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DISSERTATION

THE TRANSFORMATIVE POTENTIAL OF MACHINE LEARNING IN THE ENERGY DISTRIBUTION SECTOR: A CASE STUDY OF E-REDES

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Abstract

Climate change poses one of the greatest challenges of the 21st century, requiring a fundamental transformation of energy systems to reduce carbon emissions and support global sustainability goals. The energy transition aims to shift away from fossil fuels towards renewable energy sources while ensuring energy security and efficiency. In this context, energy distribution companies play a crucial role in enabling this transition by integrating new technologies and managing the complexities of modern energy grids.

The methodology employed in this research is a qualitative case study. Data was collected through semi-structured interviews and an analysis of external and internal documentation, providing a comprehensive understanding of the company's efforts to contribute to the energy transition, and access how Machine Learning (ML) can help challenging the current regime.

This thesis examines how E-REDES, as a Distribution System Operator (DSO), is leveraging ML in order to contribute to the energy transition. Given the early stages of ML adoption in DSOs, this research acknowledges that it is still too early to derive substantial results from these initiatives, thus substantial and measurable outcomes have yet to be fully realized. Instead, the study aims to assess the current contributions of ML to the energy transition and whether these applications can drive systemic changes to the current energy regime.

The findings reveal that while ML significantly improves efficiency and supports the integration of renewable energy, it primarily functions as a tool for optimization rather than disruption of the current energy regime. The study concludes that ML, in its current applications, contributes to accelerating the energy transition but does not yet have the transformative power to challenge the existing system.

Keywords: Sustainability, Energy Transition, Machine Learning, Energy Distribution

Resumo

As mudanças climáticas representam um dos maiores desafios do século XXI, exigindo uma transformação dos sistemas energéticos com o objetivo de reduzir as emissões de carbono e apoiar os objetivos globais de sustentabilidade. A transição energética visa reduzir a utilização de combustíveis fósseis substituindo-os por fontes renováveis de energia, assegurando, simultaneamente, a segurança e a eficiência energética. Nesse contexto, as empresas de distribuição de energia desempenham um papel crucial ao integrar novas tecnologias e gerir as complexidades das novas redes de energia.

A metodologia utilizada nesta pesquisa é um estudo de caso qualitativo, com foco na E-REDES. Os dados foram recolhidos através de entrevistas semiestruturadas e da análise de documentação externa, explorando os esforços realizados pela empresa para contribuir para a transição energética.

A presente dissertação pretende explorar como a E-REDES, enquanto Operadora da Rede de Distribuição (ORD), está a utilizar o Machine Learning (ML) para contribuir para a transição energética. Dado que a adoção de ML, nas DSOs, ainda se encontra numa fase inicial, este estudo reconhece que ainda não foram alcançados resultados mensuráveis e significativos. Assim sendo, o objetivo do estudo é avaliar as contribuições atuais do ML para a transição energética e se essas aplicações podem gerar mudanças sistêmicas no regime energético atual.

Os resultados revelam que, embora o ML tenha potencial para melhorar significativamente a eficiência operacional e apoiar a integração de energia renovável, o mesmo funciona maioritariamente como uma ferramenta de otimização, ao invés de disrupção do atual regime energético. O estudo conclui que, considerando as suas atuais aplicações, o ML contribui para acelerar a transição energética, mas ainda não possui o potencial transformador necessário para desafiar o sistema existente.

Palavras-Chave: Sustentabilidade, Transição Energética, Machine Learning, Distribuição de Energia

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Glossary

DER - Distributed Energy Resources

DSO – Distribution System Operator

EV – Electric Vehicles

HV – High Voltage

IPMA - Portuguese Institute for Sea and Atmosphere

LV – Low Voltage

ML – Machine Learning

MV – Medium Voltage

ORD – Operador de Rede de Distribuição

V2G – Vehicle-to-grid

1. Introduction

Climate change is one of the most pressing global challenges of the 21st century, demanding urgent and comprehensive action across multiple sectors, including energy (United Nations, 2024).

The energy sector has a major impact on the climate. According to the United Nations "the energy supply sector (electricity, heat, and other energy) is the largest contributor to global greenhouse gas emissions, responsible for approximately 35% of total emissions" (United Nations, 2021). As the Federal Ministry of Economic Cooperation and Development from Germany states "these emissions must be reduced dramatically, which can only be achieved by phasing out of fossil fuels", which means an energy transition process (Energy and Climate, n.d.).

The shift towards renewable energy sources, such as wind and solar, is critical to reducing carbon emissions and ensuring a sustainable future. However, the energy transition involves more than just changing the source of energy; it requires optimizing the entire energy system to ensure efficiency, reliability, and the integration of variable renewable energy. Energy distribution companies are key players in this transformation, as they are responsible for managing the complexities of modern electricity grids.

In recent years, the growing adoption of digital technologies has offered new opportunities for optimizing energy systems. Among these technologies, machine learning (ML) holds promise. However, while the potential of ML is significant, its application in the energy sector, particularly within Distribution System Operators, remains in its early stages.

This research focuses on the case of E-REDES, the largest DSO in Portugal, and explores how the company is integrating machine learning to address some of the challenges associated with the energy transition. While substantial results from the implementation of ML are still in an early stage, this study aims to assess how machine learning can support the company in optimizing energy distribution while also contributing to the broader goal of the energy transition as a socio-technical transition.

By focusing on E-REDES, this case study aims to:

- Explore how ML is incorporated into E-REDES' operations;
- Identify the opportunities and barriers arising from these ML initiatives;
- Assess whether ML-based innovations can accelerate the energy transition by disrupting the existing socio-technical system.

This study advances the application of Geels' Multi-Level Perspective (MLP) framework within the energy sector, providing a structured lens for understanding how niche innovations like ML interact with socio-technical regimes and the broader energy transition. Additionally, through the case study of E-REDES, this research explores real-world ML applications in grid management, offering actionable insights for energy DSOs aiming to integrate ML technologies. Moreover, by identifying gaps and challenges in ML adoption, this work sets the stage for future research and policy development. These contributions aim to enrich the ongoing discussion on the role of emerging technologies in accelerating the energy transition, providing both theoretical insights and practical implications.

The study employs a qualitative research design, specifically a case study methodology, to capture the complexities of ML integration within E-REDES. Semi-structured interviews coupled with the analysis of both external and internal documentation, form the basis of the data collection process.

The current work consists of six chapters, with the first one corresponding to introduction and in the second chapter scientific literature about the study was reviewed and analyzed. The third one is the methodology chapter, where detailed research design is described. Then, the following chapter is parted into three sections: the first one is dedicated to the application of the theoretical framework to the energy transition, giving some context about the relevance of the DSOs in the energy transition, and the second and third is data presentation and discussion of results obtained through collection of empirical data. Finally, the sixth chapter describes conclusions and limitations of the current study along with suggestions for further studies.

2. Literature Review

This chapter aims to present, in an organized way, a theoretical frame to this study. As a first step, the main concepts are described which includes the concept of transition and socio-technical transition. Afterwards, it is presented the Multi-Level Perspective Framework used to understand such transitions.

2.1 *Concept of Transition*

The origins of the concept of transition can be traced back to ancient philosophical inquiries into the nature of change and transformation. Aristotle, in his seminal work "Physics," discussed transition as a fundamental aspect of natural processes, highlighting the perpetual flux and motion inherent in the cosmos (Aristotle, 1984).

Having said this, transition, as a concept, has a very rich history. Originally, it was used when referring to changes from one state or condition to another, often in the context of natural systems like ecosystems or populations (Kralik et al., 2015). Over time, this concept has evolved and been adapted across disciplines, becoming a subject of study among scholars in sociology, economics, technology studies, and beyond. Transition studies often involve interdisciplinary approaches, in order to understand the complex processes of change in various domains (Markard et al., 2012).

While pinpointing the exact origins of studying transitions is challenging due to its interdisciplinary nature, certain periods and developments have contributed to the emergence of transition studies in different domains.

From these diverse perspectives emerge conflicting definitions and interpretations of transition. Some scholars view transition as a linear progression through distinct phases, while others emphasize its nonlinear and emergent nature. Fairclough and Wodak (1997) defined transition as a “passage from a well-known defined point of departure to a unitary and well-defined destination”. In contrast, Rotmans (2000) defines transition as a “fundamental restructuring of societal systems, characterized by shifts in technological, economic, and institutional arrangements”. For Lieberthal and Lieberthal (2003), transition was a paradigm shift that “would challenge both the viability and desirability of conventional values, economic structures and social arrangements”. Lastly, Raskin et al. (2002) take a broader systems perspective on transition, viewing it as a holistic transformation of socio-ecological systems. They argue that transition involves changes in human values, behaviors, and relationships with the environment, necessitating shifts towards sustainable development pathways.

Geels (2002, 2007) contributes to the discussion by introducing the concept of socio-technical transitions, focusing on the interplay between technological innovation and societal change. He defines transition as a “multi-dimensional process involving interactions between technological regimes, niche innovations, and broader socio-cultural contexts”. In order to provide a structured way of understanding and analyzing the complex dynamics involved in societal transitions, Frank Geels introduced the Multi-Level Perspective Framework.

2.2 *Socio-Technical Transitions Frameworks*

The concept of socio-technical transitions represents a paradigm shift in the study of technological change and innovation. Emerging within the field of innovation studies, socio-technical transitions theory offers a holistic framework for understanding how societies transition from using one technology or way of doing things to another (Geels, 2005). At its core, socio-technical transitions emphasize the interconnectedness between technological systems, social practices, and institutional structures.

As mentioned before, Geels significantly contributed to the development and elaboration of the socio-technical transitions concept by introducing the Multi-Level Perspective (MLP) framework, which offers a theoretical lens for analyzing socio-technical transitions. Within this framework, socio-technical transitions are viewed as complex processes involving interactions between technological innovations, societal structures, and cultural norms across different levels: niche innovations, socio-technical regimes, and socio-technical landscapes (Geels, 2011). Throughout the years, different frameworks have been introduced by various scholars, whose theories offer different perspectives or emphasize different aspects of transitions. As examples, there is Strategic Niche Management (SNM), Socio-Technical Regime Framework, Innovation Systems Approach, etc.

While each of these frameworks may emphasize different aspects or approaches to understanding socio-technical transitions, all of them acknowledge that transitions are complex and long-term processes involving multiple actors, systems, and interactions which must be studied based on insights from multiple disciplines. Furthermore, all frameworks consider the role of agency and governance in shaping transition pathways and outcomes. Moreover, they all emphasize that much more than just technological innovation, government regulations, etc., societal change plays a crucial role in driving and shaping transitions. According to Elzen et al., (2004), transitions are fundamentally about societal change, understood as a shift in socio-technical regimes, which involves altering practices, rules, and normative expectations. Rotmans shared the same perspective. For him, transitions require more than just technological innovations or policy interventions. They necessitate fundamental changes in societal structures, behaviors, and values. (Rotmans et al., 2001).

The importance of societal change is particularly evident in sustainability transitions, which aim to shift societies towards more sustainable pathways that address pressing environmental, social, and economic challenges.

2.3 *Sustainability Transitions*

Sustainability transitions represent broad, long-term transformations aimed at shifting entire systems towards more sustainable modes of production and consumption (Markard et al., 2012). Socio-technical transitions are one way to understand and achieve these broader sustainability transitions, focusing on the interplay between technology, society, and institutions. According to Markard et al. (2012), a sustainability transition is a long-term, multi-dimensional and fundamental transformation of large socio-technical systems towards more sustainable modes of production consumption. They include profound changes in ways of doing, thinking, and organizing, as well as in underlying institutions and values (Loorbach et al., 2017). Emerging against the backdrop of growing environmental concerns and calls for sustainable development, sustainability transitions seek to reconcile economic prosperity with ecological integrity and social equity. At its core, sustainability transitions emphasize the need for systemic change across multiple domains, including energy, transportation, agriculture, and urban development (Geels, 2011). These transitions require coordinated efforts to reconfigure existing socio-technical systems and address pressing environmental, economic, and social challenges. By fostering innovation, mobilizing social movements, and reshaping policy frameworks, sustainability transitions offer a pathway toward achieving long-term environmental sustainability and human well-being (Smith et al., 2005).

2.4 *Multi-Level Perspective Framework by Frank Geels*

Even though the MLP framework has been constructively criticized over the years, it is still a fruitful middle-range framework for analyzing socio-technical transitions, particularly those aimed at sustainability. Thus, for the purpose of this work, the MLP framework will be analyzed.

The MLP framework addresses the complexity and multi-dimensionality of socio-technical transitions by examining the interactions between different levels of socio-technical systems: niche innovations, socio-technical regimes, and socio-technical landscapes (Geels, 2018).

Niche Innovations

At the core of the MLP framework are niche innovations, which refer to radical innovations that emerge in protected spaces, shielded from the mainstream market pressures and regulatory regimes. These niches serve as incubation zones where novel technologies, practices, and organizational forms can develop and mature. Niche innovations are crucial as they represent the seeds of potential future regimes, offering alternative solutions to existing socio-technical challenges (Geels, 2020).

Socio-Technical Regimes

The next level within the MLP frameworl is the socio-technical regime, which comprises the dominant practices, rules, and shared assumptions that guide the activities of various actors within a specific domain. These regimes are relatively stable and resistant to change due to the alignment of technological artifacts, infrastructures, regulatory frameworks, cultural beliefs, and market structures (Geels, 2020).

Socio-Technical Landscapes

The socio-technical landscape is the broadest level within the MLP framework, encompassing the exogenous macro-level context that influences both niche innovations and socio-technical regimes. This landscape includes factors such as cultural trends, political ideologies, economic patterns, and environmental changes that provide the backdrop against which socio-technical transitions occur. Landscapes are generally slow to change, but significant shifts can create windows of opportunity for regime transitions (Geels, 2020).

The MLP framework emphasizes the dynamic interactions between these three levels. Hence, to fully explain transitions it is necessary to identify these processes and the complex interactions between them.

Transitions occur when niche innovations manage to break through and disrupt existing regimes, often facilitated by landscape pressures that weaken the stability of the current socio-technical regime. This multi-level interaction is inherently complex and nonlinear, involving feedback loops, lock-in mechanisms, and co-evolutionary processes (Geels et al., 2017).

2.5 *Energy as a socio-technical system*

Energy systems are socio-technical systems, characterized by the intricate interplay between technological infrastructures, regulatory frameworks, market dynamics, and social practices (Markard et al., 2012). Viewing energy as a socio-technical system underscores the complexity of the energy transition and highlights the importance of considering technological, social, and institutional factors simultaneously.

In general terms, applying the MLP framework to the energy sector involves examining the interactions between:

- **Niche Innovations** which in the energy sector includes renewable energy technologies such as wind, solar, biomass, and hydroelectric power, as well as advancements in energy storage and integration and efficiency technologies. These innovations often emerge in protected environments, such as pilot projects or government-subsidized programs, where they can develop without immediate pressures from the existing energy market (Raven, 2007).

- The current **energy regime**, which is still characterized by centralized power generation, predominantly from fossil fuels, despite the trend to decentralized energy production. It includes established infrastructures, regulatory policies, market practices, and social norms that collectively support the status quo (IRENA, 2023; Energy Data Explorer, 2022). However, increasing environmental concerns and policy pressures are driving changes within this regime, creating openings for more sustainable practices and technologies.
- The **socio-technical landscape** that encompasses broader contextual factors such as climate change imperatives, international environmental agreements, economic trends, and societal values. These macro-level influences create pressures that can destabilize the existing regime and support the adoption of niche innovations.

2.6 *Opportunities and barriers of Machine Learning implementation*

As will be explored further in this work, Machine Learning (ML) is a niche innovation that holds significant promise for advancing the energy transition, with potential to address critical challenges in energy systems, including integrating renewable energy, optimizing grid operations, and engaging consumers. Given this work's specific focus on ML, it is important to examine the theoretical opportunities and barriers associated with its implementation in the energy sector.

ML offers transformative potential for **energy system management** by enabling real-time forecasting, predictive maintenance, and efficient demand-supply balancing. These applications are particularly valuable in decentralized, renewable-energy-based grids, where variability and complexity demand adaptive solutions. For instance, ML algorithms can enhance energy demand predictions, helping grid operators manage fluctuations in renewable generation while reducing waste waste (Geels, 2011). Furthermore, predictive maintenance powered by ML can identify equipment failures before they occur, minimizing downtime and extending the lifespan of infrastructure (Markard et al., 2012).

Moreover, in line with the transition towards decentralized energy systems, ML can help **empower consumers to become active participants** in energy production and consumption. With tools like smart meters and home energy management systems, ML enables consumers to optimize their energy usage, aligning it with periods of high renewable energy availability. This reduces costs and promotes grid flexibility. Additionally, ML-driven demand response systems can **automate adjustments in energy consumption**, helping to balance grid loads and reduce reliance on fossil fuel backup power during peak demand (Loorbach et al., 2017). Furthermore, ML is **transforming energy trading** by optimizing market operations. By analyzing vast datasets, ML can predict energy prices, forecast market demand, and identify optimal trading strategies, ensuring a more balanced and efficient energy market in increasingly dynamic conditions (Markard et al., 2012).

Despite its promise, with the implementation of ML initiatives, several challenges also come up. **High-quality, reliable data** is essential for ML, yet energy systems often suffer from fragmented or inconsistent data, particularly when integrating inputs from diverse sources such as sensors, smart meters, and weather forecasts. Insufficient data infrastructure can limit the accuracy and effectiveness of ML algorithms (Markard et al., 2012). Additionally, **regulatory frameworks** frequently fail to support digital solutions like ML, as they remain focused on traditional infrastructure investments rather than incentivizing innovation. Organizations themselves may **lack the expertise and resources** to adopt ML technologies at scale, particularly in the context of legacy systems or smaller utilities (Geels, 2004). Resistance to change within traditional energy organizations can further complicate adoption. **Ethical and privacy concerns** also present significant barriers to ML implementation. The use of ML in energy systems requires collecting and analyzing extensive consumer data, raising concerns about data protection, privacy breaches, and potential misuse. These issues can limit consumer trust and engagement, potentially slowing the adoption of ML-enabled technologies (Geels, 2011). Addressing these ethical concerns will be crucial to fostering public support for ML and ensuring equitable outcomes in the energy transition.

This discussion of ML's opportunities and barriers provides a theoretical foundation for its role in the energy transition and sets the stage for exploring its practical applications in subsequent chapters.

3. Methodology

This chapter explains and justifies the methodological decisions. Research design is the overall plan, which outlines how a research question will be addressed and specifies the objective attained through the investigation of the research question. It includes sources of data collection and describes the methods proposed to collect and analyze data (Saunders et al., 2007).

3.1 *Research design*

For the current study, qualitative research was chosen as it is effective for gaining deep insights into complex, context-specific phenomena and capturing participants' perspectives (Denzin & Lincoln, 2011). Qualitative research is particularly suitable for this study as it allows for the collection and analysis of non-numerical data, enabling the researcher to understand processes, and exploring new or under-researched areas (Creswell & Poth, 2018). Given that the objective of this research is to analyze how E-REDES is integrating machine learning into its operations, in order to contribute to the energy transition, and explore the potential impact and future possibilities of this technology, it is essential to explore the perspectives of different departments and profiles within the company. This type of qualitative data provides valuable insights not typically accessible through quantitative methods.

This research follows a descriptive study approach, which aims to provide an accurate account of the specific circumstances under investigation (Robson & McCartan, 2016). A descriptive approach is particularly appropriate in this case, as the study seeks to capture how machine learning is being implemented at E-REDES, as well as to document the practices, strategies, and operational changes that have been introduced. The research design is structured around exploring how machine learning can contribute to E-REDES' broader goals for the energy transition.

The research method chosen for the current work is a single case study. According to Stake (1995), case studies are valuable when a deep understanding of a particular instance, phenomenon, or situation is required. Additionally, case studies are effective for addressing "how" and "why" questions, especially when dealing with contemporary issues where empirical evidence may still be limited (Baxter & Jack, 2008). In this case, using a case study allows for a thorough exploration of how machine learning technologies are being integrated offering real-world insights into the complexities of this process and explore the implications for the company's strategic objectives and role in contributing to the energy transition.

E-REDES was chosen for a case study in the current work since it is the principal distribution system operator in Portugal. In 2020, 13 DSOs were operating in Portugal, 11 of which are in mainland Portugal. E-REDES is the only DSO for high voltage and medium voltage distribution systems and operates the low voltage distribution systems in 278 of Portugal's 308 municipalities, accounting for 99.5% of consumers connected at low voltage. Ten other small-scale DSOs operate municipal-level low-voltage distribution systems, supplying the remaining 0.5% of consumers (Portugal Electricity Security Policy – Analysis, n.d.).

3.2 *Company Overview*

E-REDES is a leading electricity distribution company in Portugal, responsible for the management and operation of the country's electricity distribution network.

Originally established as EDP Distribuição, the company rebranded as E-REDES in 2021 as part of the liberalization and regulatory changes in the energy sector within the European Union.

With a network spanning over 230,000 kilometers, E-REDES serves approximately 6 million customers across Portugal. The company's operations encompass the planning, construction, maintenance, and management of the distribution network, ensuring the safe and reliable delivery of electricity to residential, commercial, and industrial users.

In addition to its core operations, E-REDES is actively engaged in modernizing its network through significant investments in digital transformation and smart grid technologies. These efforts are part of the company's broader strategy to support the integration of renewable energy sources and improve the overall efficiency and reliability of the electricity distribution system.

By focusing on innovation and sustainability, E-REDES aims to align its operations with the evolving energy landscape and contribute to Portugal's energy transition goals, positioning itself as a forward-thinking leader in the electricity distribution sector. Additionally, the company places a strong emphasis on sustainability, aiming to reduce its environmental impact through initiatives such as reducing network losses and optimizing energy usage.

3.3 *Data Collection*

Data for this study will be collected through document analysis and semi-structured interviews.

The document analysis will involve reviewing E-REDES' strategic plans, technical reports, and relevant industry publications to gather background information and contextualize the company's current position and future aspirations regarding ML integration. This will provide an understanding of how E-REDES views ML as a potential driver of change.

Semi-structured interviews will be conducted to collect data for this study. The interview is one of the most important sources of information in case studies (Yin, 2009). According to Qu & Dumay (2011), interviews are an effective tool for collecting detailed information, particularly when clarification is needed, and are especially appropriate when the study aims to describe processes or understand decision-making factors. To ensure data triangulation, interview data will be supplemented with external and internal documentation. This approach offers flexibility to explore topics of interest that arise during the conversation, providing rich qualitative data that can uncover nuanced insights into the company's approach to machine learning.

Four semi-structured interviews, based on literature that was reviewed and analyzed, were conducted remotely in September 2024, and lasted approximately between 40 and 60 minutes each. Semi-structured interviews are characterized by a list of themes and questions that guide the conversation but allow for adaptation based on the interviewee's expertise or organizational role (Kvale & Brinkmann, 2009). Some questions may be altered or omitted depending on the specific context or role of the interviewee. The interview guide is provided in the appendix.

To maintain the anonymity of the interviewees, as requested by them, the reference used in the current work is Interviewee A, B, C and D. Interviewee A is an OT Data and AI Manager. The second interviewee (Interviewee B) works for System Optimization in the Grid Management Department. Next, a European Projects Manager was also interviewed (Interviewee C) and lastly, Interviewee D, who holds a position in Network Planning and Asset Management Strategy.

The interviews conducted in this research were designed to gather insights into the application of Machine Learning, at E-REDES, and its role in the energy transition. The first interview, with the individual responsible for overseeing ML development teams, provided a comprehensive overview of the various ML initiatives in the company. This allowed for a general understanding of each project, the selection of relevant initiatives within the scope of this study, and the identification of key points of contact for further exploration.

The subsequent three interviews focused on specific ML projects and their implementation. These interviews aimed to understand the role of the company and other DSOs in the energy transition, how these initiatives are applied in daily operations, and how the results generated by the algorithms are used by the teams. They also explored opportunities for further development within each project and in the broader use of ML, as well as the challenges faced during implementation. Together, these interviews provided both strategic and operational perspectives necessary for analyzing ML's contribution to the energy transition.

Given the qualitative nature of this study, the data analysis process will follow five steps: compiling, disassembling, reassembling, interpreting, and concluding (Castleberry & Nolen, 2018).

4. Data Analysis

This chapter focuses on presenting the data gathered during the research process and examining the results obtained. It is organized into two sections: the first details the data collected throughout the study, categorized by themes that align with the objectives of this work. The second section discusses the findings providing a discussion of the results.

4.1 *Multi-Level Perspective Framework applied to the Energy System*

As previously mentioned, the MLP framework covers three levels of analysis: the landscape (macro-level), the socio-technical regime (meso-level) and the niche (micro-level).

Socio-technological transitions can be explained through the interaction among these three levels as the transition basically entails a shift from an incumbent socio-technical regime to a new one, which is nurtured in the technological niche and prompted at the landscape level.

In this model, transition occurs whenever pressure at landscape level destabilizes the regime, thus creating a window of opportunity for pioneering niche-innovations to enter in the mainstream market.

4.1.1 Niche innovations

Niche innovations that could be applied in an energy sector context might range from new renewable technologies to smart grids, Vehicle-to-Grid (V2G) integration or leveraging artificial intelligence and machine learning for grid optimization. These are just a few of the many niche inventions that could be disruptive to the current energy regime.

To meet the vast energy needs of end users, smart grids "make use of communication, sensors, computers, and automation in order to improve the effectiveness, dependability, and safety of the power system" (Ohanu et al., 2024). By combining numerous digital components, including smart meters, sensors, and automated control systems, these grids improve the sustainability, dependability, and efficiency of power distribution. The idea first surfaced in the early 2000s in response to the requirement to better integrate renewable energy sources and update antiquated electrical infrastructure. Smart grids, as a niche innovation, are a change from the one-way flow of electricity to the two-way flow of electrical power and information (Surender Reddy Salkuti, 2024).

Vehicle-to-grid (V2G) integration refers to the technology of bidirectional flow of electricity between the electric vehicle and the grid. Electric vehicles (EVs) interact with the power grid and re-feed electricity from their batteries to the grid (Poullikkas, 2015). This concept emerged in the early 2000s with the rise of EVs and the need to manage increasing electricity demand flexibly.

Finally, machine learning involves using artificial intelligence techniques to improve the operation and management of power grids. Data-driven algorithms are used to forecast energy consumption, enhance the incorporation of renewable energy sources, detect anomalies, and enhance overall grid dependability (Entezari et al., 2023). Machine learning in grid management began gaining traction in the 2010s, driven by the increasing complexity of modern energy systems and the availability of large datasets from smart grid technologies.

4.1.2 Energy Regime

The energy regime encompasses energy generation, transmission infrastructure (how energy gets to workplaces/homes), and consumers' choices around energy use.

Historically, the current energy regime was characterized by the centralized generation and distribution of power networks, predominantly dependent on fossil fuels such as coal, natural gas, and oil. This system was supported by large-scale infrastructure like power plants and transmission grids, designed to transmit energy from centralized locations to consumers over long distances.

However, the current energy regime is increasingly characterized by the coexistence of centralized and decentralized systems. While traditional fossil fuel-based power plants remain a core part of the energy system, there is a growing shift toward distributed energy resources (DERs), such as solar panels, wind turbines, and battery storage systems, which allow for localized energy generation closer to the point of consumption. These new technologies are transforming the way energy is produced, distributed, and consumed, contributing to a more decentralized and flexible energy grid.

In this setup, the availability of electricity from centralized networks mostly dictates customer behavior. Consumer decisions about energy consumption are influenced by several variables, including cost, convenience, and deeply rooted habits.

The traditional centralized regime remains resilient due to well-established economic interests, extensive infrastructure, and regulatory frameworks that continue to support large-scale energy production. Nonetheless, the ongoing energy transition, driven by climate change initiatives and technological advancements, is pushing the system toward greater decentralization, though this shift is still in progress.

4.1.3 Socio-technical landscape

This landscape includes factors such as the urgent challenge of climate change, international climate agreements, volatile prices of fossil fuels, and also growing global awareness of environmental sustainability.

Scientists began to worry about climate change toward the end of the 1950s. However, the scientific community only began to unite to act on it in the 1980s, and the warnings have only escalated ever since. Recently, climate change has been considered a threat to human health and development, one of the reasons why it is one of the greatest challenges of the 21st century.

Aiming to strengthen the global response to the threat of climate change, the Paris Agreement was adopted in December 2015. Portugal was one of the 196 countries that committed to reducing emissions by 45% by 2030 and reaching net zero by 2050.

Moreover, high, and volatile oil and gas prices make fossil fuels less attractive, prompting consumers and industries to seek more stable and sustainable energy alternatives.

There is also growing global awareness of environmental sustainability, influenced by widespread media coverage, scientific reports, and advocacy by environmental groups. The increasing public consciousness pushes governments, businesses, and individuals to adopt cleaner energy practices and support policies that favor renewable energy and efficiency improvements.

As the pressure continues to intensify, it contributes to a broader shift in societal values towards sustainability, further challenging the established norms and practices of the existing energy system.

4.2 *Presentation of results*

4.2.1 The role of DSOs in the energy transition

Distribution grids are the backbone of the digital and energy transition, as they ensure a continuous and reliable electricity flow, integrate most renewable energy sources, and enable the creation of new services for consumers. But to be fit-for-purpose in an increasingly decarbonized, decentralized, and digitalized power system, there is an urgent need to ramp up investments in Europe's distribution grids.

For this reason, Distribution System Operators are at the forefront of the energy transition, playing a crucial role in addressing the challenges of integrating renewable energy and flexibility services, with 70% of renewable sources and the majority of flexibility services connected to their networks.

Beyond their role as neutral market facilitators, DSOs are innovators driving the transition towards a more sustainable future, supporting the goal of a CO2-neutral continent (Connecting the Dots: Distribution Grid Investment to Power the Energy Transition Final Deliverable, 2021).

Having said this, understanding the role of DSOs in the energy transition was a crucial perspective of the interviews. For Interviewee B, DSOs serve as facilitators of the energy transition by enabling the integration of renewable energy sources and distributed generation into the grid. This integration allows for the connection of new energy demands, such as electric vehicle (EV) charging stations, heat pumps, etc., ensuring that these systems have reliable energy for their operation.

The increasing reliance on electricity in society has elevated the responsibilities of DSOs significantly. As Interviewee B articulated, "the absence of electricity becomes more negatively perceived," underscoring the importance of a robust energy infrastructure. This presents opportunities for growth as DSOs implement new methodologies to manage the grid and engage with customers proactively.

Furthermore, as explained by Interviewee C, DSOs across Europe are now also the metering data operators, responsible for collecting, processing, and providing data to consumers. This role is vital in developing solutions that leverage this data for greater flexibility in energy management.

Moreover, the concept of "giving the power back to the consumers" is becoming increasingly relevant. According to Interviewee C, the traditional linear energy model - where production directly feeds consumption - is evolving into a decentralized system where generation occurs alongside consumption. This shift emphasizes the need for DSOs to act not just as operators but as enablers of a flexible energy market (Interviewee C). "The consumer becomes a prosumer - both a consumer and producer - and the DSOs serve as a facilitator, ensuring that the grid has the necessary capacity, and that the supporting IT infrastructure can handle a flexible network."

4.2.2 Initiatives implemented by E-REDES

During the first interview was mentioned a project called "PREDIS" which is a prominent machine learning project at E-REDES, created to facilitate the energy transition by offering short-term load and generation forecasts in high voltage (HV) and medium voltage (MV) networks. As explained by Interviewee A, PREDIS uses ML algorithms within a Big Data Cloud environment to provide these forecasts. The system handles about 100,000 customers, generating 200,000 daily predictions with two key forecasting variables (Interviewee A). These forecasts offer predictions up to five days in advance, with a fifteen-minute granularity.

PREDIS relies on several data sources, including load diagrams that provide metering data from HV and MV installations across the Portuguese electrical grid, comprising around 60 million daily records. It uses grid technical information for registry and geographic details for all electrical grid assets and installations and incorporates weather forecasts from IPMA (Portuguese Institute for Sea and Atmosphere), which are important for understanding the external factors that influence energy demand, such as temperature, precipitation, wind, etc.

By analyzing the internal documents that I was able to access, it was possible to understand that IPMA source supplies weather forecasts up to three days in advance, which are incorporated as exogenous variables in PREDIS models. The weather data, along with years of historical consumption data, is processed using a linear regression approach that minimizes quadratic error (Interviewee B).

For its daily operations, PREDIS uses an ensemble of three different models, alongside a baseline model that outputs the previous day's data. Each day, the best-performing model is selected to forecast for the next three days (Interviewee B). It should also be noted that this modelling approach earned PREDIS the Best Future of Intelligence Project award at the Portugal Digital Awards 2021 (EDP Sustainability Report, 2021).

As explained by Interviewee B, PREDIS supports E-REDES in grid management by predicting how different sections of the grid will behave, particularly when parts of the network are taken offline for maintenance which can overload other parts of the grid. "The forecasts allow for better decision-making, ensuring network stability during planned outages" (Interviewee B). Moreover, PREDIS identifies grid constraints and optimizes performance, ultimately helping to reduce losses in the network.

Looking forward, E-REDES plans to "move from central estimates to extreme value predictions". Currently, PREDIS offers one central estimate with a 50% probability of accuracy. The goal is to provide three predictions: the central one, a 90% estimate (where the actual value is below the estimate 90% of the time), and a 10% estimate for extreme cases. As Interviewee B explained "this would help in identifying potential risks when the grid is operating near its capacity limits, especially when distributed generation slightly exceeds the forecast".

Another future enhancement could include extending PREDIS to the low voltage (LV) network, which presents challenges due to the significant increase in data points (from 100,000 to 6.4 million) and less reliable data. Expanding the system will require adjustments, as "the models don't need to be as accurate, but the costs remain high, and the potential benefits are still uncertain" (Interviewee B). One significant challenge in scaling up is related to customer registry issues, which can complicate understanding the impact of predicted consumption on the grid.

Furthermore, by reading use cases and papers done on this matter, it was possible to understand that future work for this project could also include developing automated model selection mechanisms based on historical data, expanding the ensemble of models to address different data patterns, and forecasting challenges, or "exploring the use of global models to improve forecasting accuracy" as mentioned by Interviewee A.

As E-REDES continues to optimize its assets, PREDIS helps accelerate the connection of new, flexible customers, reducing the reliance on infrastructure expansions. Thus, PREDIS is seen as "a foundational project for the energy transition" (Interviewee B), particularly in facilitating the integration of flexible customers, electric vehicle chargers, photovoltaic systems, etc. However, as noted by Interviewee B, the quantitative results of these implementations will take years to measure, as no other operator, on a global scale, has enough experience to provide conclusive data on cost reductions or operational benefits.

Lastly, it is relevant to mention that with these models, E-REDES is preparing for the capacity-constrained clients – those connected to the grid with real-time limitations on their consumption or generation to avoid overloading the network. This is seen as an essential measure to reduce the dependency on infrastructure expansion and make better use of the existing grid, ultimately contributing to a faster and more affordable energy transition (Interviewee B).

Under the scope of the goal of accelerating the energy transition, another initiative currently implemented at E-REDES, called "MAPDIS", was mentioned by Interviewee A.

MAPDIS, a machine learning-based project, aims to predict failure probabilities in critical assets, such as high and medium voltage circuit breakers. The system calculates the probability of anomalies in circuit breaker operations, providing forecasts 15 days in advance, focusing specifically on detecting anomalous opening times.

After several years spent building a robust data set necessary for training the machine learning models, implementing a pilot version, and studying the potential benefits of predictive maintenance, the development phase was successfully completed in January 2023. As Interviewee D stated, “In 2023, we were able, for the first time, to define a preventive maintenance strategy for circuit breakers. That year, the first predictive preventive maintenance based on these models were executed."

Interviewee D also noted that “the algorithms run every four months, with each iteration identifying circuit breakers that require maintenance in the coming months.”.

Although this project has been under consideration for some time, the interviewee stressed that it is still too early to see concrete results. "It has only been a year since it was implemented, and we do not yet have a clear sense of the actual impact this will have, as results are not immediate but rather medium to long term. One year is a very short timeframe to observe cost savings or efficiency improvements," said Interviewee D.

Nevertheless, the interviewee highlighted that the main benefits of MAPDIS include improvements in service quality indicators, as failures can be addressed before they occur. “By acting proactively, the number of incidents caused by circuit breaker failures is likely to decrease, reducing interruption times, and while other failures might still occur, circuit breaker malfunctions are the most common”. Another benefit is the optimization of operational efficiency – “scheduled maintenance allows teams to visit sites and perform maintenance tasks in a planned manner, as opposed to responding to unexpected failures” which optimize resources by ensuring that teams are in the right place at the right time. Additionally, the costs associated with proactive maintenance are significantly lower. “If a circuit breaker fails, repairs can be costly, whereas predictive preventive maintenance involves smaller actions that can extend the lifespan of the equipment” (Interviewee D).

As MAPDIS is still relatively new, the project remains in a phase of continuous improvement. Key improvements include the introduction of a quarantine feature, designed to exclude circuit breakers that underwent recent maintenance, thus preventing unnecessary site visits. Additionally, further work on feature engineering is planned, which will involve incorporating new variables like maintenance records, cyclical variables, and spatial data to enhance model accuracy.

While machine learning projects like PREDIS and MAPDIS have made significant progress in optimizing E-REDES' operations, the energy transition requires more than just technological advancements. E-REDES understands that to truly facilitate the energy transition, it must also focus on encouraging societal changes, which include consumer behavior. This commitment is outlined in the company's sustainability report, where E-REDES highlights its responsibility to improve community well-being, invest in local communities, and promote the adoption of cleaner energy and more sustainable behaviors.

Recognizing the importance of these broader challenges, E-REDES is also implementing initiatives aimed at engaging consumers in the transition. One such initiative is the InterConnect project.

The InterConnect project was a major initiative in which E-REDES participated, aimed at laying the foundation for the future of smart energy management solutions across Europe. The project was tested across seven large-scale sites, including in Portugal, Belgium, Germany, the Netherlands, Italy, Greece, and France, and its main goal was to bring efficient energy management within reach of end-users by promoting energy-saving behaviors and facilitating interaction between digital homes, buildings, and the electrical grid.

The InterConnect project was funded by the European Union (EU) and brought together 50 European entities. Following the adoption of the EU Action Plan on Digitalizing the Energy System in October 2022, the project added a new objective: contributing to the development of a Common European Reference Framework (CERF) for energy-saving applications, aiming to ensure that future consumer-facing energy applications enable users to reduce their energy consumption, reduce energy costs and better respond to signals from grid operators.

At the heart of InterConnect is the Energy App, which offers to the consumers several different services, such as:

- Participation in Flexibility Markets, which is applicable for consumers who are also energy producers**;**
- Analyses of consumption patterns providing recommendations for tariff changes or contracted power adjustments. By accessing data from smart meters,

the app offers insights into the user's energy usage trends, which “can lead to better energy efficiency or even cost savings” (Interviewee C);

- Manage Generation and Demand Constraint. As explained by Interviewee C, the app integrates real-time and forecast data from ENTSO-E and cross-references it with data from E-REDES regarding substation capacity, to provide a map that shows periods of time where there may be grid constraints. If consumption is higher than generation at any given time, consumers are prompted to reduce their energy use. Conversely, when there is excess energy production, particularly from renewables, the app encourages users to increase their consumption, helping balance the grid and avoid overloads;
- Awareness about energy sources. The app also integrates data from the REN platform, which provides insights into the sources of energy being used at any given time. This feature helps influence consumer behavior by “encouraging energy use when the grid is powered by cleaner energy sources, such as wind or solar, and discouraging consumption when the system relies on fossil fuels” (Interviewee C).

These solutions incorporate digital technologies like Artificial Intelligence, Blockchain, Cloud, and Big Data, all built on open standards like SAREF (The Smart Applications Reference Ontology), ensuring interoperability between equipment and systems while safeguarding user privacy and cybersecurity.

This project is a vital component in enabling consumers to play an active role in the energy transition. By using the InterConnect apps, consumers can engage more directly with the energy market, thereby contributing to sustainable energy use and the integration of renewables.

The InterConnect project is already in the implementation phase. As Interviewee C noted, “the framework implementation began this September,” marking a significant step forward in realizing the project's potential. By enabling real-time interaction between consumers, devices, and grid operators, InterConnect helps align consumer behavior with the broader goals of the energy transition.

4.2.3 Barriers faced by E-REDES

E-REDES has made significant progress in implementing advanced technologies such as machine learning and business intelligence tools. However, several barriers have been identified in the process, affecting both technological development and consumer engagement.

One of the most critical challenges faced by E-REDES is related to **data quality and timeliness**. For example, according to internal documentation about the MAPDIS 2.0 project, and Interviewee D, this is a challenge that takes time to overcome, especially when it is necessary to integrate data from different sources. “These models are highly dependent on the quality of both the asset records and the data we have, because the lesser data we have, the less reliable the outputs are”. In the case of MAPDIS, it was necessary to have a history of all previous interventions carried out on the various pieces of equipment, as well as the failure history of each one. (Interviewee D).

Another major obstacle is the difficulty in obtaining real-time data with the necessary cybersecurity measures in place. In applications that rely on real-time data, delays in data retrieval can impact the ability to make quick and informed decisions about grid management. Interviewee B emphasized that achieving a balance between speed and cybersecurity is a persistent issue, particularly for real-time applications that are crucial for grid efficiency.

Internally, one of the barriers is the lack of **sufficient training in machine learning**. As mentioned by Interviewee B, while E-REDES is on the right track in terms of adopting new technologies, there is a need for additional training to enable employees to fully leverage these innovations.

As an example, it can be mentioned the company’s ongoing transition to new data exploration tools such as Azure Data Factory and Databricks. While this shift is necessary for handling larger volumes of data and deriving insights, it requires significant investment in workforce training to ensure that business areas can become self-sufficient in data usage and maximize the value derived from these tools.

Another challenge relates to **consumer behavior and engagement**. E-REDES has launched awareness campaigns aimed at encouraging consumers to adopt more sustainable energy practices. However, as Interviewee B pointed out, these campaigns often face resistance, as people are reluctant to trade personal comfort for the more abstract goal of benefiting the energy sector. Interviewee C considers there is a lack of understanding among consumers regarding the impact small changes in their energy consumption habits can have on the broader system.

Lastly, another significant barrier to the wider adoption of ML technologies within E-REDES, as noted by Interviewee B, is the **regulatory framework**, which is not fully aligned with the requirements of the evolving energy system. Interviewee B pointed out that "the functioning of the electrical system is changing, thus the regulatory landscape needs to adapt accordingly". Currently, many regulations and incentives focus on rewarding DSOs for infrastructure expansion, rather than promoting efficiency or flexibility in grid management. For example, DSOs are often incentivized based on the amount of physical infrastructure they maintain, instead of being encouraged to leverage ML and other digital solutions to maximize grid efficiency.

4.2.4 Further opportunities with ML

The energy transition presents numerous challenges for Distribution System Operators (DSOs) like E-REDES. Among these, improving grid resilience, predicting energy usage patterns, and integrating renewable energy sources are crucial. Machine learning has already shown potential in improving grid management and predictive maintenance, but several additional opportunities exist where ML could further transform energy distribution and management.

One of the key opportunities highlighted by Interviewee B is using ML to improve **service restoration predictions** following power outages. As Interviewee B explained, "when there's a service interruption, it's important that customers have an idea of how long it will take for the service to be restored." The restoration time depends on various factors, such as the nature of the fault, the availability of repair teams, and whether the customer can be supplied from another section of the grid.

“Machine learning is well-suited to estimate these variables by analyzing past data from similar interruptions and using real-time grid conditions” (Interviewee B). ML algorithms could predict outage duration more accurately, providing dynamic forecasts that would help improve customer communication. Additionally, by using real-time data about team availability and grid conditions, ML can help DSOs like E-REDES optimize resource allocation - sending the right repair teams to the right locations and ensuring that customers are reconnected as quickly as possible.

Another opportunity for ML, as mentioned by Interviewee B, is its use in **fraud detection**. ML models can learn to recognize fraud patterns or “reasonable” consumption behavior, helping DSOs detect unusual activity that might suggest energy theft or billing inaccuracies. By analyzing historical consumption data, ML can identify anomalies and flag them for further investigation.

This would allow E-REDES to address fraudulent activity more efficiently, reducing revenue loss and ensuring a fairer distribution of energy costs. As Interviewee B pointed out, "ML can learn fraud patterns or reasonable consumption behaviors,” which would be valuable for detecting irregularities early, potentially saving significant operational costs.

4.3 *Discussion of data*

The purpose of this study was to explore whether machine learning, as applied by E-REDES, can disrupt the current socio-technical system of energy distribution. Considering Geels’ Multi-Level Perspective (MLP) framework on socio-technical transitions (Geels, 2002, 2011), this section will analyze the findings to determine the potential of ML-based innovations to transform the energy system.

The energy transition is a complex process involving technological, societal, and institutional changes. According to the MLP framework, transitions occur through interactions across three levels: niche innovations, socio-technical regimes, and the socio-technical landscape (Geels, 2002). Within this study, the PREDIS and MAPDIS projects can be considered niche innovations, as they utilize ML.

PREDIS demonstrates significant potential for optimizing grid management through improved forecasting and load balancing. However, its impact remains primarily within the existing operational framework, addressing efficiency rather than driving systemic change. For PREDIS to become transformative, it would need to contribute to broader decentralization efforts and enable greater integration of consumer-driven energy sources, thus challenging the traditional centralized energy regime. While it is a step toward modernization, its current scope reflects incremental rather than revolutionary change.

On a similar note, MAPDIS showcases the power of predictive maintenance in enhancing grid reliability and reducing costs, particularly through the early detection of infrastructure failures. While this project represents an important innovation, its transformative potential is constrained by its focus on optimizing existing assets rather than fundamentally altering the energy system. As it stands, its impact aligns more closely with improving the efficiency of the current regime than disrupting it.

While both projects introduce technological advancements that improve operational reliability, their focus remains on optimizing the existing regime rather than transforming it. According to Geels (2011), niche innovations capable of transformative change often introduce entirely new ways of doing things that disrupt or challenge the established socio-technical system. In contrast, PREDIS and MAPDIS function as incremental innovations within the current regime, helping E-REDES enhance operational efficiency without fundamentally altering the structure of the energy distribution system. These projects reduce costs, improve grid management, and provide valuable insights, but they do not disrupt the centralized nature of the current energy regime.

The InterConnect project, another initiative mentioned, moves closer to the notion of a niche innovation with potentially transformative implications. By engaging consumers more actively and promoting the concept of prosumers (those who both produce and consume energy), InterConnect encourages decentralization and increased consumer involvement in energy systems This aligns with the shift towards decentralization and increased consumer engagement in energy generation and consumption - a key aspect of the energy transition (Rogers, 2018). By encouraging consumers to become prosumers (both producers and consumers of energy), InterConnect supports the development of new practices that could challenge the existing regime.

However, the success of such initiatives depends on consumer willingness to change behaviors, which remains a significant barrier. As Interviewee B noted, “Campaigns to raise consumer awareness are helpful, but when the time comes, people are often reluctant to sacrifice comfort for the abstract idea of doing good for the energy sector.” This reflects the challenges in altering societal practices and norms, a crucial component of socio-technical transitions (Shove & Walker, 2007).

While ML offers significant opportunities for optimizing energy distribution processes, several barriers prevent it from achieving its full transformative potential. First, the quality of the data required for ML models poses a significant challenge. As Interviewee B noted, “all data sources present challenges in terms of quality,” which can limit the accuracy and reliability of the predictions made by the ML algorithms.

In addition to data quality, the current regulatory framework is not yet fully aligned with the energy transition goals, which hinders the widespread adoption of digital technologies like ML. As Interviewee B highlighted, “the regulator must understand that the functioning of the electrical system, established 20 - 30 years ago, is changing.” Existing regulations and incentives are not yet fully aligned with the goals of the energy transition, particularly in terms of promoting the widespread adoption of digital technologies like ML. For example, current regulations still reward distribution system operators (DSOs) based on the volume of physical infrastructure they maintain, rather than incentivizing more efficient use of the grid.

Another significant barrier is the reluctance of consumers to change their energy consumption habits. As part of the energy transition, DSOs like E-REDES need to engage consumers and encourage them to adopt more sustainable behaviors. However, Interviewee B pointed out that despite awareness campaigns, people often resist changes that might reduce their immediate comfort, a key aspect of behavioral inertia in socio-technical transitions (Shove & Walker, 2007). Technological advancements like those in InterConnect can only have a transformative impact if they are accompanied by shifts in societal behaviors and consumption patterns.

Thus, the comparison between theoretical barriers and opportunities outlined in the literature and those observed in E-REDES highlights several key alignments and discrepancies. The literature identifies data quality and regulatory challenges as significant barriers to implementing ML in energy systems (Markard et al., 2012; Geels, 2011). These issues were echoed in the findings, particularly with regard to the challenges of integrating diverse datasets and adapting regulatory frameworks to support digital solutions. Similarly, the opportunities for improving grid resilience, consumer engagement, and predictive maintenance highlighted in the literature (Loorbach et al., 2017) align closely with the practical applications observed in PREDIS and MAPDIS.

Within the MLP framework, the energy regime is made up of entrenched infrastructures, market practices, regulatory policies, and social norms that support the current system. While PREDIS and MAPDIS contribute to optimizing these processes, they operate within this existing regime rather than fundamentally challenging it.

For instance, while PREDIS helps reduce the need for new infrastructure, it does not disrupt the centralized system of power generation. Instead, it supports the integration of renewable energy sources by improving the efficiency of grid management. Similarly, MAPDIS improves predictive maintenance practices but does not alter the broader dynamics of energy consumption or generation.

Nonetheless, while these projects primarily focus on optimization, the potential for ML to enable broader systemic changes such as facilitating prosumers (consumers who also produce energy), reducing reliance on fossil fuel infrastructure, and improving real-time energy management cannot be overlooked. As Geels (2011) suggests, incremental innovations can accumulate over time and contribute to larger shifts within the regime. By enabling DSOs to predict and manage grid demand more dynamically, ML could contribute to the creation of a more distributed, flexible, and resilient energy system. Interviewee B even suggested that ML could eventually help E-REDES manage the grid with “smaller safety margins,” reducing the need for large-scale infrastructure investments. This indicates that over time, ML could support a more decentralized and flexible energy system, especially as the adoption of renewable energy and flexible consumers becomes more widespread. As the technology evolves and regulatory frameworks adapt, DSOs could use ML to lead broader systemic changes in how energy is generated, distributed, and consumed.

The socio-technical landscape, which includes macro-level factors such as climate change imperatives, international environmental agreements, and societal values, exerts pressure on the energy regime to adopt more sustainable practices. E-REDES' adoption of ML technologies can be viewed as a response to these landscape-level pressures, particularly the need to reduce greenhouse gas emissions and integrate renewable energy sources into the grid. Projects like PREDIS and MAPDIS contribute to these goals by making the grid more resilient and efficient, thereby supporting the broader decarbonization efforts aligned with European and global climate targets.

However, as previously noted, these initiatives do not yet have the capacity to transform the energy regime on their own. They must be complemented by changes in policy, market structures, and consumer behavior to achieve the full potential of the energy transition.

5. Conclusions

This thesis set out to explore the potential of machine learning in transforming energy distribution and contributing to the energy transition. The research question guiding this study was: *Does Machine Learning have the potential to disrupt the energy distribution regime and drive the energy transition?* To answer this, three key objectives were established:

1. Explore how ML is incorporated into E-REDES' operations;
2. Identify the opportunities and barriers arising from these ML initiatives;
3. Assess whether ML-based innovations can accelerate the energy transition by disrupting the existing socio-technical system.

To achieve these objectives, this study employed a qualitative research design, using semi-structured interviews with key stakeholders within E-REDES. These interviews provided valuable insights into the role of ML technologies in grid management, predictive maintenance, and operational efficiency, as well as the broader challenges faced by DSOs like E-REDES.

Relative to the first objective, this study found that ML is being integrated into specific projects such as PREDIS and MAPDIS, which focus on improving load forecasting and predictive maintenance. These innovations allow E-REDES to better manage the grid, reduce operational costs, and increase efficiency. These tools are primarily enhancing operational capabilities by making more accurate predictions and reducing the need for new infrastructure investments.

Regarding the second objective, several opportunities and barriers were identified. ML provides significant opportunities in areas such as fraud detection, service restoration prediction, and improving grid resilience. However, barriers such as data quality issues, regulatory constraints, and consumer engagement challenges were found to limit ML's full potential. As Interviewee B pointed out, these applications show promise but require better data integration, updated regulatory frameworks, and improved cybersecurity measures to be fully effective.

With respect to the third objective, the findings suggest that while ML innovations contribute to efficiency and may help accelerate the energy transition, they do not have enough transformative power to fully disrupt the existing socio-technical regime. As confirmed by the interviewees, these technologies support ongoing changes within the system but are not radical enough to fundamentally shift the centralized nature of energy distribution. Instead, ML is primarily a tool for optimization, enhancing operational aspects rather than reshaping the structure of the energy grid. However, in the longer term, cumulative incremental innovations like these may gradually push the energy regime toward greater decentralization and sustainability.

This study contributes theoretically by advancing the application of the Multi-Level Perspective (MLP) framework to digital innovations, particularly Machine Learning (ML), in the energy transition. Specifically, it demonstrates that while ML is primarily deployed for incremental improvements, its transformative potential is contingent on overcoming systemic barriers, including regulatory inertia and data integration challenges. Furthermore, this study bridges the gap between theoretical discussions on sustainability transitions and the specific application of ML technologies.

From a practical standpoint, this work offers actionable insights for other DSOs seeking to leverage ML in the energy transition. The research highlights specific opportunities for optimizing grid management and these insights can guide companies in scaling ML applications to achieve greater efficiency and sustainability.

Additionally, the study identifies critical barriers—such as data quality issues, regulatory misalignments, and organizational resistance—that must be addressed to fully realize ML's transformative potential. The findings emphasize the importance of investing in data infrastructure, fostering collaboration between stakeholders, and aligning regulatory frameworks with innovation goals. This practical guidance is particularly valuable for industry practitioners aiming to integrate ML technologies into their operations while navigating complex socio-technical systems.

The present study was carried out with several limitations. First, the research was limited to semi-structured interviews within a single organization, which may not provide a comprehensive view of ML's impact across the broader energy sector. Additionally, since ML initiatives like PREDIS and MAPDIS are still in the early stages of implementation, it is difficult to assess their long-term impacts with certainty. The study also faced data availability limitations, as quantitative results regarding cost reductions and efficiency improvements are still being developed and could not be fully analyzed at this stage.

For future research, it would be interesting to explore quantitative analyses of the long-term impacts of ML on grid management and operational efficiency, once more data is available. Another important avenue for future work would be to investigate the role of regulatory reforms in enabling ML technologies to reach their full potential in the energy sector. Moreover, expanding the scope of research to include other DSOs or even international comparisons could provide valuable insights into how ML can be leveraged to drive the energy transition more broadly. Lastly, consumer engagement and behavioral changes remain critical aspects of the energy transition, and future studies should delve deeper into how ML-based solutions can influence and enhance consumer participation in more sustainable energy practices.

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7. Appendices

My name is Beatriz Santos, and I am currently developing my master´s final thesis in Management and Industrial strategy at ISEG. The goals of the thesis are in-depth understanding of how ML is incorporated into E-REDES' operations, exposition of the opportunities and barriers of ML integration in energy distribution and assessing whether ML-based innovations can accelerate the energy transition by disrupting the existing socio-technical system.

First of all, I want to thank you for the participation in this interview, because it will contribute to a great extent to the development of my master´s thesis. The interview will consist of several open questions, to which I would like to hear your opinion, based on your experience at E-REDES.

If you give your consent, I would like to record the interview with the goal to ensure that the data extracted is complete and consistent. The duration of this interview is approximately 60 minutes. Also, I want to ensure you that the information provided in the interview will be treated only by me and only with the purpose of developing thesis, your personality can stay anonymous if you wish so.

To start with I would like to ask you:

- Can you please describe your role in the company? How long have you been in this role?
- How do you perceive the role of DSOs like E-REDES in the energy transition?
- In your opinion, what are the key responsibilities and opportunities for DSOs in this transition?
- Innovation is critical, and machine learning has been highlighted as a key area, especially for predicting customer energy consumption and optimizing grid management. How is E-REDES currently utilizing machine learning?
- Can you provide specific examples of projects where machine learning has been implemented?
- What have been the results of these machine learning projects so far?
- Are there any upcoming projects or initiatives involving machine learning that E-REDES is planning to implement?

- What are your expectations from these initiatives in terms of impact on operations and the broader energy transition?
- In your opinion, what other opportunities or potential uses of ML could E-REDES explore in the near future?
- What do you consider to be the main advantages of using ML in energy distribution?
- What challenges has E-REDES faced when implementing ML in its operations?
- Looking forward, what challenges do you anticipate? Are these challenges likely to remain the same or evolve?
- Have there been any structural, technological, or cultural changes within E-REDES to facilitate the implementation of machine learning?
- How do these changes support the integration of machine learning?
- Which external stakeholders play a role in E-REDES' initiatives towards the energy transition?
- How does E-REDES collaborate with these stakeholders to drive progress?
- Do you agree that the energy transition involves more than just internal initiatives at E-REDES, including the need for changes in customer behavior?
- How does E-REDES currently engage with and educate customers about the importance of their consumption habits?
- In your view, what more could be done to improve customer education and engagement?