lower, inducing the distribution of a more customizable target for each BU, always obeying the company's target defined in DEA. Table 9 details the criteria adopted for each case.

Table 9 - Criteria for defining the weights in the distribution of the company's target among its BUs based on forecasts and management opinion

Manager's opinion	**Forecast**	$\boldsymbol{W_i^+}$	$\boldsymbol{W_i^-}$
Increase	Increase	$\frac{1}{MASE_i}0.01$	$\frac{1}{MASE_i}$

Decrease	Decrease	$\frac{1}{MASE_i}$	$\frac{1}{MASE_i}0.01$
Increase	Decrease	$MASE_i$	$MASE_i$
Decrease	Increase	$MASE_i$	$MASE_i$

Source: Author.

As shown in Eq. (6), W_i^+ and W_i^- are the weights of the upward and downward deviation from the reference value R_i, respectively. When the manager's opinion converges with the forecast, either to increase or decrease the consumption of the analyzed indicator, an arbitrary factor of 0.01 is added to the weight in the same direction as the convergence. For example: if both indicate an increase in energy consumption in 2021 for a BU and, in addition, the MASE is small, is wished a small W_i^+, which would facilitate a target that allows the BU in question to increase its consumption, restricted to the upper limit β. Conversely, if both indicate a reduction in energy consumption in 2021, with a small MASE, the W_i^- will be small, facilitating a reduction target for the BU in question. If there is a divergence between the manager's opinion and the BU_i forecast, only the MASE is used as a weight, with the more uncertain forecasts having higher weights, depending less on the distribution of the target in these BUs for the success of the company's target. Additionally, when the manager's opinion and the forecast converge, the inverse of the MASE is adopted to define the weight. This is done to reduce the dependence on the value of the most uncertain forecast, already used as a reference in the target distribution. Thus, on this occasion, a forecast with high MASE and therefore less reliable makes the weight W smaller and thus less restricts deviations from the reference F.

Finally, with the forecasts, the prediction intervals limits, and the weights in the WGP model, the next step is to distribute the company target between its BUs. In the case of water consumption, WGP did not achieve an optimal solution, i.e., with BU conditions for 2021, it would not be possible to meet all criteria and at the same time reduce the Holding's water consumption by 32%. This result shows the importance of this step of the methodology, avoiding the definition of targets that could not possibly be achieved within 1 year. Therefore, the initial solution was to divide the target equally in 2 years, being revised the following year. Thus, Holding's target for 2021 would be to reduce its water consumption by 16% compared to 2020. In this case, a solution was found through the linear programming of WGP and BUs' targets are shown in Table 10.

Table 10 - Individual targets for water consumption

BU	**Water consumption targets for 2021**	
	in 10^3 m^3	**Deviation from 2020**
BU_1	9	-63%
BU_2	19	0%
BU_3	53	-18%
BU_4	110	-9%
BU_5	21	0%
BU_6	72	0%
BU_7	3	0%
BU_8	242	-23%
BU_9	37	14%
Holding	**566**	**-16%**

Source: Author.

From Table 10, targets for reducing, maintaining, and increasing water consumption were set for the BUs. Water consumption increase targets were allowed only for BU_9 because both the manager's opinion and the forecast indicate an increase in the consumption of this input in 2021.

BU_1 had the highest reduction target (63%). This happened because its reference value is the previous year's consumption and, therefore, its lower limit of goal distribution is based on its history, which has already presented such a variation between consecutive years, underpinning the metric of the reduction target.

In the case of energy consumption, the optimal solution was found for the maintenance target for 2021. The results of individual targets for energy consumption are presented in Table 11.

Table 11 - Individual targets for energy consumption

BU	Energy consumption targets for 2021	
	in TJ	**Deviation from 2020**
BU_1	60,338	-6%
BU_2	24	20%
BU_3	14,129	0%
BU_4	818	0%
BU_5	16	0%
BU_6	343	0%
BU_7	580	0%
BU_8	14,700	34%
BU_9	371	0%
Holding	**91,319**	**0%**

Source: Author.

From Table 11, targets for reducing, maintaining, and increasing energy consumption were set for the BUs. This occurred based on the 2021 energy consumption forecasts. Energy consumption increase targets were allowed for BU_2 and BU_8. In both cases, the target was set to restrict the increase in consumption as predicted by the models. Since BU_1 is responsible for the consumption of two-thirds of the Holding's energy, its reduction target, defined based on the opinion of the business's manager, allowed BUs with a greater tendency to increase their energy consumption in 2021 to have a controlled increase, without compromising the Holding's target of maintenance.

4 CONCLUSION

The key to the proposed methodology is the definition of corporate sustainability targets based on DEA. The forecasts have the function to support the breakdown of the company target within its business units in WGP, allowing to define individual targets that consider specificities.

Despite being a step outside the scope of the proposed methodology, the choice of indicators or KPIs for target setting is of essential importance for an effective corporate contribution to sustainable development and the SDGs of the 2030 Agenda. The Brazilian electricity sector, to which the company in the case study belongs, is constantly evolving, with numerous negative impacts that must be avoided or mitigated and positive ones that must be promoted. In a diagnosis made by REDE BRASIL DO PACTO GLOBAL (2020), with support from companies in the sector, SDG 7, SDG 8, SDG 9 (Industry, Innovation and Infrastructure), SDG 11 (Sustainable Cities and Communities), and SDG 13 were defined as priorities by the Brazilian electricity sector.

However, looking at the results, the company was eco-efficient concerning its energy consumption and eco-inefficient for its water consumption. Therefore, although energy efficiency is a priority for the sector, from the result found, it should not be a priority for the company. In contrast, water consumption, which is not considered a priority by the sector, should be a priority for the company. Although the indicator analyzed is water consumption, which corresponds only to a type of water use, the importance that should be given to this input is reinforced by the fact that electricity and gas is the sector with the highest water use intensity in Brazil.

These results reinforce the challenges of universalizing indicators and targets presented in the Introduction: a company's sustainability practices that should be prioritized do not necessarily coincide with the practices defined by the sector as priorities. Therefore, although such studies about the sector are of great importance, the company must contextualize its main impacts in the process of defining KPIs and its targets. Additionally, targets for these KPIs must induce the company to achieve social and environmental standards without compromising their competitiveness, i.e., a balance of economic, environmental, and social imperatives, while at the same time addressing the expectations of shareholders and stakeholders.

Considering the gaps in tools and methodologies for setting corporate sustainability targets presented in Chapter 1, this methodology allowed:

- Define more challenging targets: the case study company's official water consumption reduction target was 0.5%, while the methodology proposed a 32% reduction target by 2022 with a statistical, manager's opinion, and benchmarking of the major companies in the global electric sector justification;
- Integrating the target into the operation: with the WGP stage, the company's target defined in the benchmarking stage was distributed among the business units according to the specificity of each one for the target year, based on the

analysis and forecast of the historical series and the opinion of managers. This makes the apparently non-challenging target, as was the case with the energy consumption maintenance target, to be more easily materialized in the companies' operations, avoiding the failure of the target;

- Low average DEA efficiency tends to set unattainable targets: without the clustering step prior to DEA, the average eco-efficiency of companies would be 0.08 for water consumption and 0.06 for energy consumption. With the application of clustering, these eco-efficiencies changed to 0.34 and 0.55, respectively, without losing the descriptive character of the model. Therefore, clustering accomplished its objective of defining a group of companies that are more similar to the analyzed company, enabling more reliable benchmarking.

The presented case study focused solely on the environmental aspect of corporate sustainability, with no mention of the other components of sustainable development. However, as previously stated, such methodology can also be applied to social and economic aspects, either individually or combined. The breadth of application of this methodology becomes important, primarily because the literature is gradually replacing total sustainability with a narrower CSR that is dominated by the social dimension of sustainability while covering little or nothing of the environmental and economic dimensions (ALSHEHHI, NOBANEE, *et al.*, 2018).

An example of an integrated approach is defining targets that are linked to the demands of ESG frameworks. The SASB framework, for example, states in the topic Greenhouse Gas Emissions & Energy Resource Planning of its Sustainability Accounting Standard for Electric Utilities & Power Generators that the "entity shall discuss its emission reduction target(s) and analyze its performance against the target(s)" (SASB, 2018). Thus, in addition to the environmental bias of the company's activities' impact on climate change and its various negative consequences, the use of the proposed methodology to set GHG emissions targets provides the financial appeal because, as previously stated, ESG practices, enhanced by disclosure through adherence to such ESG frameworks as SASB, tend to be beneficial to the company's financial performance.

This methodology, in addition to setting targets, enables the mapping of the company's main impacts in comparison to the industry in the benchmarking step using

DEA, which is critical for prioritizing the company's sustainability management. As mentioned by ISE it is "essential to use diagnostic methodologies capable of identifying what needs to be managed, as well as mechanisms that enable the correct control of these impacts, establishing indicators to be monitored and targets to be met" (B3, 2021b).

It is critical to understand the distinction between sustainable development and ESG/CSR practices. By definition, sustainable development seeks to establish a balance between the needs of current and future generations. ESG/CSR practices are directly dictated by stakeholder demands, assessing the impacts on the business to make the best decision in terms of opportunity gains and risk reduction. A benchmarking step using methods such as DEA perfectly supports this decision-making assessment. In turn, by linking the targets to the SDGs, sustainable development is indirectly incorporated into the company's business model.

Therefore, as a result of this methodology, it is possible to meet market demands, such as those found in sustainability indexes and frameworks, while also meeting the specific demands of the company being evaluated. Thus, the environmental and social aspects converge with the company's economic/financial interests, which tends to make the target-setting process, as well as the target itself, more acceptable in the process of integrating it into governance practices.

In this study, Operational Research was used to assist in the process of setting targets for sustainability indicators with the proposed use of DEA, clustering analysis, time series forecast, and GP. In practice, companies in the same sector have different market strategies, translating into a heterogeneity of the set of variables analyzed. Using such methods becomes possible to define targets for an input using several outputs, allowing different approaches by the decision-maker.

As it was possible to see in the results, this work depends on several externalities and specificities, present in each indicator, company, and sector. Therefore, a methodological structure is proposed, based on Operational Research methods and specialists' opinions to assist and support planned targets, maintaining the commitment to the challenges present in the SDGs to achieve corporate sustainability. However, it is important to mention that the targets proposed by this methodology do not consider the carrying capacity of the ecosystems of each business unit, as they are inherent to the business itself. In other words, the same business unit may behave differently in different ecosystems.

Defining indicators and targets to measure the contribution of utility companies to SDGs is difficult, but possible and feasible. The application of the DEA method, as proposed here, can assist to identify the level of eco-efficiency of the company's performance, guiding the way to better define feasible and challenge SDGs targets. This was shown in the case study presented for a company in the electricity sector, a key sector for the transition to sustainable development and, therefore, must be prepared to act in this direction.

Future studies could use this methodology in a different sector, with different indicators for target setting or a different DEA or SFA model. Furthermore, the significance of the company's target can be evaluated in relation to global, national, and/or sectoral targets. Future research could incorporate the company's location into the methodology to account for the carrying capacity of the ecosystem in which it operates. Finally, global policies that define targets for environmental and social aspects are a trend. The Paris Agreement's climate targets are one example. As a result, it is worthwhile to integrate the methodology with other tools and methodologies for it to be applicable in these cases as well. In the case of climate targets, the methodology proposed here can be combined with the SBTi methodology to generate GHG emission targets that take into account not only climate science but also the company's specific characteristics.

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APPENDICES

Appendix I

Sample of companies (DMUs) in the electricity sector, their total water consumption **(TWC)**, energy consumption **(EC)**, **EBITDA**, renewable energy generation **(REG),** and percentage of nonrenewable energy generation **(NRGP)**. NA = data not available

DMU	TWC [10^3 m^3]	EC [TJ]	EBITDA [M. EUR]	REG [GWh]	NRGP
AES Corp_2017	1,047,850	NA	3,019	16,749	0.82
AES Corp_2018	993,510	NA	2,876	15,944	0.81
AES Corp_2019	109,440	220,958	2,868	14,637	0.81
Agder Energi_2017	NA	NA	190	8,971	0.00
Agder Energi_2018	NA	NA	169	8,860	0.00
Agder Energi_2019	NA	NA	308	7,411	0.00
Agder Energi_2020	NA	NA	241	8,293	0.00
AGL Energy_2017	95,933	490,445	1,258	3,569	0.92
AGL Energy_2018	88,521	486,675	1,415	3,963	0.91
AGL Energy_2019	87,716	483,758	1,419	4,480	0.90
AGL Energy_2020	117,820	474,512	1,251	4,557	0.90
Alperia_2017	NA	3,340	150	3,711	0.05
Alperia_2018	NA	3,099	199	4,269	0.04
Alperia_2019	NA	3,544	216	4,398	0.04
Alperia_2020	NA	3,646	229	5,135	0.04
AEP _2018	182,464	546,672	4,308	11,722	0.89
AEP _2019	167,429	489,073	4,762	13,465	0.86
AEP _2020	194,590	450,019	5,170	15,134	0.82
B.Grimm Power_2017	NA	44,988	228	101	0.99
B.Grimm Power_2018	3,660	49,928	241	112	0.99
B.Grimm Power_2019	5,080	56,513	331	774	0.94
B.Grimm Power_2020	4,480	58,705	364	1,201	0.91
Capital Power_2017	14,000	121,745	419	2,474	0.81
Capital Power_2018	21,000	141,845	481	2,192	0.86
Capital Power_2019	15,556	174,866	693	2,913	0.86
Capital Power_2020	10,471	153,568	624	4,616	0.76
Celsia_2017	2,170	9,097	343	4,927	0.22
Celsia_2018	2,130	10,371	347	4,730	0.27
Celsia_2019	1,760	9,410	344	4,374	0.22
Celsia_2020	470	4,149	294	4,340	0.05
Contact Energy_2017	403,330	17,078	316	6,795	0.20
Contact Energy_2018	325,499	17,509	282	6,802	0.21

Contact Energy_2019	302,278	14,012	305	7,487	0.16
Contact Energy_2020	322,015	12,677	257	7,085	0.17
Dominion Energy_2017	47,900	NA	5,442	4,677	0.96
Dominion Energy_2018	32,900	NA	4,486	5,864	0.95
Dominion Energy_2019	25,300	NA	4,038	5,622	0.95
Drax Group_2017	NA	NA	271	15,000	0.25
Drax Group_2018	NA	180,971	283	13,725	0.25
Drax Group_2019	NA	165,691	468	13,667	0.21
Drax Group_2020	NA	173,714	463	14,476	0.23
Duke Energy_2017	268,764	NA	8,573	10,880	0.95
Duke Energy_2018	317,974	NA	7,950	12,334	0.95
Duke Energy_2019	276,335	NA	9,721	11,967	0.94
Duke Energy_2020	257,408	NA	8,804	14,875	0.93
E.ON_2017	37,000	201,000	4,955	32,858	0.46
Edison_2017	NA	NA	3,166	5,905	0.61
Edison_2018	NA	NA	1,176	3,592	0.66
Edison_2019	NA	NA	3,331	4,377	0.65
Edison_2020	NA	NA	3,141	2,225	0.78
EDF_2017	NA	NA	13,742	57,742	0.91
EDF_2018	529,583	80,712	14,898	81,309	0.87
EDF_2019	511,594	77,472	16,723	74,692	0.87
EDF_2020	459,325	88,704	16,174	78,433	0.85
EDP_2017	28,370	291,045	3,990	40,154	0.42
EDP_2018	21,800	234,747	3,317	48,810	0.32
EDP_2019	21,736	201,318	3,706	45,192	0.32
EDP_2020	14,967	NA	3,950	48,097	0.24
Holding_2017	479	126,892	2,821	158,725	0.13
Holding_2018	481	87,092	4,429	158,068	0.14
Holding_2019	419	85,337	2,600	160,142	0.13
Holding_2020	673	91,319	1,803	175,479	0.10
Endesa_2017	66,060	684,142	3,542	6,725	0.91
Endesa_2018	24,500	615,336	3,627	9,206	0.88
Endesa_2019	6,810	507,614	3,841	10,393	0.84
Endesa_2020	NA	NA	3,783	13,415	0.76
Enel_2017	58,400	1,674,503	15,653	81,695	0.67
Enel_2018	48,700	1,550,765	16,351	98,940	0.60
Enel_2019	58,100	1,261,095	17,905	99,392	0.57
Enel_2020	20,400	1,027,197	17,940	105,360	0.49
ERG_2017	NA	19,857	472	4,756	0.34
ERG_2018	NA	20,308	491	5,333	0.29
ERG_2019	NA	20,398	504	5,455	0.31
ERG_2020	NA	17,747	481	5,236	0.32
Eversource_2018	NA	NA	2,349	251	0.00

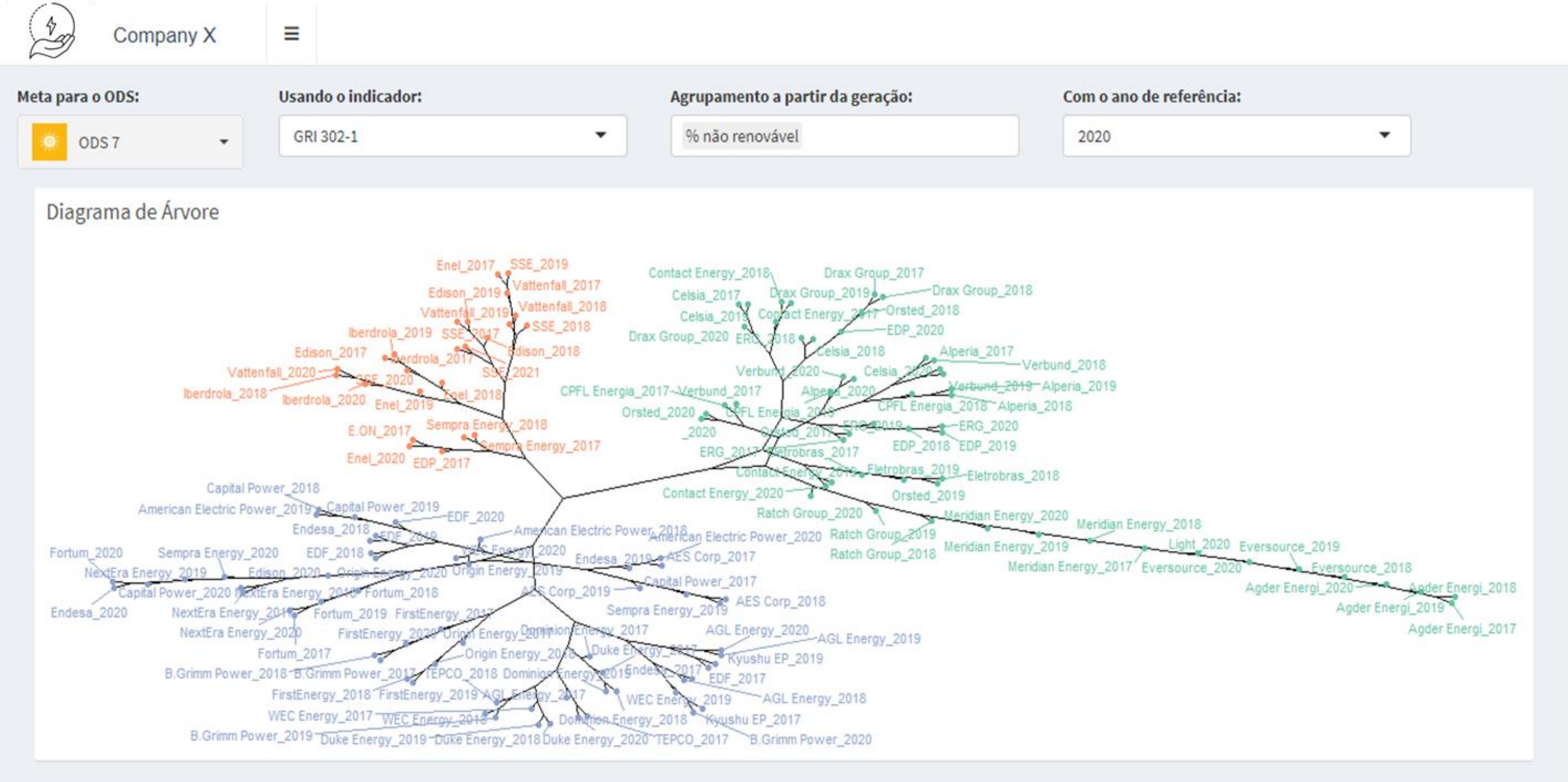
Eversource_2019	NA	1,349	2,385	37	0.00
Eversource_2020	89	NA	2,761	82	0.00
FirstEnergy_2017	155,000	NA	3,659	1,745	0.98
FirstEnergy_2018	149,300	NA	3,293	314	1.00
FirstEnergy_2019	20,855	NA	3,329	120	0.99
FirstEnergy_2020	15,946	NA	2,948	250	0.99
Fortum_2017	65,000	394,400	1,729	27,500	0.73
Fortum_2018	68,000	430,000	1,650	26,900	0.74
Fortum_2019	60,000	411,700	2,533	28,100	0.73
Fortum_2020	57,000	908,400	3,928	40,790	0.76
CPFL Energia_2017	NA	NA	1,352	8,050	0.08
CPFL Energia_2018	NA	NA	1,313	10,477	0.04
CPFL Energia_2019	NA	NA	1,449	12,874	0.02
Iberdrola_2017	84,054	440,547	7,319	50,744	0.63
Iberdrola_2018	87,742	401,627	9,349	61,754	0.58
Iberdrola_2019	88,406	427,315	10,104	59,299	0.61
Iberdrola_2020	70,644	429,650	10,010	68,066	0.58
Kyushu EP_2017	NA	NA	2,811	5,900	0.91
Kyushu EP_2019	NA	NA	2,705	6,000	0.91
Light_2020	NA	101	429	4,410	0.00
Meridian Energy_2017	11,447	NA	414	13,825	0.00
Meridian Energy_2018	11,739	NA	390	13,109	0.00
Meridian Energy_2019	12,351	NA	493	14,298	0.00
Meridian Energy_2020	12,345	NA	486	14,864	0.00
NextEra Energy_2017	113,562	NA	6,924	46,503	0.75
NextEra Energy_2018	113,562	NA	7,142	47,282	0.76
NextEra Energy_2019	140,857	NA	8,780	49,890	0.76
NextEra Energy_2020	107,578	NA	8,271	58,688	0.73
Origin Energy_2017	NA	NA	1,719	1	1.00
Origin Energy_2018	NA	NA	2,036	158	0.99
Origin Energy_2019	6,741	NA	2,007	2,901	0.88
Origin Energy_2020	6,360	NA	1,898	3,027	0.87
Orsted_2017	585	91,231	3,027	16,474	0.36
Orsted_2018	435	81,619	4,027	19,510	0.25
Orsted_2019	282	63,209	2,341	24,450	0.14
Orsted_2020	1,128	57,622	2,430	28,886	0.10
Ratch Group_2018	15,720	87,580	252	17,354	0.00
Ratch Group_2019	13,020	74,878	288	14,782	0.00
Ratch Group_2020	13,730	79,644	271	15,441	0.00
Sempra Energy_2017	9,085	NA	3,088	5,910	0.53
Sempra Energy_2018	9,842	NA	3,015	6,691	0.52
Sempra Energy_2019	7,571	NA	3,747	1,453	0.81
Sempra Energy_2020	7,949	74,784	3,676	1,764	0.77

SSE_2017	7,600	1,224	2,616	7,955	0.70
SSE_2018	5,600	1,300	2,417	9,744	0.71
SSE_2019	6,900	1,297	1,959	10,073	0.67
SSE_2020	6,900	1,203	2,465	10,752	0.62
SSE_2021	3,600	843	2,576	9,937	0.64
TEPCO_2017	9,634	1,516,012	6,879	13,275	0.93
TEPCO_2018	9,939	1,471,624	6,620	12,180	0.94
Vattenfall_2017	21,000	313,920	3,571	47,700	0.68
Vattenfall_2018	2,000	313,560	3,348	48,000	0.68
Vattenfall_2019	1,500	277,200	4,011	49,900	0.66
Vattenfall_2020	1,400	NA	4,437	54,100	0.57
WEC Energy_2017	NA	NA	2,283	2,052	0.94
WEC Energy_2018	20,000	NA	1,961	2,095	0.94
WEC Energy_2019	10,000	NA	2,195	3,011	0.91
WEC Energy_2020	10,000	NA	2,352	3,791	0.88
Verbund_2017	635	30,302	922	30,639	0.07
Verbund_2018	394	24,289	864	29,518	0.05

Source: Author based on public information provided by companies.

Appendix II

Tool created in R Shiny.




Ecoeficiência das empresas do cluster
Eco-Efficiency
1.00
0.75
0.50
0.25
0.00
Drax Group_2018
Drax Group_2020
Drax Group_2019
EDP_2018
EDP_2019
Contact Energy_2018
Contact Energy_2017
ERG_2017
ERG_2018
ERG_2019
Contact Energy_2020
Contact Energy_2019
ERG_2020
Orsted_2017
Celsia_2018
Celsia_2019
Orsted_2019
Celsia_2017
Verbund_2017
Orsted_2020
_2017
Verbund_2018
Orsted_2018
Alperia_2017
Verbund_2019
Alperia_2019
Alperia_2020
_2019
Alperia_2018
Celsia_2020
_2018
_2020
0%
Meta do Grupo
91,318.78
Meta absoluta do Grupo
0.52
Meta relativa do Grupo


Metas individuais
BU1
BU2
BU3
BU4
BU5
BU6
BU7
BU8
BU9
-25
0
25
Meta [%]