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BI Framework to understand Energy Sustainability

An E-Redes case study for Portugal's Energy Scene

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Project Work

presented as partial requirement for obtaining a Master's Degree in Data Science and Advanced Analytics

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BI Framework to understand Energy Sustainability in Portugal
An E-Redes case study for energy

by
David de Amorim Teixeira

Project Work presented as partial requirement for obtaining the Master's degree in Data Science and Advanced Analytics, with a specialization in Business Analytics.

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STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism or any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledged the Rules of Conduct and Code of Honor from the NOVA Information Management School.

[Lisbon, 15 July 2025]

David de Amorim Teixeira

DEDICATION

Firstly, I would like to express my gratitude to my tutors, Bruno Jardim and Duarte Rodrigues, for their invaluable guidance, encouragement, and support throughout the development of this thesis. Secondly, I would also like to thank NOVA IMS for providing me with the opportunity to learn with all the necessary resources and support and therefore making this research possible. Being part of such and organization has been an honor and a privilege.

ABSTRACT

This thesis explores the creation process of a Business Intelligence (BI) framework designed to improve the understanding of Portugal's energy usage and sustainability, using open-source data from the electricity operator, E-Redes. This project work leverages Kimball's Lifecycle methodology to develop a scalable data architecture that includes data ingestion, transformation, and visualization using Microsoft Fabric tools and Power BI. This framework consists of many elements such as a dimensional model with fact and dimension tables, calculated KPIs to monitor different scopes such as energy production, consumption, efficiency and sustainability. The interactive nature of the dashboard allows stakeholders to conduct impactful analyses across different temporal, geographic, and voltage-level granularities. Among the key findings were seasonal trends in consumption, the predominance of low-voltage usage, and regional disparities in energy use which are aligned with the literature found. In addition of addressing a significant gap in the literature by delivering a complete and replicable Business Intelligence (BI) framework for national-level energy monitoring this work also offers a decision-support tool for policy makers, energy providers, and sustainability researchers.

KEYWORDS

Business Intelligence; Energy Consumption; Energy Production; Energy Sustainability; E-Redes; Energy Systems; Key Performance Indicators; Kimball Lifecycle

Sustainable Development Goals (SDG):

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LIST OF ABBREVIATIONS AND ACRONYMS

API	Application Programming Interface
AT	High Voltage
BI	Business Intelligence
BT	Low Voltage
CO_2	Carbon Dioxide
CSV	Comma-Separated Values
DAX	Data Analysis Expressions
DW	Data Warehouse
DL	Data Lakehouse
ETL	Extract, Transform, and Load
GDP	Gross Domestic Product
IEA	International Energy Agency
KPI	Key Performance Indicator
kWh	Kilowatt-Hour
MAT	Very High Voltage
Mt	Megatonne
MT	Medium Voltage
PNEC	Plano Nacional Energia e Clima
SDG	Sustainable Develpment Goals
SM	Semantic Model
SQL	Structured Query Language
TWh	Terawatt-Hour

1. INTRODUCTION

One of the most pressing topics of the current century is the global transition to sustainable practices in the energy sector. The increase in energy demand due to an increasingly energy dependent world, climate change, and geopolitical conflicts are the contributing factors that lead countries to rethink their policies regarding energy consumption, production and distribution. In this context, the use of increasingly reliable data-driven decision-making techniques has become of paramount importance to be used as a support and insightful tool for monitoring energy systems and optimize operations, increasing effectiveness of government policies, business strategies and allowing all stakeholders to make informed decisions regarding energy systems and their sustainability.

In recent years Portugal's efforts to improve energy sustainability have increased significantly setting ambitious goals to achieve a renewable energy share of consumption of 49% by the year 2030 and significantly reduce the emissions of greenhouse gases, according to PNEC (2024). Although there is a great variety of open-source energy data, there is a lack of fully functional and integrated frameworks that allow users to consume this data and transform it into valuable support for decision-making. Most studies found focus only on specific subareas of energy data analytics, such as forecasting, evaluating sustainability progress, or descriptive analysis, but fall short of creating a framework that integrates various elements of data-driven analytics.

The main goal of this thesis is to address the aforementioned gap. To attain this goal, we will be developing a Business Intelligence (BI) framework that allows the extraction, processing, validation, analysis and visualization of energy consumption and production data in Portugal. The project developed follows the Kimball Lifecycle methodology, which incorporates the best data warehousing practices, dimensional modelling, ETL pipelines and KPI definitions. This plan of action will be possible to develop using Microsoft Fabric functionalities and finally a dashboard for visualization will be created using Power BI.

On a more specific note, the objectives of this study are: to develop and implement a scalable BI architecture that is capable of integrating diverse datasets, for energy data or otherwise; to define a set of key performance indicators (KPIs) relevant to the topic of energy monitoring and sustainability and calculate them; to develop an interactive and adjustable dashboard capable of providing accessible insight at multiple granularity levels across various dimensions, such as time, geography and voltage levels.

We used a collection of datasets acquired via open-source from the E-Redes website from Portugal's electricity grid, covering the period between 2021 and early 2025. The dashboard created supports energy analysis from four different scopes: energy consumption, energy production, temporal analysis and geographical distribution. This way, this project contributes to the academic literature on BI and data-driven analytics on the energy sector and also provides a practical tool to support governments, companies and other stakeholders in their decision-making process.

This thesis is structured in the following chapters: Chapter 2 represents a systematic literature review regarding energy analytics, KPI framework and dashboard design. The following section, Chapter 3, describes the methodology used, including understanding the business requirements, defining relevant business questions, outlining the data architecture, describing the data modelling and ETL design. In Chapter 4 the results obtained in the dashboard are described, analysed and compared with previous work on the subject. The final Chapter 5 concludes the project, describing the findings and limitations found in the process of developing this project

2. LITERATURE REVIEW

Amid growing global efforts to transition toward more sustainable and efficient energy systems, the need has emerged for reliable analytical frameworks that enable knowledge extraction from data and support decision-making processes. The current chapter focusses on gathering and reviewing the literature found for three main topics regarding energy studies: data-driven energy analytics, key performance indicators (KPIs), and dashboarding techniques. The compilation of these three domains of current energy management capabilities creates a basis to enable stakeholders to understand energy consumption patterns, measure the potential of policy implementation and their success, and to present energy-related information in an accessible and comprehensible format. By studying the links between advanced analytics, defining valuable KPIs and the most effective visualization tools, this literature review helps to understand how the energy sector can be studied and managed in a more efficient way. The final section of the chapter addresses the gaps identified in the reviewed literature and outlines how this project seeks to overcome them.

2.1. DATA-DRIVEN ENERGY ANALYSIS

Data-driven decision-making has become of paramount importance in the energy sector as it allows for more efficient energy usage and resource allocation, while simultaneously improving sustainability. It consists of leveraging large sets of data to conduct descriptive, prescriptive and predictive analytics that aim to improve the decision-making process for energy consumption and supply.

The challenges come due to the exponentially increasing amount of data being collected and the need for experienced researchers to address how to make use of this information by employing the most adequate techniques and extract knowledge. This supports decision-making and enables better predictions of the energy demand (Segundo Sevilla et al., 2022).

Studying energy consumption is a fundamental process to improve energy efficiency (Puddu, 2023). Energy consumption is dependent on multiple interconnected variables such as economic, social and environmental factors, as increasing urbanization leads to higher demand for energy due to the creation of new infrastructures and public and private services (Jing et al., 2022). In addition, with the rapid advancement of economies, industry inevitably grows, increasing the demand for energy, particularly in sectors that are more energy intensive (Jing et al., 2022). While technological advancements such as new devices might have a positive effect on energy demand, the increase in energetic efficiency might decrease the demand and therefore have a contradictory effect (Donti & Kolter, 2021). The understanding of these factors has become of extreme importance for policy makers, governments and other stakeholders as energy is the cornerstone of both economic prosperity and societal well-being (Donti & Kolter, 2021; Jing et al., 2022).

As we evolve towards more sustainable energy systems and practices, the ability to collect, process and analyse data becomes increasingly important (IEA, 2023) (Donti & Kolter, 2021). Data-driven solutions allow stakeholders to predict energy demand, increase the efficiency of resources, and outline policies that enhance the reliability of energy systems (Trabish, 2024). According to the International Energy Agency, data analytics plays a pivotal role in improving grid management and supporting the adoption of new sources of renewable energy (Donti & Kolter, 2021).

By carefully analysing energy data, researchers and organizations can gain deeper insights regarding how energy is consumed and distributed allowing for informed decision-making. Studying this data is vital for creating strategies that aim to increase energy conservation, balance peak load and create more reliable infrastructures. The goal of energy data analytics is to transform raw data by leveraging advanced data science techniques into useful information to identify trends, anomalies and areas for potential improvement (FM:Systems, 2024).

Among the most important benefits of data analytics is the ability to pinpoint energy systems' inefficiencies. With the adoption of smart meter technologies and other recent monitoring systems it is possible to detect sub-optimal or even wasteful practices and correct them.

Studying peak loads is essential to ensure grid stability and balancing supply and demand. Identifying the points that correspond to higher demand, utility companies can prepare the systems and assess the robustness of their distribution grid to understand if they are capable enough and therefore minimize the risks of outages. This type of analysis also enables the detection of infrastructure weaknesses and supports informed decisions regarding potential system upgrades. (Hark, 2024; Kiliccote et al., 2019).

An accurate forecast of energy consumption is crucial to understand the energy market and maintain its balance. Machine learning models trained on past data the prediction of future consumption trends and align the production of energy to balance demand and supply (Yesilyurt et al., 2024).

In summarize, several domains within data analytics are important in the study of energy consumption and production and are transforming the sector by allowing greater efficiency, significant cost reductions and improvements in the grid reliability. Advancements such as these are crucial when factored in the increasing demand for energy at a global level, rapid change in technologies and the shift to renewable energies (Donti & Kolter, 2021). Insights generated by analysing data serve as a foundation to define and study key performance indicators which are important to assess the progress in a quantitative form.

2.2. Key Performance Indicators (KPIs) for Energy Studies

Key Performance Indicators (KPIs) can significantly help in the decision-making process of stakeholders (Juan et al., 2023). The main difference between KPI and other indicators is that

KPIs are tied to an objective or goal and according to Dameri (2017), as cited in (Angelakoglou et al., 2020) KPIs can serve as a universal tool to assess how well initiatives for positive energy transformation are succeeding, enabling the monitoring of energy-related initiatives and their effectiveness. KPIs integrate strategic goals into measurable outcomes, allowing energy companies to measure and compare performance across various areas such as production efficiency, energy consumption and environmental impact (BPLAN, 2025). The real challenge comes in selecting the most appropriate KPIs as it requires expert knowledge (Huovila et al., 2019).

Defining a selection of KPIs is of extreme importance when evaluating the efficiency, reliability and sustainability of energy management systems.

The Net Energy Balance is a key metric for analysing the national energy system and represents the main starting point for studies in this sector(IEA, 2017). It represents the difference between total production and total consumption of energy in a given period. Although most studies focus on describing the different types of energy being produced and consumed within a country, the overall net balance of energy offers a more comprehensive and macro-level KPI to analyse energy dynamics. Self-Sufficiency Ratio compares energy produced and consumed in a given time. This measure can be calculated for all types of energy or as an aggregate. A value over 100 means the country has a surplus of production and is considered a net exporter (Insee, 2016). Together these metrics provide us valuable insights into a nation's autonomy and its import-export profile.

Energy Intensity of GDP is a measure that computes the total energy consumption divided by the country's Gross Domestic Product. It is a widely used and effective indicator for energy efficiency. A lower value indicates that an economy produces more output per unit of energy consumed. Examining the variations of this indicator per country demonstrates the differences in efficiency and consumptions across various regions (Ecclesia & Domingos, 2024).

The share of renewable energy within total energy production is also a crucial KPI to assess the evolution towards Sustainable Development Goals. Portugal has pledged to reduce its emissions and achieve a 93% share of renewable energy in electricity consumption by 2030, in alignment with the National Energy Climate Plan (PNEC) (APA, 2024; Reuters, 2022).

Carbon intensity is calculated by CO_2 emissions per unit of energy consumed. This metric also helps a country evaluate their progress towards proposed SDG's and track decarbonization efforts. In the case of Portugal, the country has been on the route to significantly reduced energy production from fossil fuels, therefore decreasing emissions (IEA, 2021; Reuters, 2024).

Another important key performance indicator is the energy consumption per capita. This indicator provides insights into the average energy usage per individual within a given society. For analysis across different countries this KPI reveals patterns of energy consumption and highlights how energy-intensive different nations are, taking population size into account. (Ecclesia & Domingos, 2024).

KPIs can achieve their best potential when being analysed in the most fitting context. Assessing these metrics based on geographical region, day, or hour can significantly enhance the stakeholder decision-making process. Visualizing temporal trends and forecasting the evolution of certain indicators can help give more context to the business scenario and aid in more precise data-driven objectives (Yesilyurt et al., 2024).

To summarize, the importance of KPIs is paramount in translating complex analytical information into measurable objectives aligned with the business's needs. However, their full potential is achieved when they are appropriately and effectively visualized and monitored via visualization techniques such as dashboards, enabling a diverse set of users to explore and collect insights in an interactive and intuitive way. To consolidate the indicators discussed, Table 1 presents a typological categorization of KPIs applied in energy studies, serving as a reference for future implementation and integration into business intelligence frameworks.

2.3. Dashboarding Techniques for the Energy Sector

Few describes the four main aspects of a dashboard being "a visual display of the most important information needed to achieve one or more objectives; consolidated and arranged on a single screen so that the information can be monitored at a glance" (Few, 2006). On a similar note, some authors also reference that dashboards should not be limited to a simple display of information, but as a window visualize and engage with the data meanwhile providing both dynamic and static metrics to help understand the context of the information (Kitchin et al., 2015).

Most effective dashboards are designed according to the main human cognitive principles, so that users can easily interpret complex information effectively and accurately. Some studies defend that applying the Gestalt principles such as proximity, similarity and continuation can significantly improve user interpretation and accessibility. Utilizing diverse methods of visual representation – line charts, gauges, pie charts – to visualize KPIs can help users identify patterns and anomalies (Nimbarte et al., 2024).

Some dashboards take advantage of integrating geospatial and temporal data in the form of interactive dashboards by combining heatmaps and line graphs with predictive analytics that allow users to explore energy consumption over time and in specific buildings (Jing et al., 2022).

Regarding the layout, interactions, and information placement, some dashboards offer a taxonomy, for both content and design, with a collection of best practices in order to balance complexity with usability and ensure easy accessibility and quality information. Some studies also focus on avoidable practices such as not overwhelming users, avoid visual clutter and poor design, including too much information and unimportant KPIs. Effective dashboards should maintain visual consistency and symmetrical organization whenever possible (Bach et al., 2022). Research shows that defining clear KPIs, using geospatial and temporal analysis, creating user-friendly interfaces including interactivity and transparency are among the best practices in dashboard design. (Chen & Chen, 2021; Nimbarte et al., 2024).

By using modern data analytics platforms such as Microsoft Fabric and Power BI, we can create an extensive framework to study energy analytics, with features that allow data warehousing, data ingestion, processing, transformation, modelling and building interactive dashboards linked to a robust and unique data model. These platforms allow the data to be integrated from various sources and formats with the objective of creating a framework solution for stakeholders and other users to explore.

In summary, advanced dashboarding techniques, based on a human-centred design and supported by interactive and pattern-based approaches are essential to understand complex energy data and KPIs into actionable intelligence for a wide range of users. Despite these advances, as highlighted in the next section, there remain important gaps in the literature regarding the integration of these elements into a cohesive, country-level business intelligence framework.

2.4. Limitations in Current Approaches to Energy Analytics and Visualization

Although the progress in the data-driven energy analytics field is notorious, there are still some gaps in the literature. One important challenge that remains unresolved comes from the difficulty in balancing the complexity and interpretability of advanced analytical models. Using powerful machine learning techniques and complex data models allows for an extensive and deeper analysis of the data, at the cost of the model's interpretability. There remains a lack of frameworks that create transparent and easy to interpret models for stakeholders. Another gap identified in the literature relates to the lack of expert knowledge among professionals to fully understand and use specific energy data in the correct context. Most studies focus more on specific energy consumption cases, such as buildings, houses or industries, which make it more difficult to apply the results on a broader scale. These studies often fail to consider other intricacies including patterns of building usage and geographic location. While big data analytics has the potential to improve energy systems, further research is required to understand how to use these analytical tools in a consistent way across different industries. Most notably, there is a clear gap in the literature regarding the development of a complete business intelligence (BI) framework that integrates the definition of KPIs for national-level energy consumption and production studies and their visualization through interactive dashboards. While individual components, such as KPI definition and data visualization are well-studied independently, the literature lacks an integrated BI framework that defines, manages, and visualizes KPIs for energy consumption studies at country scale. This gap highlights the need for research that connects strategy, measurement, and communication through dashboards in a unified, scalable approach. In Table 2 we find a compilation of literature found in the areas of energy sustainability, energy efficiency, energy data, KPI definition, and other areas related, that can help in the development of this project.

Table 1 - KPI for Energy Studies by typology

KPI Name	Type
Energy Consumption per capita	Energy
% Energy Consumption (Industry)	Energy
% Energy Consumption (Commercial)	Energy
% Energy Consumption (Domestic)	Energy
% Energy Consumption (Agricultural)	Energy
Net Energy Balance	Energy
Energy intensity of GDP	Energy
Energy Cost	Energy
Share of renewable Energy	Energy
Degree of energetic self-supply	Energy
Energy Savings	Energy
kWp photovoltaic installed per 100 inhabitants	Energy
Percentage of buildings in the city with smart energy meters	Energy
Carbon Intensity	Environmental
GHG Emissions	Environmental
Percentage of renewable electricity production	Environmental
Percentage of fossil fuel electricity production	Environmental
Water consumption	Environmental
Municipal waste	Environmental
Air Quality Index	Environmental
Electric Vehicles	Mobility
Number of EV charging stations	Mobility
Clean mobility utilization	Mobility
Road vehicles (car/hab)	Mobility
Bike line lengths	Mobility
Shared bikes	Mobility

Table 2 - Reference Table for Literature Review

Author	Year	Title	Area of Study
Murshed	2021	Can regional trade integration facilitate renewable energy transition to ensure energy sustainability in South Asia?	Renewable Energy
Wang et al.	2022	Impacts of digital technology on energy sustainability: China case study	Energy Sustainability
Rao N. and Pachauri S.	2017	Energy access and living standards: some observations of recent trends	Energy and Socioeconomic Impact
John P. Holdren	2001	Meeting the energy challenge.	Energy Security and Political Stability
International Energy Agency (IEA)	2024	World Energy Outlook 2024	Energy Security and Conflict
International Energy Agency (IEA)	2023	World Energy Outlook 2023	Energy Security and Conflict
Mrówczyńska et al.	2020	Household standards and socio-economic aspects as a factor determining energy consumption in the city.	Energy Consumption and Urban Policies
SGCIE	2024	Sistema de Gestão dos Consumos Intensivos de Energia	Energy Systems
Osório et al.	2018	Scheduling Model for Renewable Energy Sources Integration in an Insular Power System	Energy Systems
Worku	2022	Recent Advances in Energy Storage Systems for Renewable Source Grid Integration: A Comprehensive Review	Energy Systems and Storage
Sevilla et al.	2022	State-of-the-art of data collection, analytics, and future needs of transmission utilities worldwide to account for the continuous growth of sensing data	Energy Data
Arghandeh & Zhou	2018	Big Data Application in Power Systems	Energy Data

Barja-Martinez et al.	2021	Artificial intelligence techniques for enabling Big Data services in distribution networks: A review	Energy Data
IRENA	2019	IRENA – International Renewable Energy Agency	Renewable Energy
Ahmad	2020	A review on renewable energy and electricity requirement forecasting models for smart grid and buildings	Renewable Energy
Juan et al.	2023	Promoting Energy Efficiency and Emissions Reduction in Urban Areas with Key Performance Indicators and Data Analytics	Energy Efficiency
Dameri (cited in Angelakoglou et al.)	2017	Smart City Definition, Goals and Performance	KPI Definition
BPLAN	2024	Top 7 KPIs for Energy Efficiency Consulting Success: Unlock Your Business Potential Today!	KPI Definition
Huovila et al.	2019	Comparative analysis of standardized indicators for Smart sustainable cities: What indicators and standards to use and when?	KPI Definition
Chao et al.	2020	Indicators Framework for Sustainable Urban Design	KPI Definition
Genta et al.	2019	Key Performance Indicators for Sustainable Urban Development: Case Study Approach	KPI Definition
UNECE	2017	Collection Methodology for Key Performance Indicators for Smart Sustainable Cities	KPI Definition
Angelakoglou, K et al.	2020	From a Comprehensive Pool to a Project-Specific List of Key Performance Indicators for Monitoring the Positive Energy Transition of Smart Cities—An Experience-Based Approach	KPI Definition Smart Cities and Sustainability

3. METHODOLOGY

The Kimball Lifecycle methodology consists of a Data Warehouse (DW) and Business Intelligence development toolkit created by Ralph Kimball and various colleagues at Metaphor Computer Systems. This methodology covers a sequence of detailed steps regarding design, development and deployment phases that aim to incrementally build a DW using dimensional modelling and following a bottom-up approach (Ralph Kimball, 2008).

This methodology was chosen for its user-centric design and emphasis on query optimization to allow for operational analysis and data-driven decision-making. It focusses on studying the business requirements of the project and aligning them with the dimensional model to understand how to structure and use the data in an optimized way (Landutama & Chowanda, 2023).

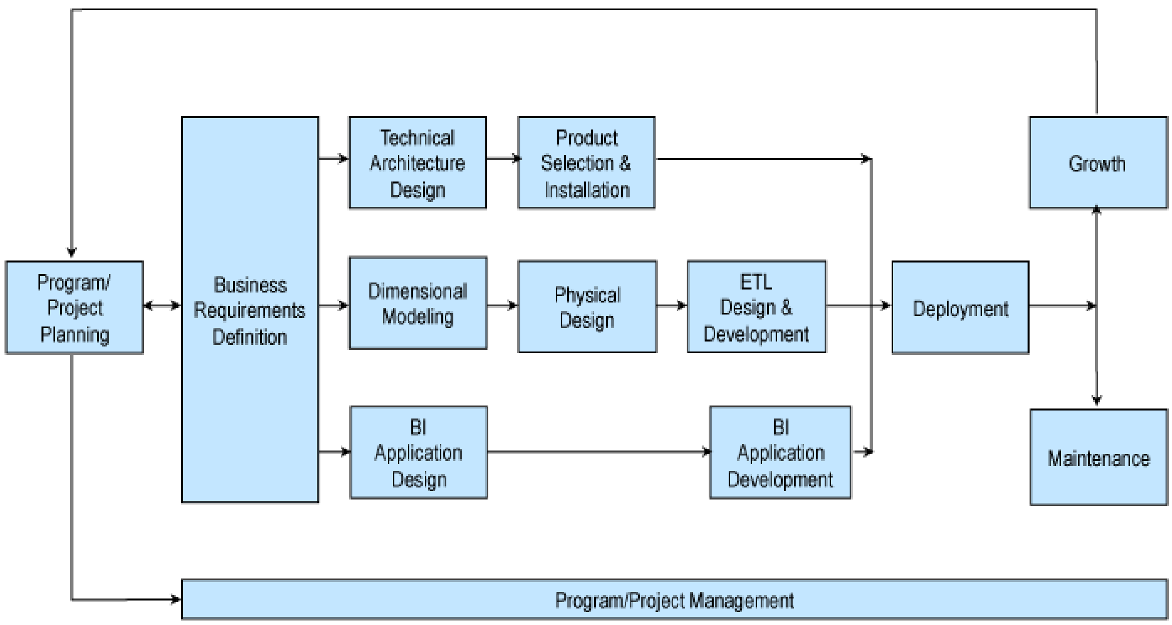


Figure 1 - Kimball Lifecycle Diagram. From (Ralph Kimball, 2008)

As illustrated in Figure 1, the Kimball methodology follows an iterative process that allows the users to revisit previous tasks ensuring high flexibility of the project.

The key phases of this methodology include Project Planning; Business Requirements Definition; Dimensional Modelling; ETL (Extract, Transform, Load), Design and Development, Data Warehouse Deployment, Business Intelligence (BI) Application Development, Maintenance and Growth.

3.1. Business Requirements Definition

3.1.1. Business Understanding

To understand the business requirements of the energy sector, it is essential to clarify the main objectives of this project, identify the stakeholders, evaluate the data, and select the key metrics to evaluate. This ensures that future steps of dimensional modelling, ETL Design and BI applications are aligned with the needs of the business and can support decision-making effectively.

The main goal of this project is to create a framework that allows researchers to study and improve energy efficiency and sustainability in Portugal and that could be easily replicated in other countries. More specifically the project aims to identify peak consumption periods to aid in implementing policies, to manage demand and supply, and save energy. To address these goals, this research proposes a set of targeted business questions. These are outlined in Table 3 and are derived from the gaps identified in the Literature Review chapter. Table 3 presents the business questions derived from the literature review, which guide the analytical approach of this study.

These questions allow us to maintain the focus of the research and understand how the different data sources can be used and interact with one another to correctly and effectively provide answers. It also guarantees data-driven and meaningful results in the context of the project. The business questions also help understand the KPIs we want to measure and their importance to the stakeholders.

Table 3 - Business Questions

Topics	Question
1. Energy Consumption	1.1. What is the level of carbon intensity in Portugal? 1.2. What is the energy intensity of GDP in Portugal? 1.3. What is the net energy balance in Portugal? 1.4. What was the total cost of energy? 1.5. What is the total national energy consumption? 1.6. How does it evolve over time (month, year)? 1.7. What is the daily consumption of energy? 1.8. What is the average consumption per capita? 1.9. Through which voltage level is most of the energy consumed? And the least? 1.10. How has each voltage level evolved over time?
2. Energy Production	2.1. What is the total national energy production? 2.2. How does it evolve over time (month, year)? 2.3. What is the average daily production of energy? 2.4. What is the average production per capita? 2.5. In which regime is most of the energy produced? 2.6. How has each production regime evolved over time?
3. Geographical Analysis	3.1. What regions (districts, municipalities) consume the most energy? And the least? 3.2. Is the consumption of energy evenly distributed between districts? 3.3. Is the energy consumption positively correlated with the population?
4. Temporal Analysis	4.1. What are the peak hours and off hours of energy consumption in day in Portugal? 4.2. In which part of the day is most of the energy consumed? 4.3. Can trends (seasonal, cyclical) be identified in energy consumption levels? 4.4. What are the peak months and off months of energy consumption in a year in Portugal? 4.5. In which trimester is most energy consumed? 4.6. What are the days of the week in which most energy is consumed?

3.1. STAKEHOLDERS

The next step is to identify the stakeholders in this business and understand the information they require.

Government entities, local and country-wide, use information about energy consumption to implement energy policies regarding energy supply and demand, and to study energy efficiency and improve sustainability in Portugal.

Energy providing companies are also a key stakeholder as they can use this information to forecast energy demand and prevent energy outages and grid failures that can heavily impact the population.

Businesses and other regular energy consumers can also be considered stakeholders as information regarding energy cost and efficiency can help save money and reduce environmental impact.

3.2. DATA UNDERSTANDING

This subchapter explores the datasets available for analysis and evaluates their relevance in addressing the business questions defined earlier. The data were collected from the [E-REDES portal] (Explore — E-REDES, 2025) and are openly accessible for research purposes.

There are four datasets included in this project are described in the Tables 4 through 7 and are the following:

The first dataset refers to information of the Total National Energy Consumption. This dataset consists of information about the energy consumed in the Portuguese territory and has the values of the consumption of installations with MAT voltage level (very high voltage), AT voltage level (high voltage), MT voltage level (medium voltage), BT voltage level (low voltage) and the total of all voltage levels.

This data is obtained by evaluating the consumption loss by voltage level every 15 minutes using meters. It contains information since January 2023 until January 2025.

Table 4 - Total National Energy Consumption variables and respective descriptions.

Variable Name	Description
Date/Time	Year, month, day, hour and minute when the energy consumed.
Day	Day of the month the energy was consumed.
Month	Month of the year the energy was consumed.
Year	Year the energy was consumed.
Date	The full date the energy was consumed.
Hour	The hours and minutes of the day the energy was consumed.
Low Voltage (kWh)	The amount of energy in kWh that was consumed at a Low Voltage level.
Medium Voltage (kWh)	The amount of energy in kWh that was consumed at a Medium Voltage level.
High Voltage (kWh)	The amount of energy in kWh that was consumed at a High Voltage level.
Very High Voltage (kWh)	The amount of energy in kWh that was consumed at a Very High Voltage level.
Total (kWh)	The amount of energy in kWh that was consumed in Total.

The second dataset reviewed pertains to the Total National Energy Produced. It contains information of the amounts of energy produced in Portugal and is divided into two components: DGM (Market Generation Diagram) that refers to the producers that are on the market, and PRE (Special Regime Production) that refers to the energy produced under a special regime. This information is also collected every 15 minutes. It contains information from January 2023 to January 2025.

Table 5 - Total National Energy Produced variables and respective descriptions.

Variable Name	**Description**
Date/Time	Year, month, day, hour and minute when the energy consumed.
Day	Day of the month the energy was consumed.
Month	Month of the year the energy was consumed.
Year	Year the energy was consumed.
Date	The full date the energy was consumed.
Hour	The hours and minutes of the day the energy was consumed.
Special Regime (kWh)	The amount of energy in kWh that was produced under special regime.
Market (kWh)	The amount of energy in kWh that was produced by market producers.
Total (kWh)	The amount of energy in kWh that was produced in Total.

The next dataset consists in information of the Monthly Consumption by Municipality. This dataset has the information of the monthly energy consumption by parish, municipality and district, and by voltage level. The information in this dataset covers the period from November 2020 to the most recent available data.

Table 6 - Monthly Consumption by Municipality variables and respective descriptions.

Variable Name	Description
Month	Month of the year the energy was consumed.
Year	Year the energy was consumed.
Date	The full date the energy was consumed.
District	Name of the district in Portugal.
Municipality	Name of the municipality in Portugal.
Parish	Name of the parish in Portugal.
Voltage Level	The type of voltage level of the consumption of energy.
Active Energy	The amount of energy in kWh consumed.
District Code	The code defined by E-Redes that identifies each district.
District Municipality Code	The code defined by E-Redes that identifies each municipality.
District Municipality Parish Code	The code defined by E-Redes that identifies each parish.

This last dataset has the information for the Location and Zip Codes. This dataset consists of auxiliary data compiled to describe the municipality of each 4-digit Zip-Code. The source is the CTT (Correios Telégrafos e Telefones) website and in total there is a collection of 1094 locations.

Table 7 - Location and Zip Codes variables and respective descriptions.

Variable Name	Description
Zip Code	The 4-digit Zip Code.
District	Name of the district in Portugal.
Municipality	Name of the municipality in Portugal.
Postal Region	The name of the parish in Portugal.

3.3. Technical Architecture Design

In this phase of the Kimball Lifecycle, the focus is placed on defining the structure and technological tools required to develop and support the Business Intelligence (BI) framework. Within the scope of this project, various functionalities offered by Microsoft Fabric (Microsoft, 2025) are leveraged to construct the core components of the proposed design.

Regarding the data source, the data was collected from the E-Redes open-source database (*Explore — E-REDES*, 2025), in the form of CSV files and API connections.

For the data processing and ETL (Extract, Transform, Load) segment, the Dataflows Gen2 component was used to enable a low-code ETL process through Power Query. The Pipeline functionality of Data Factory was employed to design the data flow layout and to validate data integrity. A Lakehouse was created to serve as the storage facility for the pre-ETL database. An initial Data Warehouse functioned as a Staging Area prior to data transformation and loading into the final tables.

Finally, a second Data Warehouse was created to store the already processed and validated data into its respective final tables using an SQL script. Inside the Data Warehouse the data was organized into Fact and Dimension tables, following the Kimball approach and organized into a star schema.

A Semantic Model was also be added to create relationships between facts and dimensions tables, linking them by their respective key. Figure 2 illustrates the theoretical architectural design proposed for this project, outlining the structural components and data flow of the Business Intelligence framework.

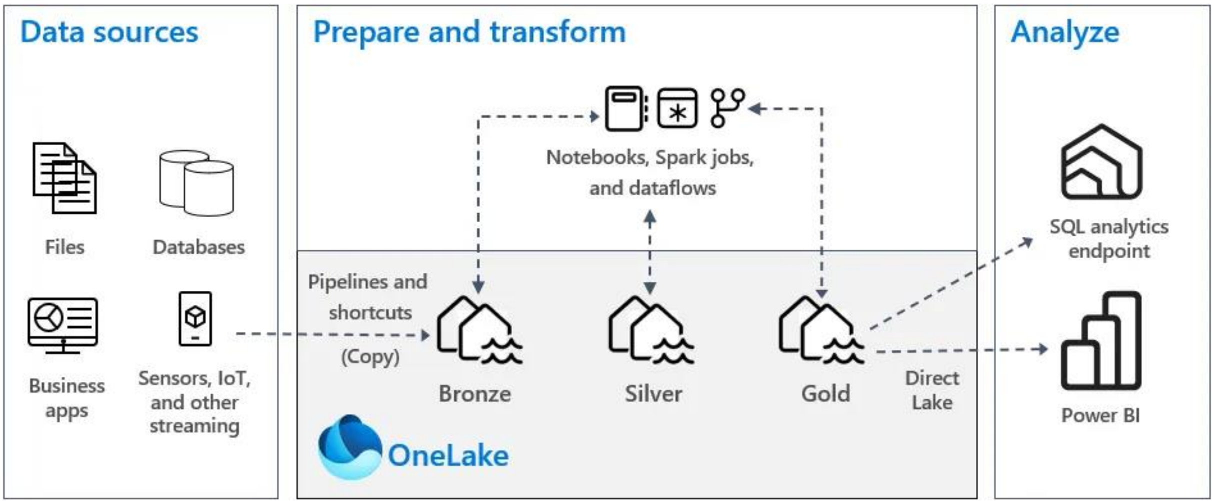


Figure 2 - Architecture Design Diagram (Bas Land, 2024)

3.4. DIMENSIONAL MODELLING

To obtain an efficient and optimized BI dimensional model for the data warehouse, the project adopted Kimball's four-step Dimensional Design Process.

Step 1: Select the Business Process

The goal of this project is to study energy markets in Portugal, as stated previously in the Business Understanding chapter, therefore the defined business process for this project is twofold: the consumption and the production of electric energy in Portugal. Using information made available by E-Redes via open source.

Step 2: Declare the Grain

The grain of this model is defined as electricity consumed and electricity produced per hour, per municipality, meaning we want to analyse how each municipality consumed energy and when.

This means that each line in the fact tables represents the amount of energy in kWh, either consumed or produced in a certain period (hours, days, months or years) in a certain region of Portugal (municipality or city) or at a national level.

Step 3: Identify the Dimensions

This project includes three important dimensions: two related to time, and one concerning the geographical location of the facts.

The time dimensions are split into Dim_Date and Dim_Time for better efficiency of the model and lower processing time. For the Dim_Location dimension, it contains the names of the municipalities and their respective cities, as well as their zip code.

Step 4: Identify the Facts

The facts used in this model are stored in the fact tables below (Table 8) and are the following:

Table 8 - Fact Tables and Descriptions

Table Name	**Description**
Facts_EnergyProduction	This table contains information of the energy produced in kWh, in special regime, in market production and in total.
Fact_EnergyConsumption	This table stores data regarding the energy consumed in kWh for every voltage level (low, medium, high and very high) and in total.
Fact_MunicipalConsumption	This table has the information for the active energy consumed in kWh in every location.
Fact_EnergyMeasurement	This table also contains information of the active energy consumed in kWh but with a higher granularity.

After considering these 4 steps to build our dimensional model, the next phase consists in designing the star schema (Figure 3) for easy querying with the dimensions and facts identified previously.

The architectural schema developed for this project is illustrated in Figure 3.

Figure 3 - Dimensional Model

3.5. Physical Design

In order to physically design this dimensional model in Microsoft Fabric, it is important to create a structure, inside the Data Warehouse, defined by an SQL query that allow for implementation of the dimension and fact tables. In this SQL query is defined the name of each table, the names of the facts, measures and dimensions, as well as their respective data types.

These tables also function as a landing spot for the processed data to be used in the next steps. If the data is not in the correct data type or is not complaint to the rules defined in the SQL script it will fail to load into the Data Warehouse tables, assuring data quality of the model.

3.6. ETL DESIGN AND DEVELOPMENT

In this step of the project, we describe the process after creating the Data Warehouse and the Lakehouse, to explain how the data is processed and organized to fit into the tables created in the DW.

After the raw data is stored on the Lakehouse as csv files and tables in the case of the data extracted from APIs, it will go through the staging area, where it will be processed and later validated using a pipeline of rules.

For the ETL process we use the Microsoft Fabric tool called Dataflows Gen2 which allows us to make all the necessary data manipulations using very little code. Table 6 summarizes these changes. For the dimension and fact tables the following transformations were applied:

In the Dim_Date table we want to have information about the dates. As such we generated a list of dates from November 1st, 2020, until January 31st, 2025, using code written in Power Query M language. Then we converted the list into a table and added a column to identify each line uniquely, a surrogate key, called sk_date. Afterwards we decided to add some attributes that describe the date itself such as the day, month and year columns, as well as a weekday column to describe the day of the week. Lastly, we converted all the data types to their determined type in the DW SQL script.

Table 9 - Dim_Date Column Descriptions

Columns	Description
sk_date	The surrogate key of the date table.
full_date	The full date in date format “dd-mm-yyyy”
day	The day of the month.
month	The number of the month of the year.
month_name	The name of month of the year.
month_abv	The 3-letter abbreviation of the name of month of the year.
year	The year number.
weekday_name	The name of the day of the week.
trimester	The number of the trimester of the year.
trimester_name	The name of the trimester of the year.

The Dim_Time table follows the same format of the Dim_Date one, as we generated a list representing each minute of one day. This table (Table 10) was done separately from the Dim_Date to avoid the repetition of the list of times for each day of the Dim_Date list and, therefore, optimizing the model and decreasing querying times. Then we converted the list into a table and created the surrogate key, sk_time. Afterwards, the hour and minute attributes were added as well as the part of day. The last step was to convert all data types to the ones defined in the SQL script.

Table 10 - Dim_Time Column Descriptions

Columns	Description
sk_time	The surrogate key of the time table.
full_time	The full time in time format “hh:mm”
hour	The hour of the day.
minute	The minute of the hour.
part_of_day	The name of the part of the day.

On the Dim_Location table (Table 11) the first step was to add a surrogate key, sk_location. Afterwards, we added a column for the Country, which would only have the value “Portugal” to facilitate using dashboard specific features, such as geographical analysis. The last step was to convert all data types to ones defined in the DW table.

Table 11 - Dim_Location Column Description

Columns	Description
sk_location	The surrogate key of the location table.
country	The name of the country.
district	The name of the district.
municipality	The name of the municipality.
parish	The name of the parish.
zip_code	The 4-digit Zip-Code.

For both the Fact_EnergyConsumption and the Fact_EnergyProduction tables the ETL process was very similar since they would be linked to the same dimension tables (Table 12 andTable 13). The first step was to merge the dataset to the Dim_Date table via full_date using a left outer join to include the sk_date, as a foreign key. The same procedure was done for the Dim_Time table joining via full_time using the same merging method and selecting the sk_time as a foreign key. Finally, we removed unnecessary columns used to merge the tables (full_date, full_time) and converted all data types to be in accordance with the DW SQL script.

Table 12 - Fact_EnergyConsumption Column Description

Columns	Description
sk_date	The surrogate key that links to the date table.
sk_time	The surrogate key that links to the time table.
low_voltage	The amount in kWh of energy consumed through low voltage.
medium_voltage	The amount in kWh of energy consumed through medium voltage.
high_voltage	The amount in kWh of energy consumed through high voltage.
veryhigh_voltage	The amount in kWh of energy consumed through very high voltage.
total_energyconsumed	The total amount in kWh of energy consumed.

Table 13 - Fact_EnergyProduction Column Description

Columns	Description
sk_date	The surrogate key that links to the date table.
sk_time	The surrogate key that links to the time table.
market	The amount in kWh of energy produced via normal market producers.
special	The amount in kWh of energy produced under the special regime.
total_energyproduced	The total amount in kWh of energy produced.

In the Fact_EnergyMeasurement table (Table 14) we started by filtering some rows called ‘Outros’ which have values from undisclosed locations, which are not possible to know. The next step was to merge the Dim_Date table with the full_date and then to apply the same merge with the Dim_Time table using the full_time column and finally the last merge with the Dim_Location using the Zip Code column to connect them. Lastly, we removed unnecessary columns to be the same as in the DW tables.

Table 14 - Fact_EnergyMeasurement Column Description

Columns	Description
sk_date	The surrogate key that links to the date table.
sk_time	The surrogate key that links to the time table.
sk_location	The surrogate key that links to the location table.
active_energy	The total amount in kWh of energy consumed.

For the Fact_MunicipalConsumption table (Table 15) we decided to start by grouping the rows by date, municipality and district and calculating the sum of the active energy. As such we obtained a dataset with the amount of energy consumed per day, in each municipality and district. Then we applied a merge on the table Dim_Date linked by the full_date value and a second merge was also applied on the Dim_Location table, linking them via Municipality. The last step was to convert all data types to ones defined in the DW table.

Table 15 - Fact_MunicipalConsumption Column Description

Columns	Description
sk_date	The surrogate key that links to the date table.
sk_location	The surrogate key that links to the location table.
voltage_level	The type of voltage level through which the energy is consumed (low voltage or medium, high and very high voltages combined).
active_energy	The total amount in kWh of energy consumed.

Table 16 - Transformations per fact and dimension table.

Table	Transformation
Dim_Date	1. Generated a list of dates from November 1st, 2020, to January 31st, 2025. 2. Converted the list into a table. 3. Added a surrogate key column (sk_date). 4. Added custom columns day, month, year, weekday. 5. Converted data types.
Dim_Time	1. Generated a list representing each minute of one day. 2. Converted the list into a table. 3. Added a surrogate key column (sk_time). 4. Added custom columns hour, minute, part of day.

	5. Converted data types.
Dim_Location	1. Added custom column Country. 2. Converted data types. 3. Replace incorrect characters. 4. Removed duplicates. 5. Added a surrogate key column (sk_location).
Fact_EnergyProduction	1. Merged with Dim_Date via full_date using a left outer join and included sk_date as a foreign key. 2. Merged with Dim_Time via full_time using a left outer join and included sk_time as a foreign key. 3. Removed unnecessary columns. 4. Converted data types. 5. Removed duplicates.
Fact_EnergyConsumption	1. Merged with Dim_Date via full_date using a left outer join and included sk_date as a foreign key. 2. Merged with Dim_Time via full_time using a left outer join and included sk_time as a foreign key. 3. Removed unnecessary columns. 4. Converted data types. 5. Removed duplicates.
Fact_EnergyMeasurement	1. Filtered rows labeled as "Outros". 2. Merged with Dim_Date via full_date. 3. Merged with Dim_Time via full_time. 4. Merged with Dim_Location via Zip Code. 5. Removed unnecessary columns. 6. Converted data types. 7. Removed duplicates.
Fact_MunicipalConsumption	1. Used column Voltage Level to create pivot columns “Baixa Tensão” and “Muito Alta, Alta e Média Tensões”. 2. Replaced nulls with 0. 3. Added custom column “Total Active Energy”. 4. Merged with Dim_Date via full_date. 5. Merged with Dim_Location via Municipality. 6. Removed rows without municipality information. 7. Removed unnecessary columns. 8. Removed duplicates. 9. Converted data types.

It also important to note that some minor changes were applied to all tables but were not mentioned before, such as changing column names, reordering the columns for easier interpretation, and in some cases removing null and duplicate values when necessary.

In order to automate the ETL process, a pipeline was created to allow for all the steps to be applied sequentially meanwhile validating each one. The pipeline started by cleaning all the data in the existing DW dimension tables so that afterwards the new data could be loaded from the respective dataflows. This step ensures that there is no duplication of information when with each iteration of creation of the process. Afterwards the data would be loaded into the DW fact tables from the fact dataflows. The image above (Figure 4) represents the pipeline process described.

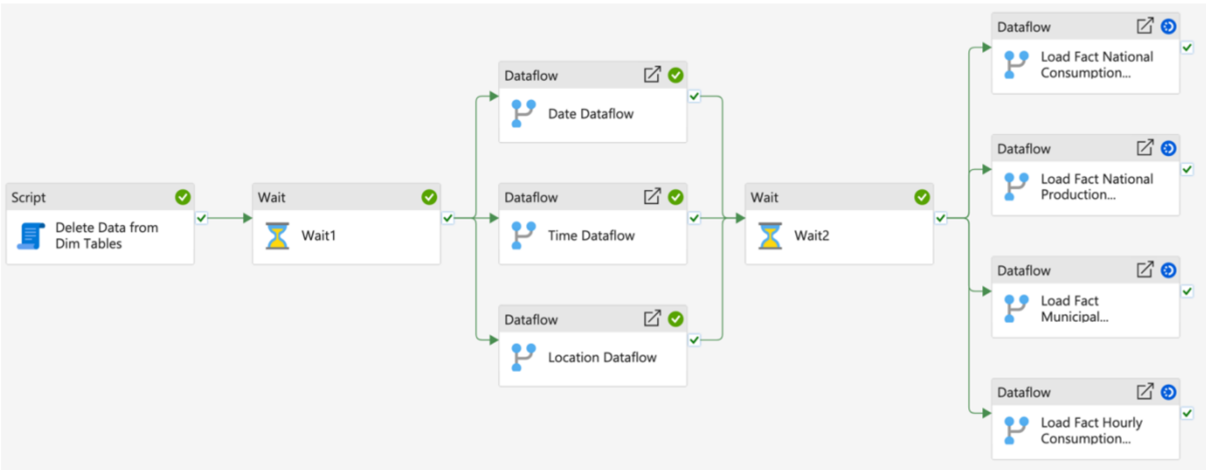


Figure 4 - Microsoft Fabric ETL Pipeline

After the date is stored in tables, a pipeline was built to validate the integrity of the data in the tables using SQL Scripts (Figure 5) to implement data quality rules.
For the validation of the dimension tables, only the Dim_Location was subject to data quality rules, as the Dim_Date and Dim_Time were developed by us and not from source files.

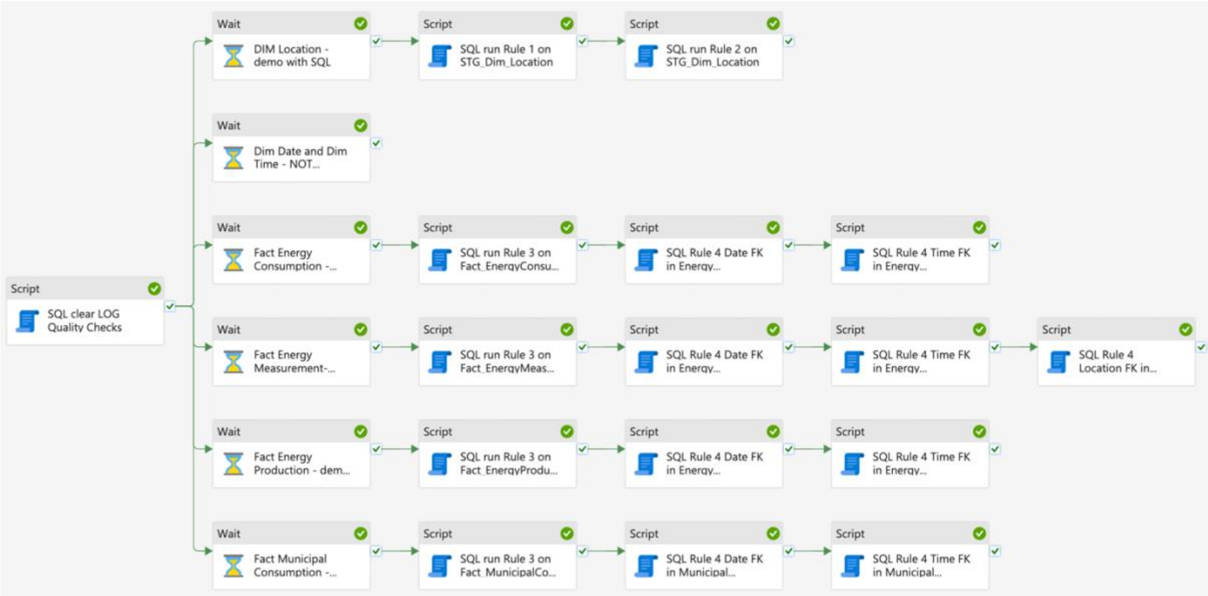


Figure 5 - Microsoft Fabric Data Validation Pipeline

Table 17 presents the data quality rules applied to each dimension and fact table.

Table 17 - Data quality and Validation Rules.

Table	**Rules**
Dim_Date	No rules applied.
Dim_Time	No rules applied
Dim_Location	Rule #1 – Check the integrity of the business key Rule #2 – Check uniqueness of the dimension attributes
Fact_EnergyProduction	Rule #3 – Check the integrity of the primary key of the Fact table (combination of foreign keys) Rule #4 – Check the relationship of the foreign key in the Fact table (does the BK exist on the Dim_Date?) Rule #4 – Check the relationship of the foreign key in the Fact table (does the BK exist on the Dim_Time?)
Fact_EnergyConsumption	Rule #3 – Check the integrity of the primary key of the Fact table (combination of foreign keys) Rule #4 – Check the relationship of the foreign key in the Fact table (does the BK exist on the Dim_Date?) Rule #4 – Check the relationship of the foreign key in the Fact table (does the BK exist on the Dim_Time?)

Fact_EnergyMeasurement	Rule #3 – Check the integrity of the primary key of the Fact table (combination of foreign keys) Rule #4 – Check the relationship of the foreign key in the Fact table (does the BK exist on the Dim_Date?) Rule #4 – Check the relationship of the foreign key in the Fact table (does the BK exist on the Dim_Time?) Rule #4 – Check the relationship of the foreign key in the Fact table (does the BK exist on the Dim_Location?)
Fact_MunicipalConsumption	Rule #3 – Check the integrity of the primary key of the Fact table (combination of foreign keys) Rule #4 – Check the relationship of the foreign key in the Fact table (does the BK exist on the Dim_Date?) Rule #4 – Check the relationship of the foreign key in the Fact table (does the BK exist on the Dim_Location?)

The results in the rules applied are stored in a table of the Data Warehouse (log_quality_checks) with the information regarding the rule number, ETL phase, ETL table, check type and the description of the result. This allows us to run the pipeline and check for inconsistencies and errors in specific tables, evaluate and correct them before storing them in tables the final Data Warehouse where they will be ready to be consumed to build visual representations.

3.7. BI Application Design and Development

Regarding these topics of the Kimball Lifecycle Methodology the goal is to describe the tools, dashboards, semantic model, and reports used to create de data visualizations with the goal of answering the business questions. Therefore, we decided to go into depth regarding these applications in the next chapter of the project where we talk about the results obtained.

3.8. Deployment, Maintenance and Growth

After ensuring the model is functioning correctly and we can respond to the business question using the dashboard reports and other analytical tools, it is crucial to focus on the maintenance part of the model to assure it functions continuously in the future. Doing so requires providing frequent updates and keeping a log of the problems encountered and their solutions. Future growth solutions might entail larger database to process or expanding the model with more dimensions or facts.

4. RESULTS & DISCUSSION

Foremost, for this chapter of the project, we will be discussing the dashboard developed and the data model used to support it, as well as the measures and auxiliary tables created to answer the business questions mentioned in section 3 and provide KPI values. Secondly, we will discuss the results and understand how the visual representations in each dashboard page answers the aforementioned business questions. Lastly, we will be analysing other related works regarding energy studies and comparing the representations and results with the current dashboard developed.

In this project we were able to create a fully operational and interactive dashboard, that includes important indicators and graphical representation of the data in an organized and intuitive way as per recommended based on the literature found in chapter 2. This dashboard also addresses the gaps found in the literature and hopes to provide a BI framework to study energy in Portugal.

4.1. DASHBOARD MODEL

After explaining the Kimball Lifecycle steps to build a Data Warehouse and implement a BI solution, we created an interactive dashboard with 4 pages, power by this data model. In this section we will describe the semantic model, the measures and all auxiliary tables and parameters created to build the visual components of the dashboard.

4.1.1. SEMANTIC MODEL

In Microsoft Fabric, the Semantic Model is a tool that allows the user to easily interact with the data source that is ready for visual representations. It consists of a logical model that organizes the model into tables and connects them via relationships (foreign and surrogate keys) and allows for hierarchies within each table. It also allows for business specific measures to be included in the tables using DAX calculations (Microsoft Learn, 2024).
Figure 6 represents the Semantic Model built on top of our data Warehouse that allows us to explore the tables and their relationships and build visualizations meanwhile ensuring consistency of the visual analysis. It shows the relationships that connect each dimension table to one or more fact tables in data model. All relationships are of the type one to many, meaning that one instance from a dimension table corresponds to one or more instances in the respective fact table.

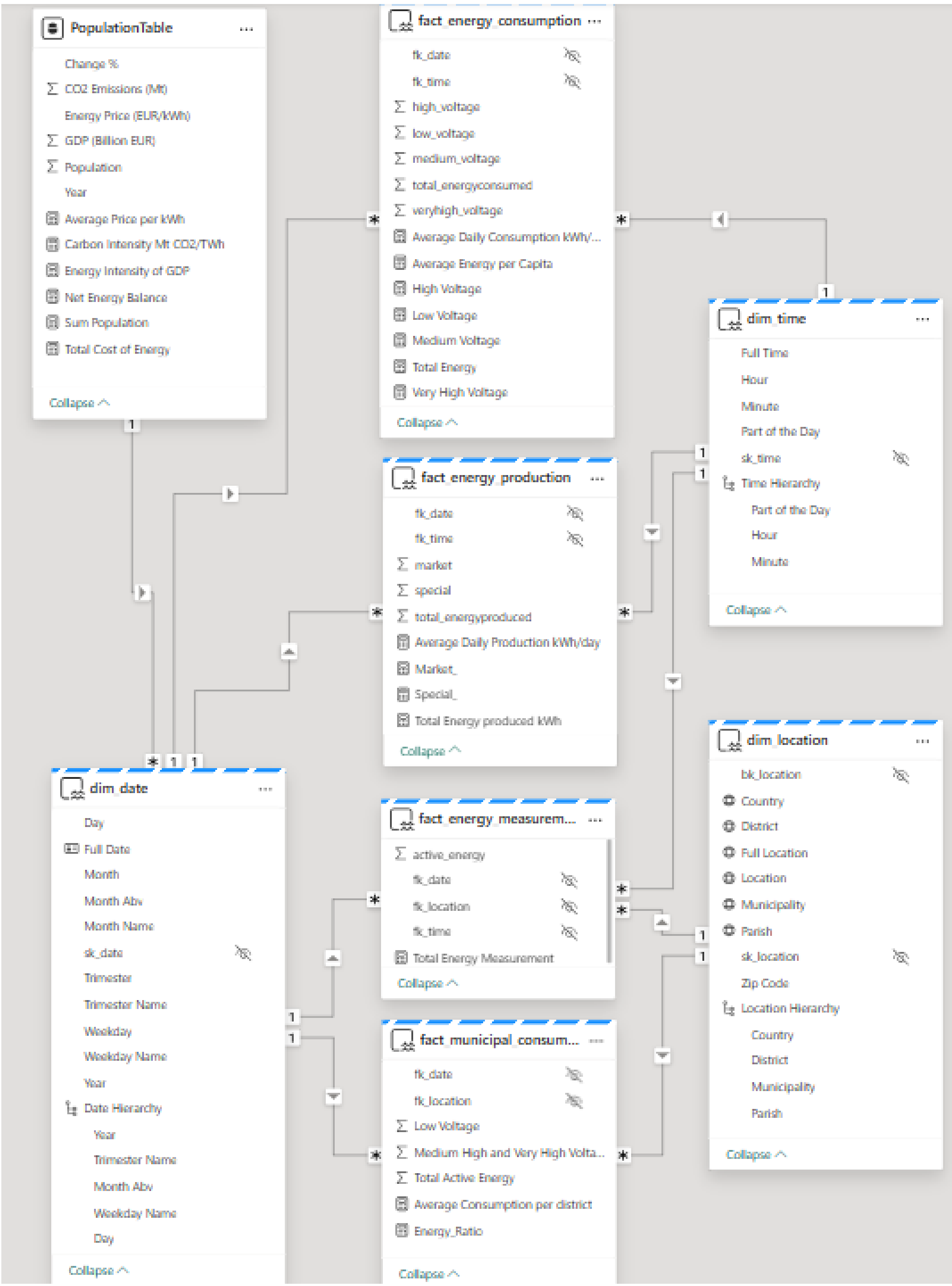
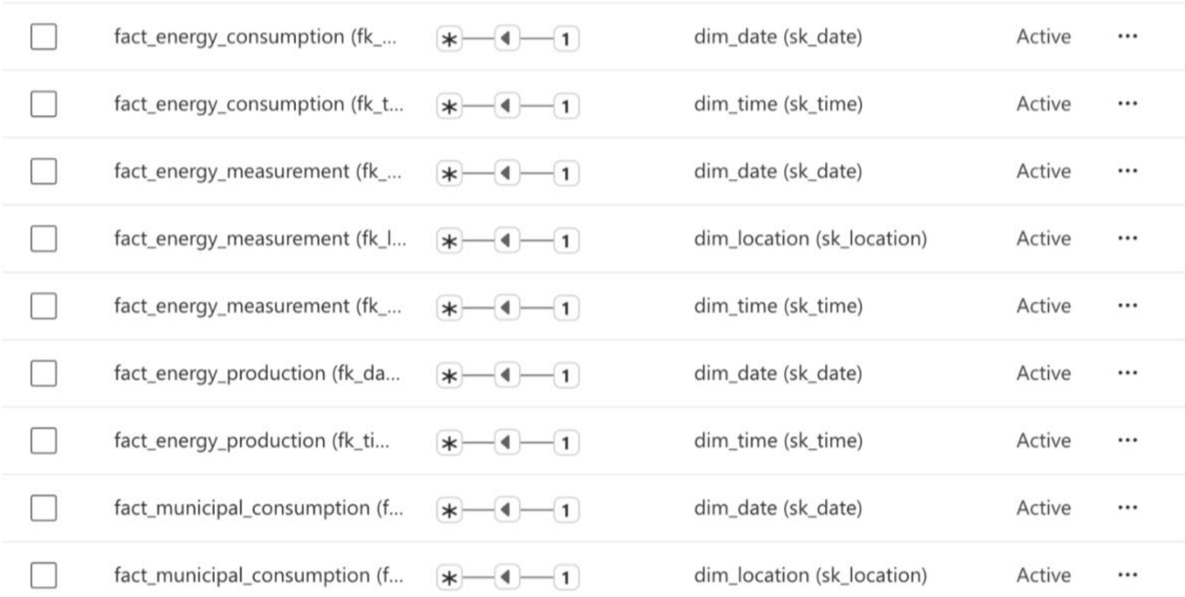


Figure 6 - Microsoft Fabric Semantic Model

The Figure 7 shows the relationships that connect each dimension table to one or more fact tables in data model. All relationships are of the type one to many, meaning that one instance from a dimension table corresponds to one or more instances in the respective fact table.



fact_energy_consumption (fk_...	dim_date (sk_date)	Active	...
fact_energy_consumption (fk_t...	dim_time (sk_time)	Active	...
fact_energy_measurement (fk_...	dim_date (sk_date)	Active	...
fact_energy_measurement (fk_l...	dim_location (sk_location)	Active	...
fact_energy_measurement (fk_...	dim_time (sk_time)	Active	...
fact_energy_production (fk_da...	dim_date (sk_date)	Active	...
fact_energy_production (fk_ti...	dim_time (sk_time)	Active	...
fact_municipal_consumption (f...	dim_date (sk_date)	Active	...
fact_municipal_consumption (f...	dim_location (sk_location)	Active	...

Figure 7 - Relationships between Fact and Dimension Tables

4.1.2. Calculated Measures

To address the business questions some measures were created to ensure either the correct KPIs were provided or as an auxiliary calculation for other KPIs and visual representations. These measures facilitate our ability to conduct temporal analysis and identify trend in the data. As mentioned before, these measures are calculated using Data Analysis Expressions (DAX) that allows to create custom calculations in Microsoft Fabric in an intuitive way, using simple aggregation functions.

Table 18 presents the measures defined within the model along with their respective descriptions.

Table 18 - Calculated Measures and their description.

Measure	Description
Average Daily Consumption kWh/day	Average energy consumed in kWh in one day.
Average Energy per Capita	Average energy consumed in kWh per person in Portugal.
Low Voltage	An auxiliar measure that calculates the sum of energy consumed in low voltage.
Medium Voltage	An auxiliar measure that calculates the sum of energy consumed in medium voltage.
High Voltage	An auxiliar measure that calculates the sum of energy consumed in high voltage.
Very High Voltage	An auxiliar measure that calculates the sum of energy consumed in very high voltage.
Total Energy Measurement	An auxiliar measure that calculates the sum of total energy consumed.
Average Daily Production kWh/day	Average energy produced in kWh in one day.
Market_	An auxiliar measure that calculates the sum of total energy produced for the market.
Special	An auxiliar measure that calculates the sum of total energy produced in the special regime.
Total Energy Produced kWh	Total energy produced in kWh.
Energy Intensity of GDP	The total amount of energy consumed in kWh divided by the total GDP in billion EUR.
Carbon Intensity.	The amount of CO2 emissions in Mt per energy consumed in TWh.
Net Energy Balance	The difference between Energy Produced and Energy Consumed in kWh.

4.1.3. AUXILIARY PARAMETERS

Some field parameters or auxiliary tables were created (Figure 8) to optimize some visualizations as well as improve navigation and interactivity of the dashboard. These tables contribute to a better interpretation of the dashboard pages.

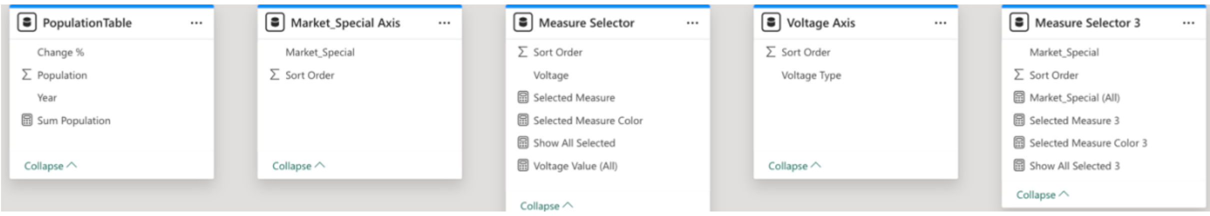


Figure 8 - Auxiliary Tables and Parameters

The Population Table contains the information for the Portuguese population for a couple of years, as well as its percentage change, the GDP values and the CO_2 emissions. It is a quick and simple solution used to calculate measures such as the consumption and production of energy per capita, the Energy Intensity of GDP and Carbon Intensity.

The Voltage Axis and the Measure Selector tables are auxiliary parameters that allow us to select and filter between different dimensions within the same graphical representation or KPI display. It also allows for colour coordination of the dimensions across the dashboard, according to a specific predetermined colour scheme, defined as a measure. In this case the dimensions can be alternated by Voltage Type, which were the measures created in the fact_energy_consumption table.

The same principle applies for the tables Market_Special Axis and the Measure Selector 3 tables, since they also were created to alternate between dimensions. In this case, the measures are type of regime in which the energy is produced, for marker or in special regime. Another colour scheme was attributed to each dimension for better and more coherent visualizations.

4.2. Dashboard Overview

As the final product of this project, we created an interactive Power BI dashboard that provides an integrated view of Portugal's energy consumption and production status. It focusses on analysing energy evolution over time and by region. This analysis can be done at multiple granularity levels and aim to give valuable insights to the stakeholders.

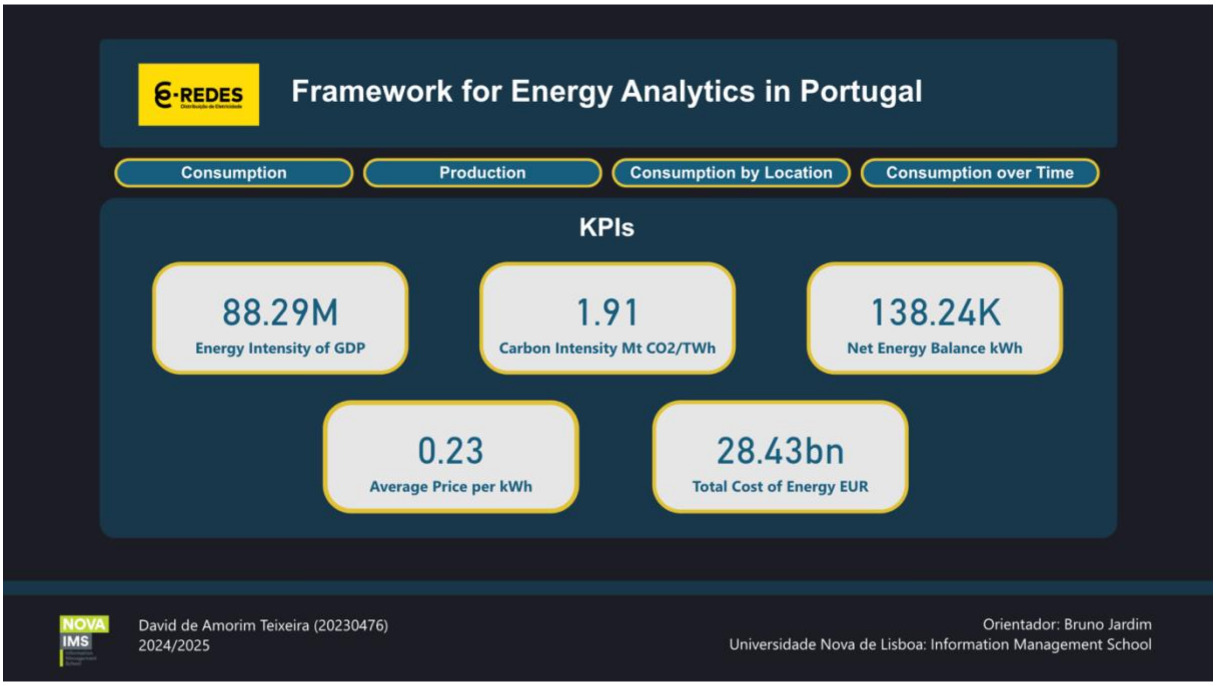


Figure 9 - Page 1 of the Dashboard - Landing Page

When opening the dashboard, the first page of our Power BI dashboard consists of simple landing page with some important KPIs to give a small context of Portugal's Energetic situation (Figure 9). One purpose of this page is to help guide the user navigate the dashboard and introduce the context of the project as well as the developers. The navigation button helps the user choose which page they want to explore first. This interactive feature is present in all the dashboard pages, allowing for easy navigation.

Figure 10 displays an overview of national electricity consumption, presented on the first page of the dashboard. It is segmented by voltage type and can be analysed over time. It enables stakeholders to study demand trends and infrastructure energy usage. The data on this page refers to the period between of January 2023 and January 2025.

On the leftmost part of the page, we can identify some multi-row Cards with some KPIs. On the top the value shows the total amount of Energy Consumed in billions, followed by the daily average energy consumed in millions and, finally the average energy per capita. All these energy metrics are expressed in kWh. Below this card, there are some simple filters like the Year and Month and a measure selector that allows some graphic to change according to the voltage level selected. The voltage levels are low, medium, high and very high voltage. On the centre of the page, we have a donut chart with the percentage share of energy consumed per voltage level. On the rightmost part of the dashboard, we can visualize a clustered bar chart that can alternate views depending on which voltage level is selected on the filter and if the option "All" is selected the bar chart shows all voltage level bars clustered in the same one. This bar chart has information of the energy consumed per voltage type in Millions of kWh. On the bottom right part of the page there is a line area chart with the information of energy consumed per month and year. This analysis can also be changed using the same measure

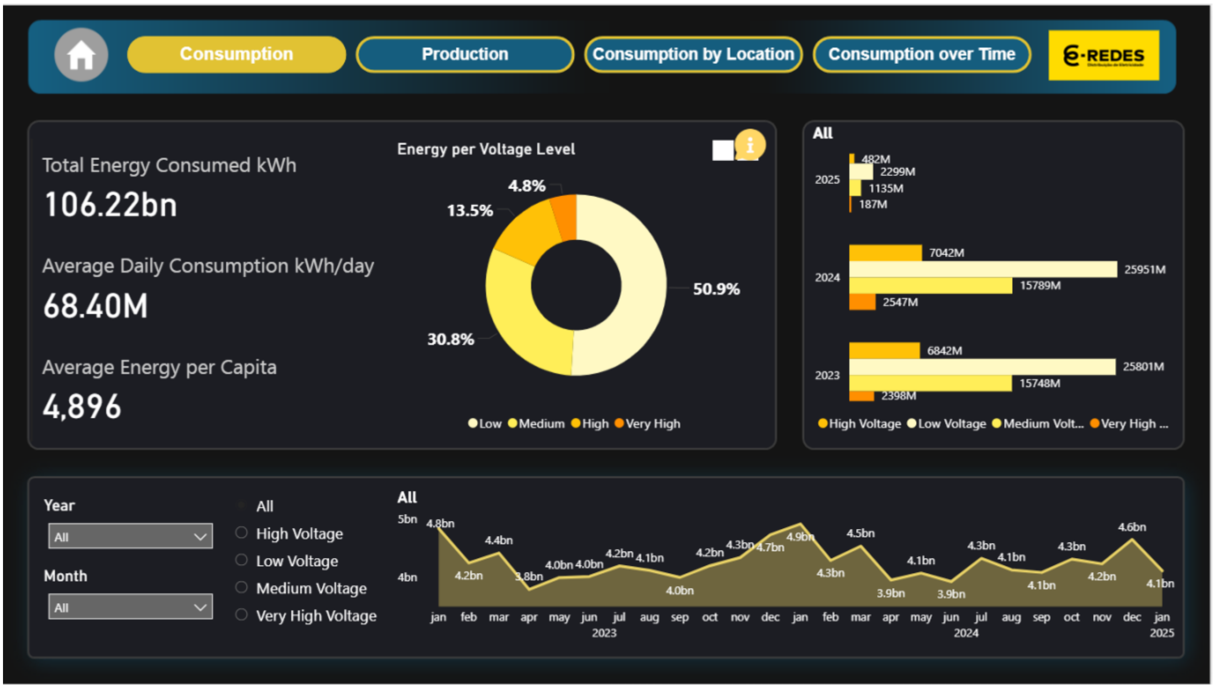


Figure 10 - Page 1 of the Dashboard - "Energy Consumption"

selector feature as in the bar chart, representing each or all voltage levels. The colours of each voltage level can be seen in the legend of the bar chart and are the same for all visual representations for easier identification.

In the next page of the dashboard, we analyse the production of energy segmented by market type liberalized or under special regime observed over time. The data on this page refers to the period between of January 2023 and January 2025.

As seen in Figure 11, the layout of the page is very similar to the previous one. The multi-row Card with the main KPIs is on the left on the centre the pie chart and on the right the clustered bar chart. In the lower section we have the filters and the line chart. The measures selector feature in this page allows to change the bar chart and the line chart according to the type of production, under special regime, by market producers or all. The colour scheme is also coherent with the legend to facilitate the analysis and in the Energy Consumption page.

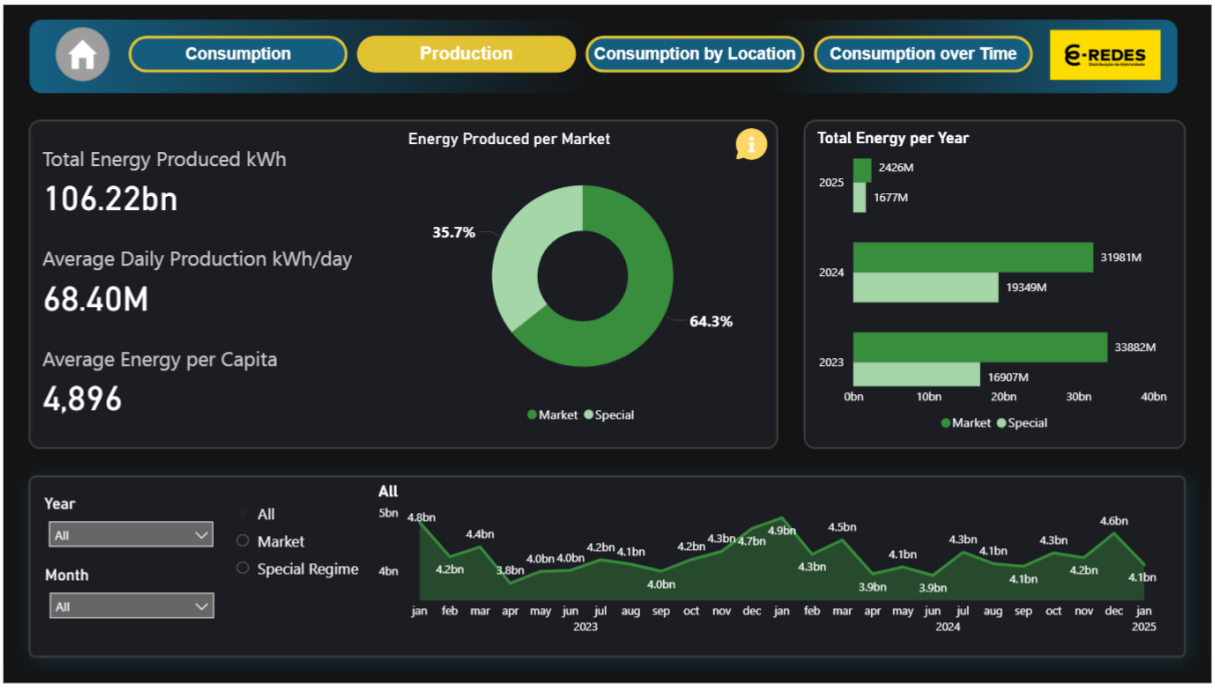


Figure 11 - Page 2 of the Dashboard – “Energy Production”

The third page of the dashboard as illustrated in Figure 12 consists of an overview of the electrical consumption per location. This analysis might be in different granularities, from district to parish and help understand the geographical distribution of energy consumption in Portugal over time. The data in this page refers to the period between January 2021 and December 2023.

Although it is a different period of the last two pages, it serves as benchmark to understand which geographical regions are more energy intensive. Starting from the left we have the section with the two multi-row Cards with KPI values for the Energy Consumed in billions, the number of districts, the number of municipalities and number of parishes. We also have in this section, the KPIs for Carbon intensity in Mt CO_2 per TWh, the Energy Intensity of GDP in millions of kWh and the Net Energy Balance in kWh. In this same section, next to the KPIs, we find a bar chart with the top 10 highest energy consuming districts in Portugal. On the lower part of the page we have, as in the previous pages, the filter section, that allow to us to filter data by year month, district and municipality. Finally, on the left section of this page we have a map that represents the energy consumption of each municipality in Portugal. The municipalities with the highest energy consumption are represented with a brighter yellow colour, and in contrast, the regions with the lowest consumption show a darker tone.

Figure 12 - Page 3 of the Dashboard – “Energy Consumption by Location”

As represented in Figure 13, the last page of this dashboard, we have an analysis by time that shows the evolution energy consumption by each month of the year, by each hour of the day and other granularities. These analysis help stakeholders identify trends in consumption as well as the yearly seasonality and the daily or weekly cycles.

Starting from left to right, on the left section of the dashboard we have the filter panel which allows the information to be sliced by year, trimester, month, weekday, part of the day, and hour of the day. On the top right part of the page, we find a line chart that displays the energy consumption over a period. The drill down options allow on the chart allows to alternate between different granularities of the date hierarchy by year, trimester, month of year, day of the week and day of the month. On the lower section of the page, we find two visual representations. The one on the left is a bar chart that represents the energy consumption by part of the day and the one on the right is another line chart that expresses the energy consumed per hour of the day.

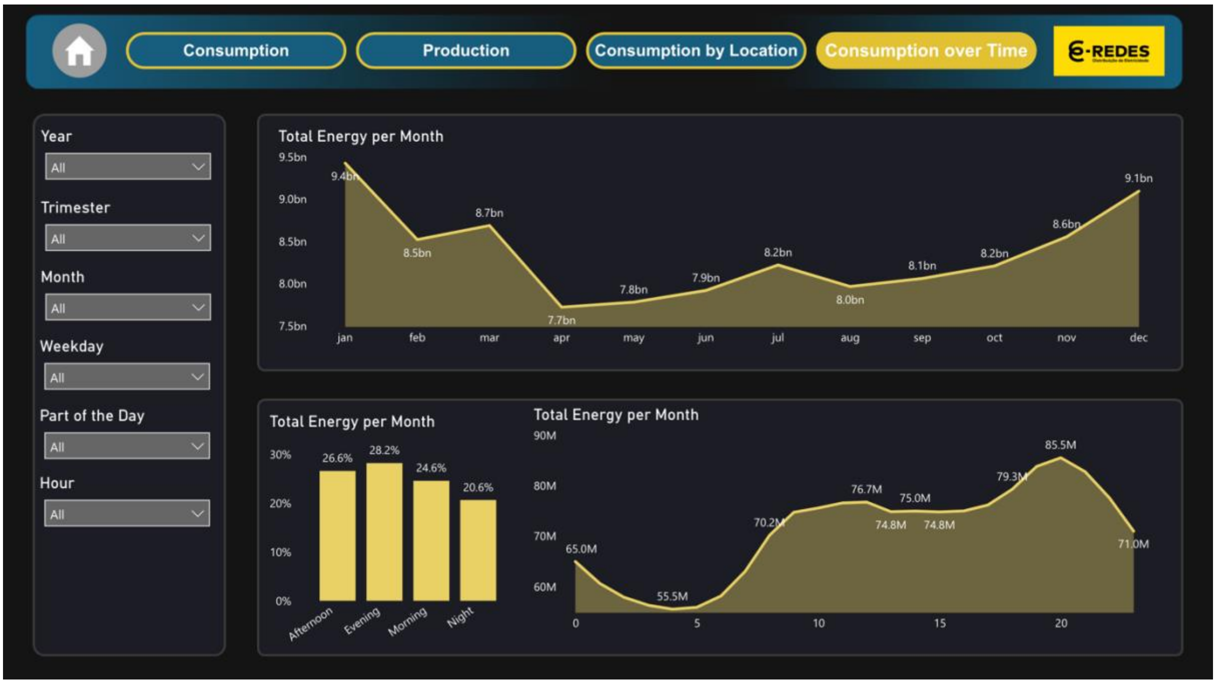


Figure 13 - Page 4 of the Dashboard – "Energy Consumption over Time"

Each page of this dashboard has a navigation panel at the top that allows for easy access to any page at any given point. The home button on the top left corner is also a quick and intuitive solution to return to the landing page. Finally, all the dashboard pages have the E-Redes logo at the top right corner that links to the website where the data was sourced from and allows the stakeholders to know more about the company, their services, and about the origin of the data itself. All dashboard pages were equipped with filtering capacities that allow for a dynamic exploration of the data for all graphical visualizations.

4.3. Dashboard Results

In this part of the chapter, we will be discussing how effective the dashboard is at answering the proposed business questions in the scopes that were defined in Chapter 3 – Energy Consumption, Energy Production, Geographical Analysis and Temporal Analysis.

The structure of the dashboard was designed address each business scope in the most effective way. This meant creating a page almost fully dedicated to each one of the scopes and creating the most adequate visualizations and data representations to answer each business question.

On the first page of the dashboard, we give some information regarding important KPIs in the scope of energy consumption and sustainability in Portugal, as we can see in Table 19.

Table 16 - BQ for Energy Consumption and Sustainability

Business Question	**Answer**
1.1 What is the level of carbon intensity in Portugal?	For 2023 and 2024 the value of carbon intensity reached 1.98 Mt CO2 per TWh.
1.2 What is the energy intensity of GDP in Portugal?	For 2023 and 2024 the value of Energy of GDP was 84.9M kwh per billion Euros.
1.3 What is the net energy balance in Portugal?	Between 2023 and 2024 the Net Energy Balance was positive: 138.24k kWh. This means Portugal produced more energy than it consumed.
1.4 What was the total cost of energy in Portugal	Between 2020 and 2024 the total cost of energy consumed was 28.4 billion Euros.

As referred on the last subchapter (4.2), on the second page of the dashboard we address the Energy Consumption in Portugal. In the Table 20 below we find the answers that can be found on this page to the proposed business questions.

Table 17 - BQ for Energy Consumption

Business Question	**Answer**
1.5 What is the total national energy consumption?	Between 2023 until Jan 2025 the total energy consumed in Portugal was 106.2 billion kWh.
1.6 How does it evolve over time (month, year)?	Higher consumption of energy in colder months and lower consumption in hotter months, showing seasonality. The values for 2023 and 2024 did not show a significant variation.
1.7 Through which voltage level is most of the energy consumed? And the least?	The most used voltage level for energy consumptions is through Low Voltage – 50.9% - which indicates that the majority of energy is consumed by regular households and small businesses. The least used voltage level was Very High Voltage – 4.8% - which correspond to the consumption of energy from large industrial operations.

	The remaining 44.3% of energy consumed is through medium and high voltage levels, which correspond to common industrial facilities and large commercial businesses.
1.8 How has each voltage level evolved over time?	For the Low Voltage we identified a seasonal trend similar to the overall consumption and no significant changes from the previous year (2023). For the Medium Voltage level there is slightly higher consumption in summer months, however there is no clear evidence of seasonality. For the High Voltage level small variations across time, no seasonality identified. For the Very High Voltage level, there is a slight dip in hotter months (July and August), but relatively constant otherwise.
1.9 What is the average daily consumption of energy?	From Jan 2023 to Jan 2025 the average energy consumption was 139.4 million kWh per day.
1.10 What is the average consumption per capita?	From Jan 2023 to Jan 2025 the average energy consumed per capita was 4,896 kWh.

The third page of the dashboard relates to the Energy Production in Portugal. In the Table 21 below we can find the answers to the proposed business questions for this scope:

Table 18 - BQ for Energy Production

Business Question	**Answer**
2.1 What is the total national energy production?	Between 2023 until Jan 2025 the total energy produced in Portugal was 106.2 billion kWh.
2.2 How does it evolve over time (month, year)?	Higher production of energy in colder months and lower production in hotter months, showing seasonality. In accordance with the consumption patterns.
2.3 What is the average daily production of energy?	From Jan 2023 to Jan 2025 the average energy production was 139.4 million kWh per day.
2.4 What is the average production per capita?	From Jan 2023 to Jan 2025 the average energy production per capita was 4,896 kWh.
2.5 In which regime is most energy produced?	The majority of the energy is produced by common market producers 64.3%.
2.6 How has the production in each regime evolved over time?	For the common market the energy produced varies similarly to the overall production, showing the same

	seasonality. However, a significant decrease is noticed between February and May of 2024, which corresponds to an increase in special regime production.

On the fourth page of this dashboard, we will find the information regarding the Geographical distribution of energy consumption in Portugal, and the business questions answered in this section are listed in Table 22.

Table 19 - BQ for Geographical distribution of Energy Consumption

Business Question	**Answer**
3.1 What regions (districts, municipalities) consume the most energy? And the least?	Between January of 2021 and December of 2023 and he district that consumes the most energy is Lisbon, with 25% of total energy consumed, and Porto, with 17%. Together these districts are responsible for almost half of all energy consumed in Portugal. The districts that consume the least energy are Portalegre (0.7%) and Guarda (0.7%).
3.2 Is the consumption of energy evenly distributed between districts?	Lisbon and Porto account for most of the energy consumed in Portugal (27% and 19%). The top 6 districts that consume most energy account for around 83% of all consumed energy in Portugal and are all coastal districts.
3.3 What is the average consumption per district? And per municipality?	Between Jan 2021 and December 2023 the average energy consumption per district is 4.2 billion kWh.

Lastly, on the last page of the dashboard, we will assess the business questions in the scope of the evolution of energy consumption over time, as we can see in Table 23.

Table 20 - BQ for temporal analysis of Energy Consumption

Business Question	Answer
4.1 What are the peak hours and off hours of energy consumption in a day in Portugal?	The hour in which most energy is consumed in a day is 20h with 42.3 million kWh of energy consumed and the off-peak hour is 4h with 27.6 kWh of energy consumed, in 2023.
4.2 In which part of the day is most of the energy consumed?	Most energy is consumed in the Evening (28,2%), followed by the afternoon (26,6%).
4.3 Can trends (seasonal, cyclical) be identified in energy consumption levels?	We can identify that the consumption increases in colder months (October through Mach) and decreases in the hotter months (April through September).
4.4 What are the peak months and off months of energy consumption in a year in Portugal?	The peak month of energy consumption is January with 4.7 billion kWh, and the off-peak month is April 3.8 billion kWh, in 2023.
4.5 In which trimester is most energy consumed?	The 1st Trimester is the most energy intensive one.
4.6 What are the days of the week in which most energy is consumed?	During weekdays the consumption is similar, but it decreases significantly in the weekends, reaching the lowest value on Sundays.

4.4. Comparative Analysis

In this subchapter of the project, we will compare the results obtained from the final Power BI dashboard with other studies and papers on the same topic of energy analytics and sustainability. Comparing our work with other literature found can improve our understanding of the current strong aspects and limitations of the developed framework.

Regarding the scope of Energy Consumption and Production, our conclusions confirm a clear seasonality in both consumption and production, peaking in the winter months and dropping in summer months, aligning with the results from Puddu (2023) and Jing et al. (2022). In both these projects, it is argued that temperature variations are a primary driver of energy demand. As a more specific example of this result, Segundo Sevilla et al. (2022) reported that consumption peaks in southern Europe are similar to Portugal's, validating the work that was conducted in our temporal analysis.

Furthermore, our analysis revealed that over 50% of the energy consumed is through low voltage levels, indicating that residential buildings and small businesses are the primary consumers of energy in Portugal. This aligns with IEA (2022), which states that 99.5 % of the consumers in Portugal are connected to the low voltage grid.

In terms of the hourly analysis of energy consumption in a day we found out that 8pm is the hour of peak energy demand and between 4am and 5am is the period of lower energy consumption, which can be compared with the analysis made for the UK´s energy consumption via online dashboards (Energy Dashboard, 2025).

In the geographical analysis, we also concluded that Lisbon and Porto account for nearly half of all energy consumed in Portugal which is expected due to the higher population density and industrial activities. These results are aligned with the findings of Mrówczyńska et al. (2020), who found that bigger cities are prone to higher levels of consumption due to the higher population density and industrial and commercial activities.

While several studies identified during this project—such as (IEA, 2024) —focus exclusively on national-level energy analysis, the framework developed herein enables a more granular evaluation at the municipal and parish levels. This detailed resolution offers novel insights that are rarely presented in existing literature. It allows for the implementation of localized energy policies as emphasized by Huovila et al. (2019) which is also an identified gap in the city-level energy and sustainability studies.

From the KPI calculated in our project the values for Carbon Density (1.91 Mt CO_2/TWh and Energy Intensity of GDP (88.29 million kWh/ billion Euros) are within the range of the values found in Ecclesia & Domingos (2024). In addition, Portugal shows above average values for energy efficiency KPIs which suggest the country's great efforts to achieve the desired goal by 2030 mentioned in the PNEC and as reported by Reuters (2022).

Using data that reflects the context of the problem is also key according to Chao et al. (2020) and Angelakoglou et al. (2020). By using energy data detailed by voltage type and production regime, as well as by municipality, we are able to produce context specific analysis in our framework.

According to Bach et al. (2022) creating a consistent and organized layout, colour coordination and geo-temporal interaction are considered to be best practices in dashboard building. These features are all part of our Power BI solution. Additionally, the data model created using Microsoft Fabric's features allows for real-time interactivity while maintaining performance and a reliable connection to the data model, which might be considered a challenge in some works (Arghandeh & Zhou, 2018; Segundo Sevilla et al., 2022).

Previous studies, including Jing et al. (2022) and (Chen & Chen, 2021), have developed comprehensive approaches to data analytics or dashboards related to the energy sector. However, few have managed to create a full business intelligence scalable and adaptable framework from ETL and data warehousing to semantic model and a Power BI dashboard. This project bridges the gap in literature for missing integrated BI frameworks for energy studies.

5. CONCLUSION AND FUTURE WORKS

5.1. CONCLUSION

One of the main goals of this project was to deliver a solid Business Intelligence (BI) platform for data-driven analysis and to build a foundation to understand Portugal's energy related activities and sustainability that would be accessible to any stakeholder and potential policy makers. The current literature revealed a gap on an integrated BI methodology that connects energy analytics with user-friendly and accessible tools for visualisation. This gap was filled by this work by creating integrated data warehousing techniques with KPI formulation and the development of a dashboard using Microsoft Fabric.

For this project, we decided to follow the Kimball Lifecycle methodology which served as a guide for the structure of every step of the project allowing to develop a data warehousing system that would be linked to our dashboard. The different components of the dimensional model created used multiple Microsoft Fabric functionalities such as Lakehouse and Warehouse to store initial, pre-processed and validated data, Dataflows Gen2 for ETL and other steps and a Semantic Model to organize and link the final data tables. The dimensional model created was optimized to deliver analysis for the energy data and study patterns across temporal and geographical dimensions.

By implementing an interactive Power BI dashboard, we were able to answer the business questions initially proposed, as suggested in the first steps of the Kimball Lifecycle methodology. The questions were organized into different categories according to the scope of the business requirements. The categories were Energy Production, Energy Consumption, Temporal Analysis and Geographical Analysis. Using various comprehensible and interactive visualization techniques, we were able to create insightful analysis and answer key business questions regarding the different scopes of energy consumption and production, efficiency and which enabled a dynamic dissection of the different voltage types and production types. By including KPIs such as Net Energy Balance, Energy Intensity of GDP and Carbon Intensity, the project is aligned with the following Sustainable Development Goals: SDG 7 – Affordable and Clean Energy; SDG 9 – Industry, Innovation and Infrastructure; SDG 11 – Sustainable Cities and Communities; SDG 12 – Responsible Consumption and Production; SDG 13 – Climate Action (United Nations, 2017).

Regarding the results obtained through the Power BI dashboard visualisations we were able to gather valuable insights for Portugal. For starters, Portugal's energy consumption demonstrates clear seasonality, with higher usage during colder months and a considerable drop during the summer season. Low voltage energy accounted for over 50% of total consumption, meanwhile very high voltage energy represented the lowest share, around 5%, reflecting that the majority of energy is consumed by regular households and small businesses and only a small part for bigger industrial operations. On the production side, the biggest share of energy was produced from common producers on the market, although a significant increase on the special regime production was noted in early 2024. As per the geographical analysis of the data, Lisbon and Porto are the top districts for energy consumption and combined are responsible for nearly half of all energy consumed in the country from January 2021 to December 2023. The Net Energy Balance was positive, and important KPIs such as Carbon Intensity (1.91 Mt CO_2/TWh) and Energy Intensity of GDP (88.29M kWh/bn EUR) were successfully calculated and visualized, offering a comprehensive overview of national energy sustainability.

One of the stronger aspects of this project lies in the possibility to visualize energy related data at different levels of granularity across the different dimensions and allows the stakeholders, from governments and potential business owners to support their decision making. Another key strength of this project consists of the adaptability of this framework to other countries or energy systems and the ability to be expanded and include other related datasets in order to enrich the analysis.

5.2. Limitations and Future Works

Despite being able to implement a fully working dimensional data model that supports a versatile dashboard using Power BI, we encountered some limitations through the course of developing this project. Starting with the data, some datasets had missing data, such as the geographical identifiers (Zip Codes) that had to be added via manual imputations, and some spelling errors in municipality names due to accent marks or special Portuguese characters, that had to be corrected or accounted for. In addition, as we used multiple datasets to have a more complete and detailed vision of the energy scene in Portugal we encountered the problem of inconsistent temporal analysis, since some files only had information until Dec 2023 and others starting in Jan 2024. Another limitation regarding the files, occurs in the importations section of the project, as the files were too large to be connected via API and add to be imported as CSV files to ensure a stable and reliable data.

With the limitations of our work being exposed, it is important to consider future developments of the project. Forecasting models could be added using a machine learning model to help predict energy consumption and anticipate demand peaks and production trends and therefore increase the dashboards utility. As mentioned before, we could not use API connections to the E-Redes website, therefore using real-time data automatically could be a future improvement, allowing for a more dynamic monitoring of the grid. Additionally, some datasets could be added to provide a more complete analysis, for example to discriminate the different types on energy sources (gas, hydro, wind, etc) and allowing for a more comprehensive view of Portugal's energy sustainability. Expanding this analysis to a world-wide level could also be in the scope of future works as it would allow for benchmarking and comparative analysis between countries.

In summary, this thesis demonstrates how an integrated business intelligence (BI) framework for energy studies can improve our comprehension of national energy systems and result in the development of business-related and sustainability-related decisions. The scalability and accessibility of this project create a foundation for future academic research to shorten the gap in energy analytics and reporting field.

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