Navigating Uncertainty: Quantifying Residual Load and Enhancing Portfolio Resilience for EDP Portugal

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Dissertation written under the supervision of Professor Miguel Nogueira

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Abstract

Decarbonizing the energy sector is crucial to achieve climate goals set by international agreements. Energias de Portugal (EDP), which relies heavily on renewable energy, may face significant challenges due to increased potential variability and uncertainty in energy generation caused by climate change. These changes significantly influence the residual load, which is formally defined as the difference between total electricity demand and renewable energy supply. The thesis employs an innovative methodology that uses climate data with advanced predictive analytics to first assess EDP's current residual load and later estimate future residual loads and its implications until 2045. It is novel in integrating different data, including company-specific data, high resolution climate data amongst others, to provide climate scenario risk assessments. Simulations are conducted to explore strategic mitigation paths such as energy storage expansion, optimizing investments, or bitcoin mining for excess energy utilization. The results show increased residual load in the future, mainly influenced by intensified climate extremes, including anticipated droughts that significantly affect hydropower production, which makes up 75% of EDP's generation portfolio in severe climate scenarios. The originality of the study is in translating climate risks into interpretable financial terms for EDP and providing concrete recommendations for strategic adaptation especially concerning portfolio expansions. While EDP's current investments, including large-scale batteries and diversified renewable assets, are increasing resilience, this research quantifies further diversification. Ultimately, this thesis highlights the need for proactive, data-driven planning to ensure long-term financial stability and operational reliability of renewable-centric energy providers in a climate-uncertain future.

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Resumo

A descarbonização do setor energético é fundamental para alcançar as metas climáticas acordadas a nível internacional. A Energias de Portugal (EDP), que depende em grande medida de fontes renováveis, enfrenta desafios crescentes associados à variabilidade e incerteza provocadas pelas alterações climáticas. Estas mudanças afetam diretamente a procura energética não colmatada por produção renovável, ou seja, a carga residual. Esta tese utiliza uma metodologia inovadora, que integra dados climáticos detalhados e técnicas avançadas de análise preditiva, para avaliar e projetar a carga residual da EDP. A metodologia combina múltiplas fontes de dados, como informações específicas da empresa, séries climáticas históricas e projeções futuras para realizar simulações que explorem estratégias eficazes de mitigação, incluindo a expansão do armazenamento energético, a diversificação de investimentos renováveis e soluções não convencionais, como a mineração de bitcoin para aproveitamento de excedentes. Os resultados apontam para um aumento significativo na volatilidade da carga residual, especialmente devido à intensificação de eventos extremos como secas, que afetam substancialmente a produção hidroelétrica, que representa 75% do portfólio da EDP. A originalidade deste estudo reside na tradução destes riscos climáticos em termos financeiros tangíveis, oferecendo recomendações concretas para uma adaptação estratégica. Embora a EDP já invista em baterias de grande escala e ativos renováveis diversificados, este trabalho evidencia a necessidade urgente de uma maior diversificação e inovação adaptativa, realçando a importância de um planeamento proativo e baseado em dados para assegurar estabilidade financeira e operacional num futuro climático incerto.

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Palavras-chave: carga residual, risco climático, energia renovável, EDP, resiliência do portfólio, descarbonização, modelagem climática, CORDEX, armazenamento de energia, mineração de bitcoin

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List of Abbreviations

CORDEX	Coordinated Regional Downscaling Experiment
EDP	Energias de Portugal – Portugal
E-Redes	Portuguese Electricity Distribution System Operator
ECMWF	European Centre for Medium-Range Weather Forecasts
ERA5	ECMWF Reanalysis 5th Generation
EU ETS	European Union Emissions Trading System
EV	Explained Variance
GWA	Global Wind Atlas
GWh	Gigawatt-hours (1 million kWh)
kWh	a unit of energy equal to one kilowatt of power expended for one hour
LightGBM	Light Gradient Boosting Machine, high-performance, tree-based gradient boosting framework designed for fast training and low memory usage.
MAE	Mean Absolute Error
ML	Machine Learning
MLflow	Machine Learning Workflow Platform
MWh	Megawatt-hours
NMAE	Normalized Mean Absolute Error
NRMSE	Normalized Root Mean Squared Error
PV	Photovoltaic (Solar Power)
QDM	Quantile Delta Mapping
RCP	Representative Concentration Pathway
REN	Redes Energéticas Nacionais (Portugal's Transmission System Operator)
RL	Residual Load
RMSE	Root Mean Squared Error
ROI	Return on Investment
SRTM	Shuttle Radar Topography Mission
SSP	Shared Socio-economic Pathway
ssrd	Surface solar radiation downwards
strd	Surface thermal radiation downwards
tp	Total Precipitation
TWh	Terawatt-hours (1 billion kWh)
VRE	Variable Renewable Energy (PV, Wind, Hydro)

1 Introduction

Decarbonizing the energy sector is critical to achieving the Paris climate goals, as emissions from power generation were the highest of any sector in 2024 (Electricity 2025, 2025). That year, power generation was responsible for 13.8 out of 41.6 billion tons of CO_2—roughly 33% of global emissions. In contrast, the EU's power sector contributed only 31% of the EU's annual greenhouse gas emissions 20 years ago and managed to reduce its share by another 6 percentage points by 2022 (Statista, 2024).

As a result, the EU now boasts one of the least carbon-intensive energy supplies in the world. This reduction can be attributed to numerous legislations and subventions that were implemented in the last years that prompted energy providers to opt-out of carbon intensive energy sources and expand into renewable electricity generation. One of the most significant initiatives introduced in 2005 is the EU Emissions Trading System (EU ETS), a market-based mechanism that assigns a cost to carbon emissions.

While decarbonizing the energy sector has successfully reduced carbon intensity through initiatives, these measures have also introduced new challenges. According to extant research, the primary issues are the management of variability—that is, the fluctuations in generation output—and uncertainty—that is, the inability to predict output with high accuracy (Bastian-Pinto et al., 2021). Coupled with climate change, which brings more frequent extreme weather events such as prolonged droughts and wind lulls, this variability is expected to intensify in the coming years (Gernaat et al., 2021).

The quantification of residual load (RL) risk and cost is therefore imperative for energy providers with a substantial share of Variable Renewable Energy (VRE) sources. RL refers to the remaining electricity demand that must be met by controllable resources (such as conventional power plants, storage, or imports) after subtracting VRE contributions from total demand (Ruggles & Caldeira, 2022). By assessing the scope of the risk and associated costs, energy providers can develop effective strategies to manage the associated financial and operational challenges under different climate trajectories.

In this dissertation, I focus on quantifying the climate risk for Energias de Portugal (EDP), focusing on the Portuguese market. Climate risk is defined as a combination of hazard, exposure, and vulnerability (Fakhruddin et al., 2020). Through its exceptionally high share of

VRE’s, accounting for 95% of electricity generation (EDP Results Report 2024), EDP’s portfolio is especially exposed to the mentioned hazards.

Several recent studies have investigated the associated climate risks of the VRE network expansion (Plaga & Bertsch, 2023), the concrete impacts on the specific VRE’s (wind, solar, hydro) and the associated requirements for climate energy resilience at the macro level (Jasiūnas et al., 2021; Schill, 2014). However, there is a lack of concrete translation into financial terms and analysis at the micro level. My thesis aims to address this knowledge gap by providing a value proposition through a data-driven approach. Utilizing climate model data across various trajectories, it forecasts the evolution of RL based on EDP's specific portfolio composition, enabling a more precise assessment of future financial impacts. Specifically, I will address the following questions:

- What is the impact of variable renewable energy on EDP’s RL, given the company’s consumption profile and market share?
- How could different climate trajectories, extreme weather- and consumption scenarios influence and affect the RL and its financial burden?
- Which strategic mitigation measures can optimize EDP’s portfolio resilience under these projected scenarios and current state?

This research is structured as follows: First, I will review existing literature on decarbonization and its implications, introduce the concept of RL as well as climate risk, discussing both physical and transition risks for the energy sector broadly and with a specific focus on Portugal. Then strategies to mitigate it will be explored. In the third chapter I will outline the extensive data preprocessing required and explain the methodology employed in this thesis. It explains how I quantified the RL for the last two years followed by the formulation of consumption profiles and the use of climate model data to estimate future VRE production towards 2045. This approach enables the projection of RL evolution under different climate scenarios. The results chapters will present key findings derived from this methodology, including a discussion exploring the most effective strategic responses for EDP from a broader perspective and the limitations. Finally key takeaways and future research directions will be concluded.

2 Literature Review

2.1 Energy Sector Decarbonization

In order to reduce the effects of climate change, carbon dioxide emissions from energy need to be reduced. Under the 2015 Paris Agreement, countries committed to limit the increase in global average temperature to well below 2 °C (and pursue 1.5 °C), which effectively requires a rapid transition to low-carbon energy systems (Paris Agreement, 2015). The decarbonization of power generation is at the center of climate strategies, as achieving net-zero emissions by 2050 won't be possible without eliminating fossil fuel use in electricity generation. As a result, expanding VRE capacity is viewed as crucial, not only for cutting emissions, but also for improving energy security by reducing dependence on imported fossil fuels. For example, the European Union's long-term strategy for carbon neutrality depends both on energy efficiency and renewable-based electrification to meet climate targets (Martins et al., 2022).

This transition howevertransition, however, comes at the cost of increased variability in RL, which endangers grid stability and requires adaptionadaptation strategies (Suna et al., 2025). Climate change can further amplify this variability and add to the risk of grid instability and raise RL costs for energy providers (Papadis & Tsatsaronis, 2020).

Furthermore, the lack of predictability, especially in photovoltaics (PV) and wind generation makes it harder to match electricity supply with grid demand (Castro & Crispim, 2018). Both the variability and the lack of predictability can add to the costs of energy providers, as they are forced to either invest more heavily into storage solutions, buy energy at the market or utilize plants for which they may need to buy EU ETS.

While the EU has made significant progress in reducing emissions, individual members, such as Portugal, illustrate both the opportunities and challenges of this transition. Portugal has historically been highly dependent on energy imports. This reliance on imports and the feed-in tariffs program has led Portugal to aggressively pursue domestic VRE sources as a path to greater energy independence and emissions reductions (Proença & St. Aubyn, 2013).

In fact, increasing VRE capacity is at the core of Portugal's decarbonization strategy, as outlined in its Green Growth Commitment (PGGC 2030, 2015). A significant portion (71%) of Portugal's electricity comes from VRE's, with hydropower providing 28% of consumption in 2024, wind 27%, PV for nearly 10% (*REN*, 2025), but this comes with its own challenges: the country's hydropower generation is subject to high inter-annual variability depending on rainfall. In dry years, electricity imports or backup generation rise to compensate for low hydro output. To manage this, Portugal leverages a strong grid interconnection with Spain (the Iberian market) and is investing in other VRE's such as solar and in storage solutions to buffer against hydrological fluctuations (NECP Portugal 2030, 2019).

Although increasing renewable energy capacity supports decarbonization targets, integrating variable renewable energy (VRE) into the grid introduces new operational challenges. One such challenge is managing residual load fluctuations caused by variable generation, which is crucial for ensuring system reliability. This topic is explored in the following section.

2.2 Residual Load

RL plays a critical role in power system operations because it is the load that must be covered by dispatchable generation at all times to maintain a balance between supply and demand. Failure to account for it can significantly increase costs. Peak RL is especially important, as it determines the necessary amount of capacity needed to ensure reliable power supply during periods when VRE output is low. For instance, extended periods of low Wind and PV production can lead to very high RL's that threaten the continuity of supply (Ohba et al., 2023). During such events, the shortfall has to be covered by other means or if not possible, imported, which exposes providers to volatility in fuel and electricity prices. Further the reliance on expensive peaking power plants or imports, increases, often driving up wholesale electricity prices and operational costs (Bessa et al., 2019). Conversely, during periods of high VRE generation and low demand, RL can reach negative levels, thus necessitating either power reduction measures or export capabilities.

Optimizing RL is therefore vital, as it directly determines both operational decisions and financial outcomes. The integration of additional VRE sources causes both timing and magnitude of RL peaks to shift (Ohba et al., 2023). Energy providers should prepare for intermittent VRE "droughts": multi-day periods of low VRE generation caused by lasting high-pressure weather systems. For example, a widespread wind drought in Europe in 2021 sharply reduced wind generation and led to a surge in natural gas-fired generation, which subsequently led to unusually high electricity prices (Ohba et al., 2023). The insufficient contracted power generation availability forced suppliers to purchase their power requirements at high market prices, which in return reduced their profitability.

On the other hand, during periods of low RL (when VRE are abundant and demand is modest), market prices can drop to very low, or in extreme cases, negative levels, impacting generators' revenues. This two-way volatility means that energy providers must develop strategies to manage the economic risks associated with RL fluctuations. In short, RL is directly related to the cost of balancing the grid: the larger and more erratic the RL, the greater the potential cost and financial uncertainty for energy providers. Integrating climatic trends and extreme event probabilities into capacity planning is recognized as crucial for maintaining reliability under these swings (Ohba et al., 2023).

Due to its high share of VRE, Portugal itself has strong RL dynamics. The impact of RL fluctuations on energy procurement is evident in recent statistics: after several wet and windy years in which Portugal was a net exporter of electricity (e.g., exporting around 2–5 TWh in 2016–2018), the situation reversed in dry years. In 2022, an exceptionally dry year, Portugal’s net electricity imports surged to 9.3 TWh, roughly double the imports of the previous year (Fulghum, 2025). Such anticipated events prompt Portugal to invest in mitigation solutions such as battery projects, reinforce transmission links with Spain and France, and exploring new dispatchable renewable options such as green hydrogen and biomass (NECP Portugal 2030, 2019).

EDP also understands the increasing importance to control RL as the share of VRE in its generation portfolio continues to grow. To reduce the associated risks, EDP is employing portfolio diversification, robust hedging, and flexible hydro assets, particularly pumped storage, to optimize operational efficiency and financial performance amid market volatility (EDP Annual Report 2023). However, the company's exposure to RL volatility remains clear. In the first nine months of 2024, EDP experienced a notable 38% reduction in residual thermal demand, corresponding with a recovery in hydro production (EDP Q3 Report 2024).

Managing residual load effectively is further complicated by climate change, which amplifies generation variability and unpredictability through physical and transition risks. The following section discusses these climate-related risks and their implications for energy systems in detail.

2.3 Climate Risk

While the energy sector undergoes decarbonization, it faces significant climate-related risks that must be managed accordingly. The energy sector encounters two primary risk categories which include transition risks from low-carbon economic policy changes and physical risks caused by climate change, impacting energy systems. The successful energy transition depends on proper management of both transition risks and physical risks. Transition risks highlight the financial and regulatory uncertainties of moving away from fossil fuels, while physical risks underscore the importance of building climate resilience into energy infrastructure. The physical risks receive their quantification through the Representative Concentration Pathway (RCP) scenarios and Shared Socio-economic Pathways (SSP). RCP2.6 is a peak-and-decline pathway with strong mitigation and stabilizing radiative forcing at 2.6 W/m^2 by 2100. RCP4.5 assumes stabilization without overshoot at 4.5 W/m^2, while RCP8.5 reflects a high-emission baseline reaching 8.5 W/m^2 by 2100 with minimal mitigation (van Vuuren et al., 2011). The RCPs receive additional socio-economic projections through SSPs which present five alternative futures including sustainability (SSP1), middle development (SSP2), regional rivalry (SSP3), inequality (SSP4) and fossil-fueled growth (SSP5) with detailed narratives and quantitative data for population, GDP, energy, land use and emissions and varying degrees of climate adaptation and mitigation challenges (Riahi et al., 2017).

2.3.1 Transition Risks

Transition risks refer to the financial, regulatory, technological, market, and reputational challenges companies face as they adapt to climate change policies, emissions reduction targets, and shifts to renewable energy. These risks come from evolving policies, technological disruptions, changes in market demand, and stakeholder expectations, and can result in increased costs, asset devaluation, or reduced competitiveness. (TFTC, 2017)

The power sector in Europe functions as the main driver for emissions reduction efforts thus making these risks more significant in the region. The European Union's climate policies (e.g. emissions trading, renewable energy targets, coal phase-out commitments) have a direct impact on the operations and profitability of energy companies. For example, the EU Emissions Trading System (EU ETS) gives carbon emissions a price that has climbed to record highs (around €100 per ton in 2023) – substantially raising operating costs for fossil-fuel power generation (UNEP et al., 2024). The carbon emission price will continue to increase according to Bloomberg's projection which shows a $146 target for 2030 (Global Carbon Market Outlook

2024, 2024). In general, sudden changes or tightening of such policies can create regulatory uncertainty, making it difficult for firms to plan investment and can makes existing assets non-compliant.

Market dynamics are also shifting: the emergence of VRE at ever-decreasing costs is intensifying competition and could erode the market share of traditional utilities. In addition, investors and lenders are increasingly factoring climate change into their decisions. Investor and reputational risks are growing as financial institutions divest from high-emitting industries and stakeholders demand credible net-zero strategies. (UNEP et al., 2024)

Portugal's ambitious expansion of VRE reduces its exposure to these outlaid transition risks. However, its high dependence on energy imports could become a challenge if energy prices rise, directly affecting consumers and energy-intensive businesses, creating an uncomfortable dependency that can impact the economic growth trajectory.

As EDP has already committed to fully divest from carbon emitting technologies by 2030, political and regulatory risks should be less of a concern. However, the associated transition costs could lead to higher energy prices, which would directly affect EDP. For instance, the EDF group, the French pendant to EDP, estimates that a €10/tCO_2 rise in EU ETS carbon pricing would create a €900 million/year competitive advantage through lower carbon intensity (World Business Council for Sustainable Development, 2023).

2.3.2 Physical Risks

Physical risks quantify the direct impact of climate change on assets, operations, and supply, and are often divided into acute risks (from extreme weather events) and chronic risks (from long-term shifts in climate patterns) (TFTC, 2017). Climate change could amplify climate-related disruptions beyond the norm, leading to previously rare events such as prolonged droughts and extended periods of low wind activity, further increasing vulnerability (Ebinger & Vergara, 2011). Besides that, other extreme climate events such as heatwaves, floods and wildfires are increasing in frequency, affecting energy generation, transmission, and distribution (Nik et al., 2021). As a result, energy companies are facing higher maintenance and repair costs and, often, higher insurance premiums to pay for these increasing risks (UNEP et al., 2024).

The produced wind power, and its consistency / predictability primarily depends on how climate change alters wind patterns. Variability in large-scale atmospheric circulation patterns, such as the North Atlantic Oscillation and El Niño–Southern Oscillation, will continue to impact wind energy more than long-term climate change—at least through the mid-century (Pryor et al., 2020). Localized studies in Europe show that there is a steady decrease in wind resources in most regions under SSP 5 and SSP 8.5 scenarios (Davy et al., 2018). A more recent assessment by Martinez & Iglesias, 2021 partially confirmed these results and found a general decline in wind power density in Northern Continental Europe and the Central Mediterranean under SSP5-8.5 by up to 35%. For Portugal, high-resolution multi-model assessments suggest significant sub-regional variability in projected wind energy density (WED). On average, annual changes on WED are expected to remain below 10% under the RCP4.5 scenario and reach up to 15% under RCP8.5. Spatially, elevation and distance from the coast are critical: elevated areas in the north and central-eastern parts of the country and the south-western coast are projected to face annual WED decreases of more than –10%, with up to –35% in autumn under RCP8.5. Meanwhile, central-western Portugal may experience modest increases of less than 10%, mainly in summer (Nogueira et al., 2019). Seasonal projections by Russo et al. (2023) show significant variations, with winter wind speeds potentially increasing by 45% while summer wind speeds could decrease by 45%.

Hydropower is the most stable and dependable VRE, yet variations in precipitation, elevated evaporation, altered river dynamics and enhanced frequency of extraordinary weather conditions create major issues for hydropower operations. While hydropower potential may increase in parts of Eastern Africa and India, Southern Europe and South America are likely to face declining output due to reduced rainfall patterns (Solaun & Cerdá, 2019). According to Blackshear et al. (2011) reservoir-based hydropower plants may face reduced storage capacity due to prolonged dry periods, while run-of-river hydropower projects are sensitive to short-term fluctuations in river discharge. The water scarcity in the Mediterranean climate of Portugal leads to a predicted 41% reduction in hydropower by 2050 (Teotónio et al., 2017). Fortes et al. (2022) also point out that there will be competition between using scarce water resources for power generation or agriculture which is why they are even more cautious and predict a potential reduction in hydropower between 26%-56% by 2050. Notably, an extreme drought in 2022 cut EDP's hydroelectric generation in the Iberian market by 38% compared to the previous year which reduced the hydro performance by at least 163 million euros (Integrated Annual Report EDP, 2022).

PV presents the least physical risk among all the considered technologies due to the fact that it is on the one hand the smallest contributor and on the other hand research has shown that climate change will not substantially decrease PV potential on a global level but regional changes in energy production are to be expected (Gernaat et al., 2021). These regional variations may be due to variation in cloud cover, temperature, and atmospheric pollutants. PV supply by the end of the century will likely range from -14% to +2% with the largest declines in Northern Europe (Jerez et al., 2015). That being said, extreme heat and overcast conditions can significantly reduce PV efficiency and shorten the lifetime of today's PV systems (Feron et al., 2021). Thermal cycling, humid heat and potential-induced degradation cause system performance to decrease over time, and this leads to annual losses of about 0.88% in hotter climates and 0.48% in cooler climates (Dreves, 2024). Climate models for Portugal show that solar radiation and will increase in winter by 30–45%, while the reverse is true for summer and autumn under SSP5-8.5 (Russo et al., 2023).

Interestingly for Portugal, one study found a strong negative correlation between wind and PV generation, meaning that low wind periods often coincide with high PV output, helping to balance the grid. (Castro & Crispim, 2018).

The studies reviewed show that climate-related physical risks to renewable energy systems vary by region - and that under future scenarios, RL may both increase in magnitude during certain periods and become more volatile during extreme weather events or seasonal fluctuations, making accurate forecasting and planning much more difficult. EDP faces substantial financial consequences from these physical risks because power outages force the company to purchase additional energy while requiring additional hedging mechanisms. The high concentration of hydroelectricity (75%) in EDP's portfolio makes the company especially susceptible to climate change-induced droughts. The navigation of these challenges requires energy stakeholders to adopt adaptive planning along with continued diversified VRE investment and implementation of grid flexibility and storage technologies to reduce RL and market uncertainty exposure.

In light of the outlined climate risks, particularly under various RCP scenarios, exploring strategic mitigation measures to bolster resilience against the potential impacts is essential. This brings us to the next topic: specific resilience-building strategies.

2.4 Potential Mitigation Measures

To ensure a stable and secure electricity supply in more and more VRE-dominated systems, power operators can deploy mitigation strategies. Storage facilities can store surplus energy from VRE generation when production exceeds consumption which helps to lower system load fluctuations and decrease other generator ramping requirements (Ould Amrouche et al., 2016). In addition to shifting energy, storage provides fast-response reserves to stabilize frequency during abrupt changes. Key storage technologies used at scale include pumped hydro storage, battery energy storage, and thermal storage. Other emerging storage technologies (compressed air energy storage, flywheels, hydrogen energy storage via power-to-gas, etc.) are also being developed to address VRE variability (W. Wang et al., 2022). Large-scale storage systems encounter two main difficulties: their expensive initial setup and the challenges of obtaining financial returns from stored energy (Abrell et al., 2019). Fortunately, innovation and smart policy, like incentivizing storage via capacity markets or payments for ancillary services, are gradually overcoming these hurdles (H. Lund et al., 2016).

While storage and demand response can reduce net load, there remains a need for flexible generation that can quickly ramp up power supply when needed. The definition of flexible generation includes power plants which demonstrate both fast output adjustments and reliable performance to meet changing RL requirements. Key categories of flexible generation include conventional thermal plants adapted for flexibility, hydropower, and emerging carbon-neutral options like hydrogen-fueled plants. The goal is to balance the grid at all timescales, from second-by-second regulation to multi-day power shortages, at a reasonable cost to minimize RL (Beaudin et al., 2010).

Market mechanisms together with demand-side flexibility play an equal role to technological solutions for handling the remaining load in power grids that contain a high percentage of VRE. The Iberian power grid together with other efficient cross-border trading systems enable operators to benefit from varying weather patterns and customer demand profiles. Although, this creates cost uncertainty for energy suppliers, as market prices fluctuate and hedging or insurance measures cause indirectly costs.

While imports have been an effective safety net, there is a strategic aim to reduce this dependence for energy security and economic reasons (Bruegel & Jaller-Makarewicz, 2024). The recent outage on the 28th of April 2025 makes that crystal clear.

Positively, excess renewable energy can be monetized. It can be sold when prices are favorable, stored in energy storage systems, or used in novel ways, such as bitcoin mining, to provide flexible load and diversify revenue streams. In cases where energy prices are low, switching excess power to Bitcoin mining instead of grid injection can significantly increase financial returns (Bastian-Pinto et al., 2021). Another benefit of that is that unlike traditional industrial loads, Bitcoin mining is interruptible and be ramped up or down in real time to help stabilize electricity supply and demand (Velický, 2023). A study analyzing the Texas energy grid (ERCOT) found that nearly 93% of curtailed renewable energy could be redirected to bitcoin mining, generating a profit of approximately $239 million per year (Niaz et al., 2022).

As Portugal's largest energy provider, EDP carries significant responsibility for enhancing the country's RL management capabilities. This is why EDP is investing in large-scale lithium-ion batteries and has the strategy to compensate shortages through pumped hydro. EDP plans to install over 500 MW of batteries worldwide by 2026, a portion of which will be in Portugal (EDP Annual Report 2023). EDP is also testing innovative ideas such as floating PV on hydro reservoirs. This hybrid approach allows PV to directly charge the battery or provide daytime power while the hydro plant saves water for night, effectively increasing flexibility during darkness. EDP and the Portuguese government are also exploring other possibilities such as hydrogen production from excess renewables (Bruegel & Jaller-Makarewicz, 2024). EDP highlights in their strategic outlook that the produced hydrogen can then store the excess energy providing a solution for long-duration storage and seasonal energy balancing (EDP Annual Report 2024).

3 Methodology

3.1 Project methodology

This research aims both to determine current RL and forecast RL and its financial implications under different climate trajectories. Approximating the RL of EDP is a manifold task.

My main assumptions are: All VRE’s are available 100% —never offline for maintenance— and continuously feed power into the grid & EDP’s hydro output mirrors the country wide output based on EDP’s hydro market share and EDP has to serve Monthly Consumption Market Share (%) * Current Consumption. For the future I assume that EDP wants to at least keep its current average market share over the last two years.

First and foremost, it is essential to obtain reliable VRE output data at the highest possible temporal granularity. This is because only highly granular data can accurately capture the true RL. Aggregated or less granular data, such as daily averages, could mask short-term fluctuations in supply and demand. To achieve robust predictions of power output, I gathered metadata (Appendix A) for all EDP plant locations (hydro, wind, and PV) and extracted the relevant climate variables from the climate models for each site to make climate induced predictions. Aggregating these than gives me a reasonable estimate of EDP’s VRE production within a certain timeframe.

After validating the prediction models against historical data, I used the validated models and critical assumptions to estimate the residual load under projected climate conditions, as well as under various RCP and consumption scenarios, up to the year 2045. The final stage of the analysis integrates the model-derived predictions and forecasts with simulations to quantify the impacts of residual load, identify mitigation strategies, and translating these findings into financial implications.

3.2 Data Collection

This thesis requires a variety of data from different data sources to answer my research questions. The data collection involves plant metadata, climate data (ERA5 & Cordex), consumption and VRE production data, training data and pricing data for energy market prices, ETS prices and Bitcoin prices for the reanalysis timeframe. My capacity obtained is very close to the actual capacity reported by EDP in their financial reports and the maximum deviation is at 2.8% for hydroelectric power.

To make predictions for renewable output based on climate models it is critical to collect the exact plant locations and corresponding metadata, as conditions can already differ significantly just across Portugal. The locations of PV and hydro plants were obtained through EDP's official website and *openstreetmap*. For wind farms I utilized *TheWindPower.net*, thanks to the generosity of the provider, who kindly provided it free of charge to me. In total I collected data of 150 plants (51 hydro plants, 87 wind farms and 11 PV plants). To verify the completeness of the data I compared the sum of my obtained capacities with the ones EDP lists in their Operating Data Preview 2024, their Annual Report 2023 and Reuters 2024.

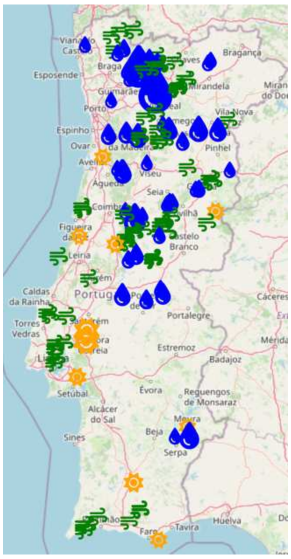


Figure 1: EDP's Plants by Type & Capacity

Type	Official Capacity (MW)	My obtained Capacity (MW)
Photovoltaic (eoy 2024)	540	539
Wind (eoy 2024)	1,185	1,198
Hydro (eoy 2024)	5,078	5,220

Table 1: Obtained vs. Official Plant Capacities

The core of my thesis is the climate data. My thesis requires high-quality climate datasets covering both recent historical conditions (2023–2025) and future projections (2025–2045) to derive power outputs based on climate variables (e.g., wind speed, solar irradiance, temperature). Using reliable climate inputs ensures that the estimated power outputs reflect realistic atmospheric conditions, which is essential for credible analysis outcomes.

Variable	**Description**	**ERA5 Unit**	**Cordex Unit**
Surface solar radiation downwards (*ssrd*)	Downward shortwave radiative flux at the surface.	$J\ m^{-2}$	$W\ m^{-2}$
Surface thermal radiation downwards (*strd*)	Downward longwave (thermal) radiative flux at the surface.	$J\ m^{-2}$	$W\ m^{-2}$
2m air temperature (*t2m*)	Air temperature measured two meters above the surface.	K	K
10m eastward wind (*u*)	Eastward component of horizontal wind at 10m above surface.	$m\ s^{-1}$	$m\ s^{-1}$
10m northward wind (*v*)	Northward component of horizontal wind at 10m above surface.	$m\ s^{-1}$	$m\ s^{-1}$
Total Cloud Cover (*tcc*)	Fraction of sky covered by clouds.	%	%
Total Precipitation (*tp*)	Accumulated water depth from all precipitation types.	m	$kg\ m^{-2}\ s^{-1}$

Table 2: Collected Climate Variables - Overview

For historical climate data, I use ERA5, a global reanalysis dataset, providing detailed atmospheric records from 1950 onward at ~31 km resolution with hourly intervals. ERA5 (the successor to ERA-Interim) incorporates extensive observations with modern modeling, yielding high-fidelity climate information for baseline years (Hersbach et al., 2020). This ensures that the 2023–2025 climate variables used in my models are based on a state-of-the-art reconstruction of actual weather. However, a limitation is the 31 km resolution, which in some cases may lead to mapping the true weather conditions to the actual plant. For future climate (2025–2045), I rely on the Coordinated Regional Downscaling Experiment (CORDEX). The CORDEX framework produces regional climate projections at high spatial resolution (~0.11° or ~12 km) by downscaling outputs from global models. Such downscaled ensembles provide a foundation for climate impact studies and services, supplying credible fine-scale climate inputs for the future period (Jacob et al., 2020). This approach captures localized climate variations, allowing more accurate assessment of potential impacts on plant power generation than coarse global models alone.

To benchmark and validate the accuracy of my predictions, and to generate realistic granular consumption patterns until 2045 reliable time-granular consumption and production data is of high importance. E-Redes, the company responsible for managing the electricity distribution networks in mainland Portugal, provides such data on 15min intervals starting in 2023. By combining monthly market share data from Entidade Reguladora dos Serviços Energéticos (ERSE) with EDP's specific market shares for different types of VRE, I can approximate EDP's contribution to total electricity consumption for each time interval. My data is further refined by incorporating detailed data from REN-Portugal's national electricity transmission grid operator-which provides precise production breakdowns by energy source in megawatts (MW) from the early 20th century on, which I then convert to kilowatt-hours (kWh) during my data preparation process.

While assumptions and calculations based on climate variables are sufficient for wind and hydro power, it makes sense to train a machine learning (ML) model to estimate the power output of EDP's PV sites. In order to train a model based on the climate variables I have, not only do I need metadata for PV farms, but also their exact location. The National Renewable Energy Laboratory provides such data with coordinates for different PV sites with different capacities all over the US in 2006, with power outputs in 5-minute intervals. A key limitation is that the dataset comprises synthetic data points. Nonetheless, it remains the only available large-scale dataset suitable for training models across plants of varying capacities. As ERA5 climate variables are only available on an hourly basis and Cordex only on a three-hourly basis, I apply interpolation approaches for the different climate variables to have the data also available in 5-minute intervals.

To estimate the costs associated with purchasing energy from the market or operating plants that require carbon offsets, I use actual market prices from 2023 to 2025, and project future trends based on weather conditions and established forecasts. Hourly energy prices for Spain and Portugal were obtained from REN. To assess the cost of carbon offsets, I refer to EDP Portugal's estimated expenditures for 2021, 2022, and 2023 and integrate this data with historical ETS price trends from the International Carbon Action Partnership and the median forecast from financial institutions such as Bloomberg and Deutsche Bank through 2030. In addition, to assess the investment costs of expanding storage capacity or increasing VRE deployment, I use projections from the *World Energy Outlook 2024*, which provide estimates under different climate scenarios and regional contexts.

3.3 Data Preparation

I have carefully designed my data preparation pipeline to ensure the efficient integration of diverse data sets to enable a robust analysis. The data preparation process is fully configurable, encapsulates around 60 functions dedicated to serve different purposes (downloading, cleaning, manipulation) and runs automatically within an MLflow pipeline framework. The pipeline handles data batch processing while it monitors the status of missing data at all times to provide reproducibility together with efficient resource management and data integrity for the analytical workflow. The complete data preparation time requires around 48 hours depending on network speed.

First, the pipeline retrieves the most recent E-Redes data on electricity production and consumption from 2023 onwards and concatenates it with the data from REN. This data is then enriched by the respective carbon-/electricity prices observed at all times. Also, EDP's monthly observed market shares are merged to the data. It then extracts the required climate variables from the ERA5 dataset, covering the period 2023-2025 for Portugal and 2006 for the United States. The next step involves obtaining EU CORDEX data from 2025-2045 with specific attention to iteratively filter the Portuguese subset for improved storage and computational performance.

The pipeline employs vectorized operations to perform accurate time-based mapping of climate data to plant locations through nearest longitude and latitude coordinate alignment per timestamp and climate scenario. It assigns a site identifier to ensure the nearest distance calculation only executes once. Because CORDEX and ERA5 data are timestamped in Coordinated Universal Time (UTC), while U.S. PV plants, for example, operate on local time, the pipeline incorporates time zone localization to harmonize temporal data. Further, differing units are adjusted to the same, and an interpretable scale. For instance, the precipitation is adjusted from m / $kg\ m^{-2}\ s^{-1}$ on one hourly / three hourly to a common unit mm/h.

The PV data is further enriched by incorporating additional predictors such as solar elevation, elevation and clear sky index. These parameters were derived from the longitude and latitude of each site using the Shuttle Radar Topography Mission (SRTM) dataset (*srtm* library) and the *pvlib* Python library, respectively. The SRTM dataset provides high-resolution digital elevation models of the earth's surface. The *pvlib* Python library enables users to calculate the clear sky index through its open-source solar power system simulation functions. The index measures how actual solar irradiance compares to clear sky irradiance to indicate cloud cover and atmospheric conditions. The additional predictor solar elevation represents the sun's height above a specific location at a particular time and was calculated by *pvlib*. By adding these variables from other sources, I reduce the need for bias correction for the solar model. Outside the time constraints of this thesis, adding reference data, ideally satellite data, and performing quantile mapping would likely further improve the results, as the special grid is still inadequate for places with high variability in surface irradiance, such as Portugal (Urraca et al., 2018). Other feature engineering steps include calculating trigonometric transformations of time-related variables to capture cyclical patterns in the data.

Further, to match the temporal resolution of the PV data with the climate data, I applied interpolation techniques tailored to specific variables. Variables with smooth diurnal cycles, such as *t2m* and *ssrd*, were interpolated using a cosine-based method to capture their sinusoidal patterns. Conversely, variables such as *tcc* and *tp*, which can change abruptly, were interpolated linearly to accurately reflect their variability.

Last but not least solar elevation-based filtering is conducted to eliminate unnecessary nighttime observations which results in condensed 130 million rows. A subset of observations with negative solar elevation angles was retained to allow the model to better learn and accurately predict nighttime conditions.

3.4 Descriptive Analysis

First, a look at Portuguese electricity consumption shows clear intra-day, intra-week and seasonal patterns, as well as a modest increase of 1.1% from 2023 to 2024. Consumption is highest on weekdays, falls at weekends and is lowest on national holidays. Visually there's no clear long-term trend - daily demand is consistently around 140 GWh - but there are pronounced seasonal variations: in winter, daily consumption ranges from around 120 GWh to peaks of over 185 GWh; in summer, it ranges from around 110 GWh to 155 GWh. As my forthcoming scenarios will require explicit assumptions about demand, it's equally important to examine RL - demand net of renewable generation - as it captures the combined effects of both consumption and production.

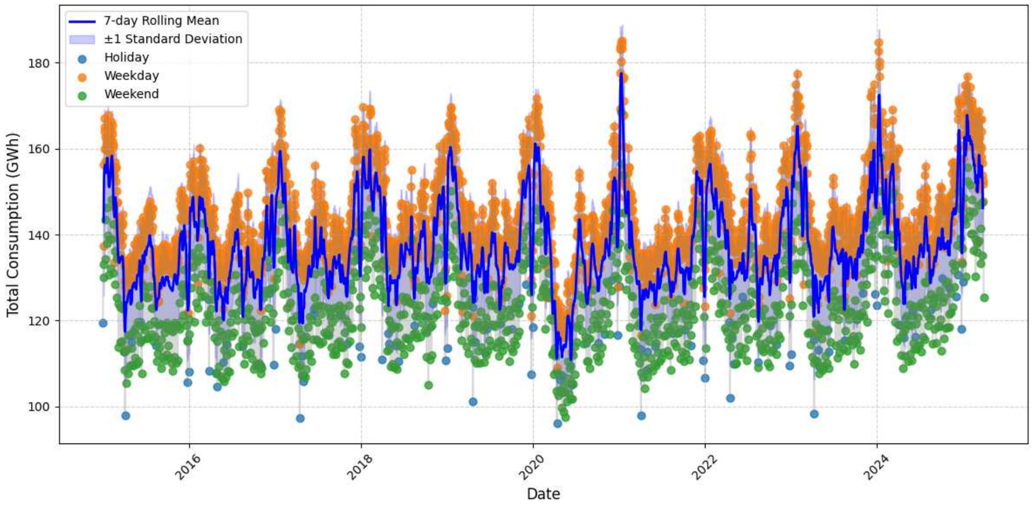


Figure 2: Daily Consumption over Time

Looking at energy production from VRE sources, hydropower is, with exception of the summer, the largest contributor to Portugal's renewable energy production. Specifically, hydroelectric production peaks in the fall and winter seasons and declines from spring on.

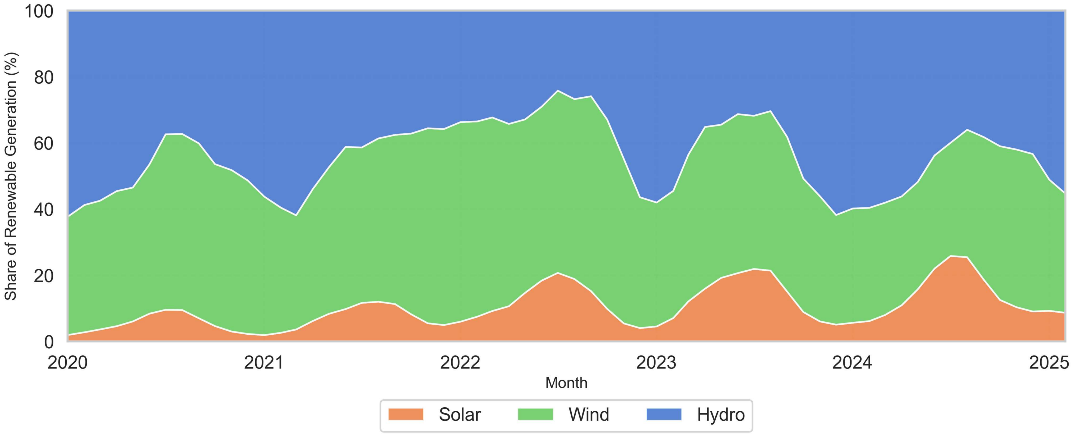


Figure 3: Monthly VRE Mix 2020-2025

Wind power, on the other hand, has its lowest production levels mainly in the first part of the year, gradually compensating for the reduced hydropower generation until the third quarter. PV power clearly peaks in the summer, and its contribution appears to be increasing over time, presumably primarily due to additional installed PV capacity, which is reasonable, as we will see later.

When analyzing the intraday generation patterns, wind power emerges as the most consistent energy source throughout the day, with its lowest hourly average production (~1 GWh) in summer and its peak in winter (~1.8 GWh). Hydropower, on the other hand, reaches its minimum at around 2 a.m., increases its production in the morning, decreases slightly at noon, and reaches its maximum at around 7 p.m., consistently providing at least 30% of the total VRE production in all seasons. A closer look also shows that excess energy generated during the night and midday is stored in pumped storage plants for use during the evening peak, thus optimizing hydropower production.

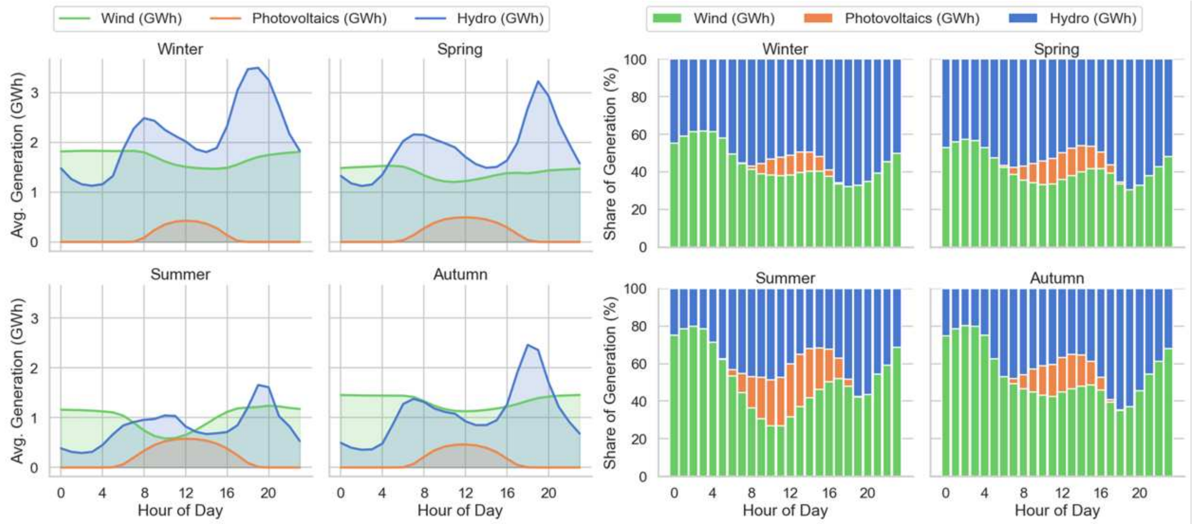


Figure 4: Generation of VRE by Season & Time of Day

PV generation, which follows a sinusoidal pattern, contributes the smallest share (consistently below 25%) to total production, with its maximum output (~0.7 GWh) occurring in the summer around midday. During these peak summer hours, PV generation almost equals the output of wind energy.

The average daily RL of the least five years (2020-2024) measured as the amount not served by VRE's stands at 56.24 GWh, which considering the average Portuguese daily energy price of 78 Euro per MWh over the reanalysis data amounts to energy imports valued up to 4.4 million euros each day assuming 100% VRE production. On an annual basis, the financial costs associated with RL - calculated by multiplying the 15min RL by the current electricity price – would average approximately €1.6 billion annually since 2023. Given EDP's average market share of 37.9% between 2023 and 03/2025 and considering its disproportionately high exposure due to its significant reliance on VRE, its estimated annual cost attributable to RL would be around €0.6 billion. This figure does not include additional costs such as insurance premiums or premiums associated with long-term price agreements and contracts.

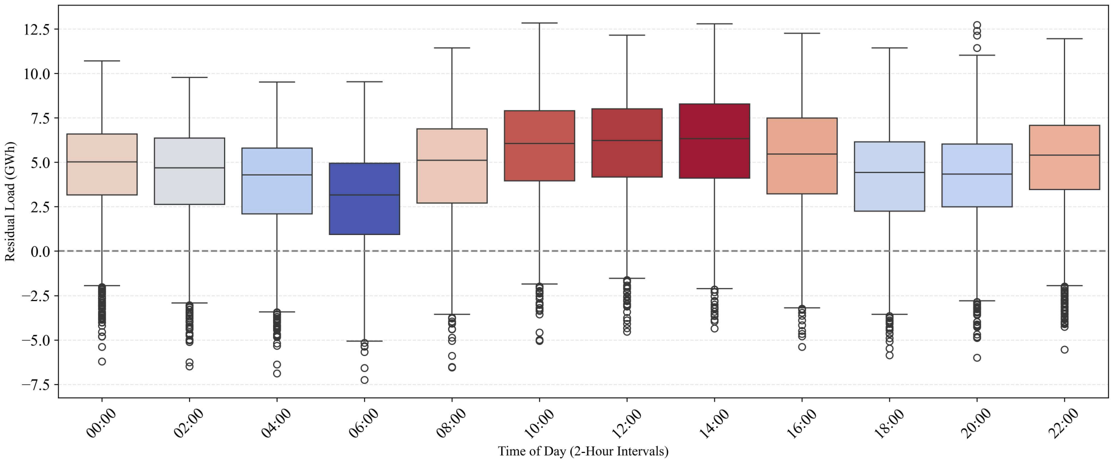


Figure 6: RL Distribution by Time of Day (2-Hour Intervals)

EDP itself doesn't disclose detailed costs in their annual reports. However, for 2023 they reported a group wide cost of energy of 6.7 billion euros, which encompass both purchases from third parties and the internal cost of generation (EDP Annual Report 2023). Considering that EDP's global installed capacity is 26.6 GW, of which 19.3 GW are VRE's and its footprint of 6.8 GW in Portugal, their cost of energy in Portugal is at least 1.7 billion euros. Therefore the 0.6 billion estimate is probably at the lower end of the true value. An examination of its intraday pattern shows that RL is highest during business hours.

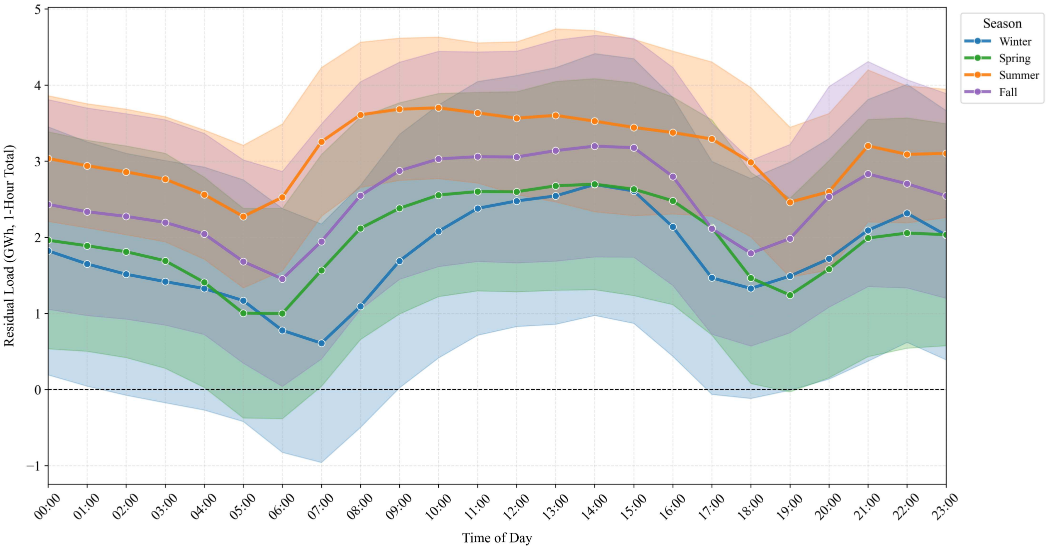


Figure 7: Average Hourly RL- Confidence Bands by Time of Day

In contrast, during the night, when energy demand decreases, the dependence on non-VRE sources decreases significantly, occasionally reaching negative values - indicating periods when Portugal exports surplus energy.

The seasonal analysis shows an increased vulnerability in summer from night to midday, while winter shows the highest RL from midday onwards. In addition, winter shows the greatest variability in RL, while fall shows the least.

Figure 8: Development of daily RL from 2010 - 03/2025

Over the years the effects of increases in installed VRE capacity can be clearly observed and since 2010 the average RL has decreased from its peak of 32.206 GWh in 2012 to just 13.924 GWh in 2024 which corresponds to a reduction of almost 60% in a span of 13 years. Since 2018 and notably first in 2021 there are even multiple periods, all falling within the winter season of negative RL, so an energy surplus generated on a daily level that can be monetized through exporting. On the negative side, the variability has clearly persisted or even increased in relation to the on average shrinking RL profile as evidenced by the increasing coefficient of variation.

For example, in the summer of 2022, likely influenced by drought conditions, RL reached about 100 GWh - a level last observed in 2019-but then dropped rapidly to -2 GWh in the following winter. While some of this variability can be attributed to the growth of VRE sources, as discussed in the literature review, a significant portion is also likely due to extreme weather events, such as the drought in 2022. Rapid shifts in consumption can be ruled out as a driver, as consumption is initially without a clear trend but has a clear repeating seasonality, and levels in the summer of 2022 were comparable to previous years. Thus, despite a decreasing average RL, volatility has not decreased, but has become more pronounced, underscoring the system's increased sensitivity to both renewable integration and climatic extremes.

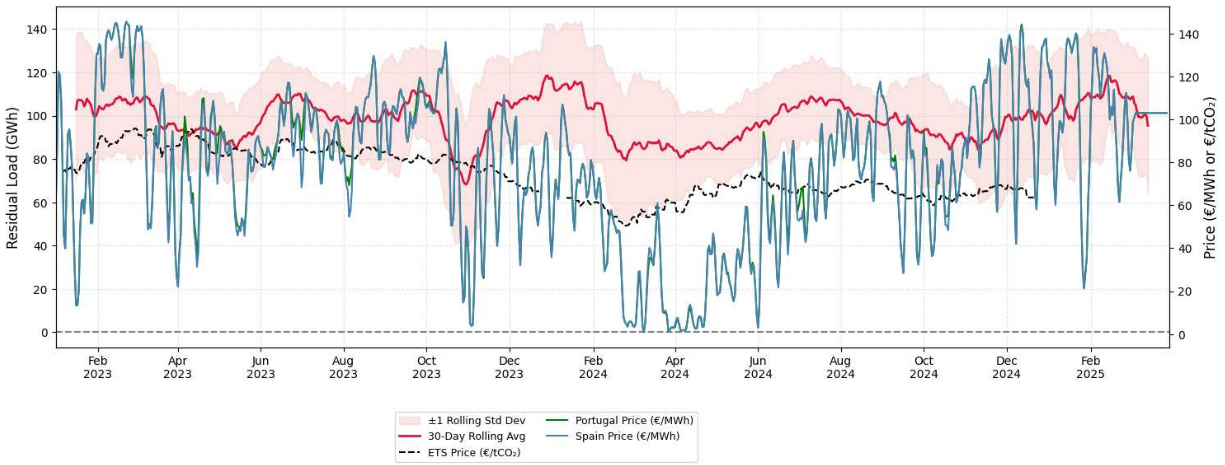


Figure 5: RL vs. Energy and Carbon Prices (2023–2025)

The analysis of the correlation between energy prices and RL clearly shows that elevated RL-periods typically coincide with high electricity prices. Specifically, the correlation coefficient between RL and Portuguese electricity prices is 0.46, while for Spanish electricity prices it is 0.43. In addition, electricity prices in Spain and Portugal have a remarkably strong Pearson correlation of 99%, meaning that their pricing patterns were nearly identical throughout the observed period. This close alignment can be largely attributed to the similar climate conditions and shared market dynamics between the two countries. ETS prices, on the other hand, show a weak positive correlation with RL of 0.085. This weaker correlation is expected as ETS prices are traded in the whole EU and therefore are relatively unaffected by fluctuations specific to the Portuguese electricity market.

The strong relationship between RL and electricity prices has significant implications and challenges: during periods of underproduction, electricity becomes significantly more expensive to purchase, and even Power Purchase Agreements are likely to include price premiums to account for this risk. Conversely, during rare periods of overproduction, market prices fall, making it less profitable to sell excess energy. In these scenarios, alternative uses for excess power - such as pumped hydro storage, battery charging systems, or bitcoin mining - may provide better economic value.

Assessing future climate variables for Portugal is critical to understanding the production potential of VRE sources in the EDP. However, hydropower was intentionally excluded from this analysis due to its inherent complexities and modeling challenges, as highlighted by Stoll et al. (2017). According to these authors, hydropower generation is influenced by a complicated combination of environmental, operational, and regulatory factors, making accurate modeling particularly difficult. In addition, the available ERA5 and CORDEX climate datasets are insufficient for realistically estimating hydropower production, as variables such as precipitation and temperature alone do not adequately capture its complexity.

A look at the CORDEX data from 2025 to 2045 in comparison to the ERA5 data (Figure 6) shows a notable increase in climate variability, except for *ssrd* and *strd*, where volatility decreases slightly across climate scenarios. Comparing CORDEX projections (2025-2045) with ERA5 historical data (2020-2024), annual means show an increase of 2.7% for *strd* and 1.4% for *ssrd*. Temperature increases by 7.3% under the RCP 8.5 scenario and by 5.8% under the RCP 4.5 scenario. Both wind components show no real differences between the scenarios and exhibit similar distributions. *tp* also decreases consistently across all scenarios. However the statistical tests ANOVA for the means and Levene’s for variability both provide no evidence that the means or volatility is inherently different between the climate variables in the scenarios.

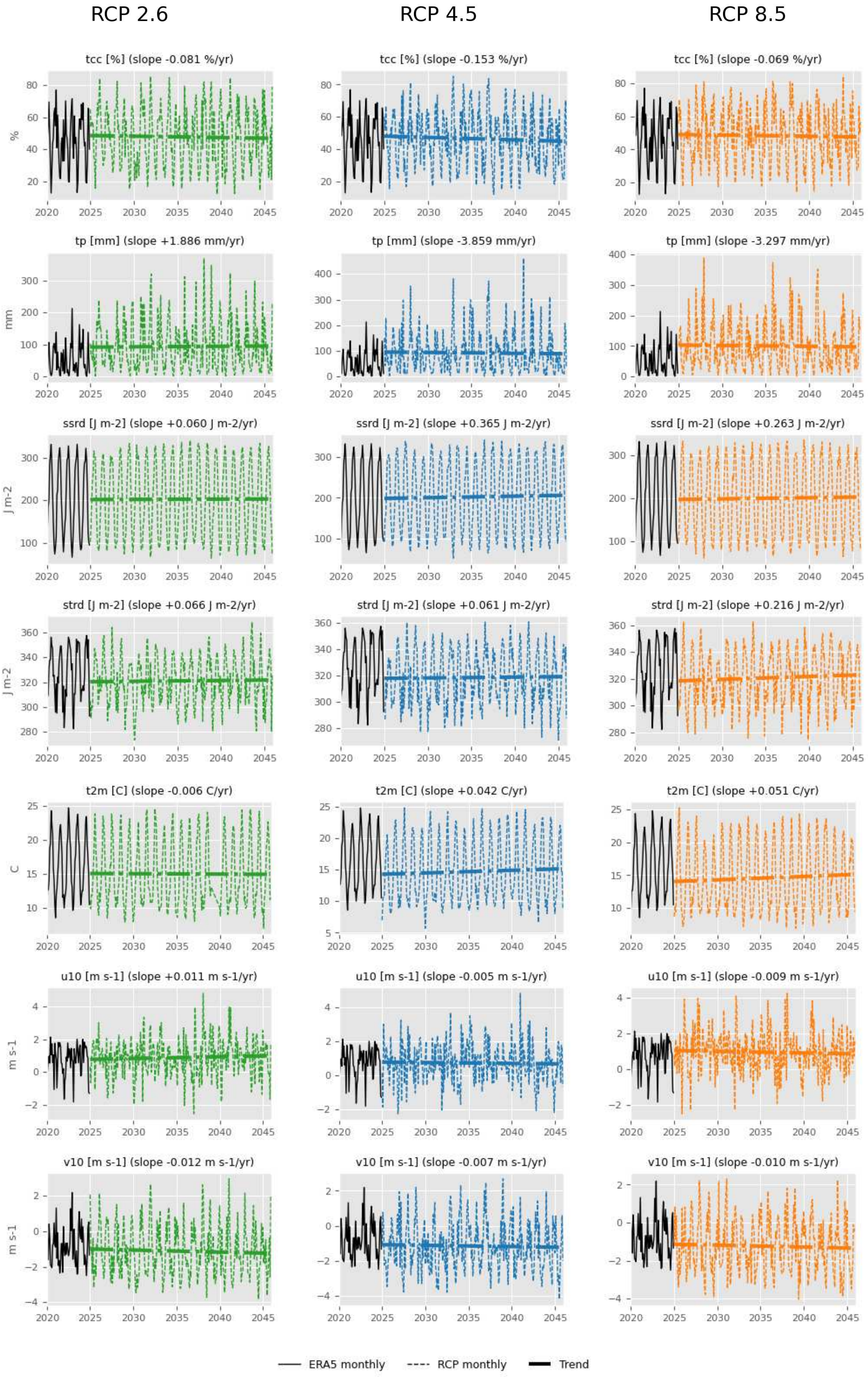


Figure 6: Evolution of Climate Variables

3.5 Predictive Analysis & Modeling

3.5.1 Photovoltaic Prediction Model

To achieve accurate power predictions, I selected a tree-based LightGBM model known for its computational efficiency, interpretability and robust performance on similar meteorological datasets (Ye et al., 2023). The model was optimized using Hyperopt with both Tree-structured Parzen Estimator (TPE) and Adaptive TPE (ATPE) - an enhanced variant of TPE that accelerates convergence - combined with 4-fold group cross-validation, split on the 4 kernels of my machine, to increase efficiency and an 80/20 train-test split to mitigate overfitting. Additionally, I compared this model to a baseline dense neural network. Exact model specifications can be found in the Appendix A.

Initially, I evaluated both the full dataset (including interpolated 5-minute ERA5 climate variables) and the hourly dataset (with true hourly ERA5 observations) on matching variables distributions (Appendix A). Due to high computational requirements (about 7 hours for only 25 iterations) and limited improvements from interpolated data, I chose the smaller hourly dataset, which after filtering for observations with mapped climate variables no further than 16 km and outlier filtering still contained about 9.7 million observations. Outliers are observations with capacity factor greater than 90% which is very unlikely to happen and net zero generation during conditions which would suggest positive output based on a confidence interval—most likely due to some maintenance event or simply faulty data. In addition, lagged features were tested but showed no performance improvements and were excluded. Interaction terms were introduced to better capture feature dependencies, specifically between solar elevation and *tcc*, clear sky index (*csi*), net radiation (*netrad*), and time (hour), as well as interactions involving *t2m*, *tp*, cloud cover, and *ssrd*. These interactions significantly improved model performance.

To address over-reliance on capacity as a predictor, outputs were normalized by plant capacity and capacity-based bins were introduced, with regards to EDP’s capacities and represented through 10 quantiles, to improve interpretability and reduce bias across PV sites (1-290 MW). To further improve the model's generalizability, standardization is applied to ensure that the model remains effective when applied directly to EDP's plants. In addition, logging the target variable was tested but didn’t improve model performance. Prediction quality is assessed by examining the MEDAE, NRMSE and NMAE within capacity bins and analyzing the error quantiles at the 80th, 90th and 99th percentiles. MEDAE represents the median absolute error in MW terms, while NRMSE and NMAE represent the root mean square error and mean absolute error in normalized terms, so can be interpreted as the average percentage deviation.

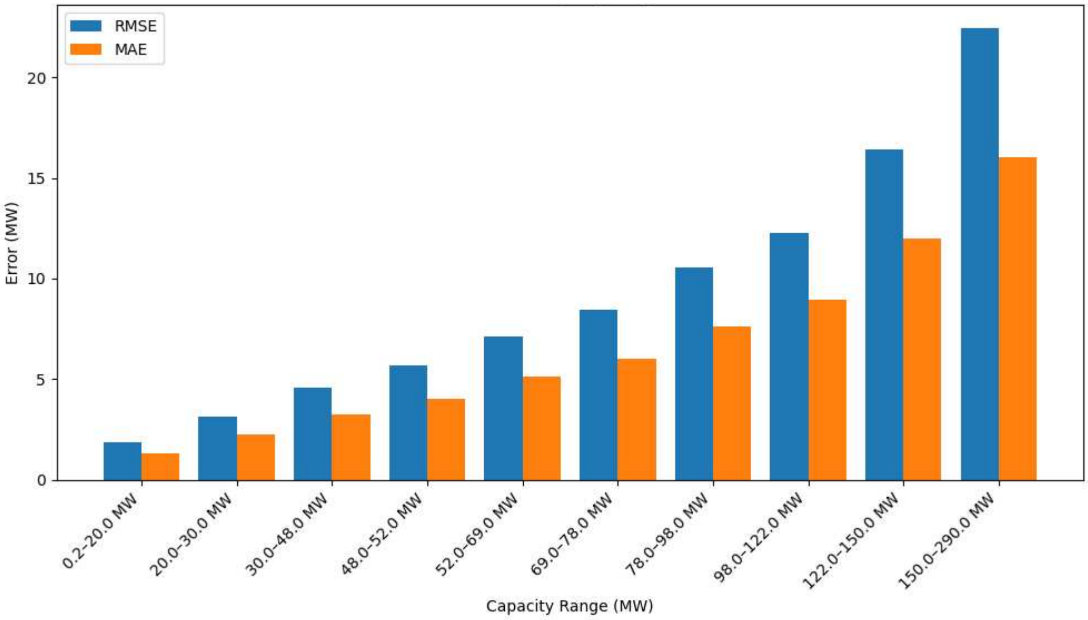


Figure 6: RMSE and MAE by Capacity Quantile

The best performing model for my application is the LightGBM model trained on normalized power outputs. It manages to explain 88% of the variation (EV) in the data and achieves a significant better MEDAE of 3MW in comparison to its peers. For my purposes, the NRMSE metric is particularly critical, as I require the model to accurately reflect and predict across the entire power spectrum, rather than excel only within certain quantiles. In addition, I've verified that the feature distributions between the training dataset and EDP's assets closely match. A summary plot of the feature distributions, optimized hyperparameters and detailed results can be found in Appendix A. The predictions themselves are fairly accurate on multiple levels. For instance, for the Cerca Photovoltaic Farm, EDP reports an average annual output of 330 GWh (EDP Notícias, 2024). In comparison, my model estimates 322 GWh for 2023 and 310 GWh for 2024 - on average that’s about 4% lower than the reported figure. Though it has to be noted that the Cerca Farm was activated in 03 / 2024 which will be considered later for the reanalysis. When applying later, the predictions get transformed to kWh per 15min.

Algorithm	*MEDAE*	*NRMSE*	*NMAE*	*EV*
LightGBM Norm (100)	**2.9969**	**0.1121**	0.0791	**0.877**
Dense NN Norm (22)	3.8310	0.1218	0.0899	0.8592
LightGBM Norm & Log (100)	3.4901	0.1488	0.0688	0.8501
Dense NN Norm & Log (24)	3.6023	0.1353	**0.0599**	0.8463

Table 3: PV Models Performance Metrics

3.5.2 Wind Model

My wind power estimation methodology is based on the frameworks proposed by Nogueira et al. (2019) and Nefabas et al. (2021) with several modifications for bias correction and statistical downscaling for my specific power output task. First, I used the 10-meter u and v wind component data from the CORDEX and ERA5 reanalysis datasets and then extend these wind speeds vertically to standard levels of 100 m and further to the specific turbine hub heights using an empirical power-law exponent. In order to get to my low temporal resolution, I apply statistical downscaling using the Global Wind Atlas (GWA) to ERA5 that offers high spatial resolution (250 × 250 m) Weibull parameters at 100 m with important local corrections for orography and surface roughness. Weibull distributions are widely used and have been found to be a reliable fit for wind distributions and wind energy applications, which is why they have been used for decades (Davis et al., 2023). As the climate model data is subject to biases I further apply a bias correction via Quantile Delta Mapping (QDM) as in Cannon et al. 2015 against the more granular ERA5 data with estimated realistic wind speed distributions through Weibull parameters on the CORDEX data as conducted in this recent study (Zekeik et al., 2024). This corrects the biases while still retaining CORDEX change signals. Ideally, I would have local weather data for each plant to do QDM on, however this wasn’t feasible within the timeframe of the thesis. Once I have the estimated the time-granular wind speeds for each plant, the instantaneous power output is calculated through the turbine power curve and finally transformed to kWh outputs on the 15min interval. I use individual turbine-specific power curves from the manufacturer, including the wind speed at the cut-in, rated, and cut-out for the turbines installed by EDP. In addition to that I explicitly consider internal losses at the lower end of 10%, particularly wake effects decreasing the wind speeds by the cube root of the expected share of internal energy losses. With more data and more time, I could have implemented a more sophisticated model such as the Jensen wake-deficit model, which rarely ranks last and are often chosen when evaluating the feasibility of a new windfarm / turbines in close proximity (Archer et al., 2018).

The accuracy of the predictions is validated against the annually available productivity data of EDP. Aggregated annual predictions for wind farms identified for individual wind farms are within ±10% of the reported production of EDP. For example, at the largest wind farm of EDP, Toutiço wind farm in Alentejo (187 MW) my model predicts energy generation of 403 GWh for 2023 and 435 GWh for 2024, while EDP claims a production of "more than 420 GWh"

(EDP Notícias, 2023). The absence of detailed, site-specific output data provided by EDP prevents the further, higher temporal resolution validation of the model's accuracy.

A further improvement of my predictions could be to integrate stochastic super-resolution methods and deep-learning QDM hybrids for finer spatiotemporal fidelity (Omoyele et al., 2024). Also, DL spatial downscaling could further improve results as in Giroux et al. 2024.

3.5.3 Consumption Model

In electricity forecasting, advanced ML models, particularly deep learning techniques such as Long-Term Memory (LSTM) networks, have gained prominence in recent years due to their superior short-term forecasting capabilities. However, while these models excel at short-term forecasting, their suitability for long-term forecasting tasks involving the strategic management and optimization of asset portfolios, where projections can span decades - in this case, up to the year 2045 - diminishes significantly. The long forecasting period and inherent stochasticity of electricity consumption patterns make deep learning approaches like LSTM computationally demanding and less effective.

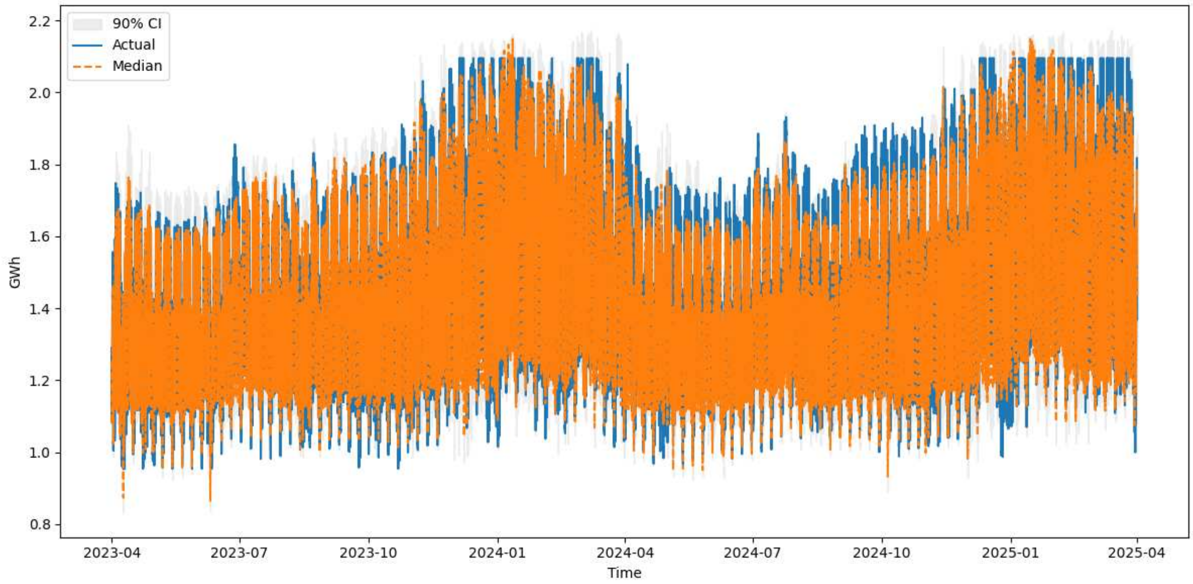


Figure 7: Consumption Forecast - Evaluation – Probabilistic Load Forecasting

The strategic requirements of my thesis which focus on long-term portfolio resilience optimization led me select conditional quantile regression models, as proposed by Wang et al. (2018) for such load forecast problems. They propose a novel probabilistic load forecasting (PLF) framework that leverages existing point forecasts by modeling the conditional distribution of forecast residuals via nonparametric quantile regression, with the point forecast included as an input feature alongside historical load and exogenous factors to capture dependencies on time, load level, and weather. In my forecast I additionally integrate the average countrywide interpolated *t2m*, as I could already prove in statistical tests that during extreme *t2m*, consumption tends to be elevated. This procedure results in different forecasted timeseries for each scenario. Without the time constraints of this thesis, one could add even more external predictors to improve forecast accuracy.

The model is trained on data from 2020 – 04 / 2023, while the last two years serve as an evaluation period. As could already be observed in the exploratory data analysis, there isn't really a true long-term growth in consumption. However, I still wanted to account for a certain diminishable growth level, considering the electrification of the economy which is especially expected to speed up from 2030 on. Therefore, two scenarios are modeled, one with no growth and one with growth rates encapsulating the anticipated energy consumption increases (REN (2021), NECP 2021–30 (2020)). My model achieves an MAE of 64.626 kWh and an RMSE of 86.041 kWh, corresponding to an MAPE of just 4.42%, which is slightly inferior but still in line with the results Wang et al. (2018) achieved.

Years	Growth Rate	Reasoning
2025-2030	0.5%	Slow electrification, urgency not fully recognized
2030-2035	1 %	More focus, subventions, full preparation to phase out of combustion engine
2035-2037	0.75%	Phasing out of combustion engine as of 2035
2037-2041	0.5%	Back to initial growth
2041-2045	0.025%	Electrification primarily conducted

Table 4: Estimated Growth Rates - Consumption Model

3.5.4 Hydro Model

As discussed in the exploratory analysis, developing a robust hydrological forecasting model involves considerable complexity and relies heavily on detailed data and variables that are either inaccessible or impractical to analyze thoroughly within the scope and timeframe of this thesis. Due to these limitations, my hydrological projections instead use actual historical hydropower generation data from REN and are scaled according to EDP's hydro market share in Portugal. According to Statista 2025, Portugal's total hydropower capacity in 2024 is approximately 8,347 MW, with EDP's reported capacity of 5,078 MW representing a market share of approximately 61%. For future projections, I use the same methodology as in the previous chapter based on data from 2020 on. A novel addition is to integrate the PV and Wind predictions as well as the consumption in the form of lag and rolling mean features, as in reality hydro power is also dispatched based on anticipated forecasted VRE production. While I have more data available, due to added hydro capacities over the years I would systematically underpredict, if I go back to much. Further it has to be noted, that hydro production patterns might change over time, depending on the type of VRE’s added to the system, as this may alter the timeframes for hydro necessity. Also especially pumped hydro also depends on the consumption as more water is released in times of high consumption coupled with low production from other VRE sources, which cannot be captured by my model.

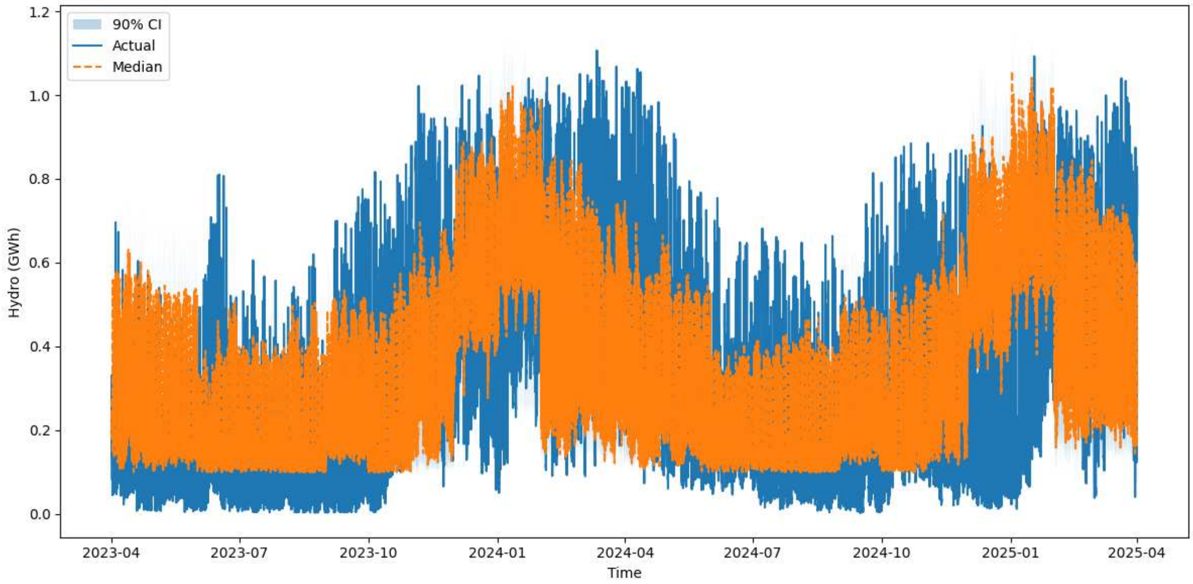


Figure 8: Hydro Forecast – Evaluation – Quantile Regression Model with Lag Features

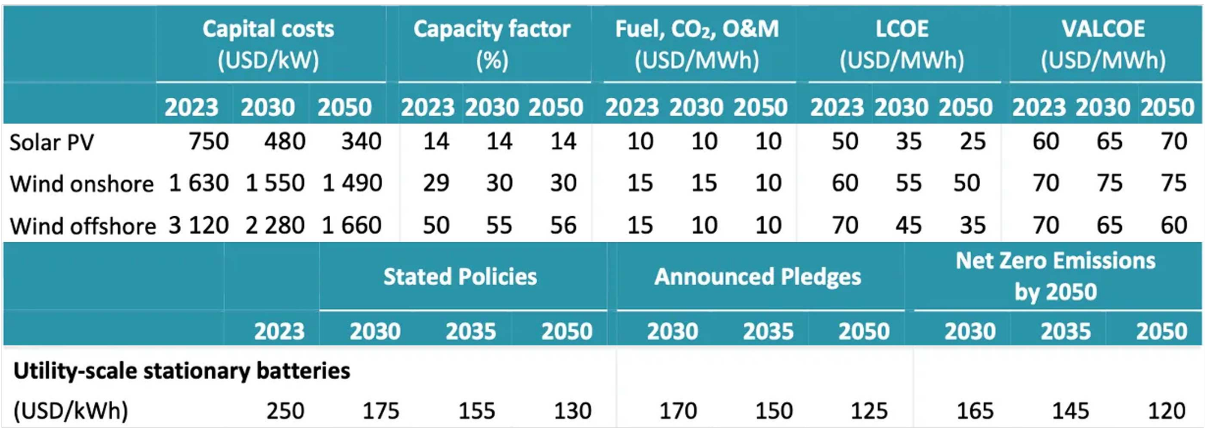
Instead of growth as for the consumption, my projections further include distinct seasonal adjustments that allow modeling of specific scenarios, such as prolonged drought conditions. Teotónio et al. 2017 estimate hydro capacity factors for RCP 4.5 and RCP 8.5. For RCP 2.6 I assume the RV_B2a scenario which in its description is the most comparable with RCP 2.6. The decrease is modeled through linear interpolation until 2045 matching it to the reanalysis values. It must be acknowledged that the hydro model used in this thesis has limitations. Given more time, resources, and access to detailed data, this component could likely yield significantly improved results. The MAE is at 150 kWh, while the RMSE is at 199 kWh, resulting in an MAPE of 30%.

Scenario	Avg. annual rate of change for EDP	Projected Hydro Capacity Factors for 2050
No CC	-	Winter: 0.627, Spring: 0.700, Summer: 0.650, Fall: 1.936
RCP 2.6	-0.3%	Winter: 1.013, Spring: 0.835, Summer 0.621, Fall: 0.742
RCP 4.5	-0.9%	Winter: 0.874, Spring: 0.782, Summer: 0.616, Fall: 0.810
RCP 8.5	-2%	Winter: 0.638, Spring: 0.570, Summer: 0.450, Fall: 0.591

Table 5: Assumptions Hydrological Forecast from Teotónio et al. 2017

4 Results and Discussion

This section of my thesis details the assessment and forecast of EDP's RL derived from my predictive models and available consumption data. It's important to emphasize that all values presented are derived from these predictive models, and the assumption that the equipment is continuously operating at full capacity (100% uptime) may result in RL estimates that are somewhat too optimistic. In addition, the future analysis has significant limitations, primarily due to the inherently underrepresented variability in both the wind and hydrological models due to data constraints. Consequently, most simulations focus on historical conditions where the quality and resolution of the data better capture realistic variability. All cost assumptions used in the simulations are derived from the World Energy Outlook 2024 projections for variable renewable energy (VRE) and storage. Despite these limitations, future projections offer valuable insight into plausible outcomes under optimistic and pessimistic scenarios.



	Capital costs (USD/kW)			Capacity factor (%)			Fuel, CO_2, O&M (USD/MWh)			LCOE (USD/MWh)			VALCOE (USD/MWh)		
	2023	2030	2050	2023	2030	2050	2023	2030	2050	2023	2030	2050	2023	2030	2050
Solar PV	750	480	340	14	14	14	10	10	10	50	35	25	60	65	70
Wind onshore	1 630	1 550	1 490	29	30	30	15	15	10	60	55	50	70	75	75
Wind offshore	3 120	2 280	1 660	50	55	56	15	10	10	70	45	35	70	65	60

		Stated Policies			Announced Pledges			Net Zero Emissions by 2050		
	2023	2030	2035	2050	2030	2035	2050	2030	2035	2050
Utility-scale stationary batteries (USD/kWh)	250	175	155	130	170	150	125	165	145	120

Figure 9: VRE / Storage Cost Forecasts (World Energy Outlook 2024)

4.1 Historical Analysis

The historical analysis provides a detailed baseline for RL at EDP, which is essential for evaluating and planning future energy scenarios. Forecast robustness was improved by constraining the forecasts of energy sources - PV, wind, and hydro - to within two standard deviations of their respective historical average market shares. This method significantly reduced forecast volatility, affecting about 5% of PV forecasts (mostly during the initial growth phase) and about 10% of wind forecasts.

EDP's hydro forecasts were derived from Portugal's national hydro production data, scaled proportionally to EDP's market share of 61.99%. Observations from 2020 to 2024 show average capacity factors of 18.7% for hydro, 29.9% for wind and 11.6% for PV.

The average 15-minute RL for EDP is about 0.137 GWh, resulting in an average daily RL of about 13.14 GWh-about 30% of Portugal's total RL. Given EDP's average market share (37.7% from January 2023 to March 2025), this indicates effective performance; however, underproduction relative to consumption occurs 71% of the time, especially during business hours in the summer. Peak RL’s reach up to 0.62 GWh per 15-minute interval, with the 90th percentile at 0.29 GWh.

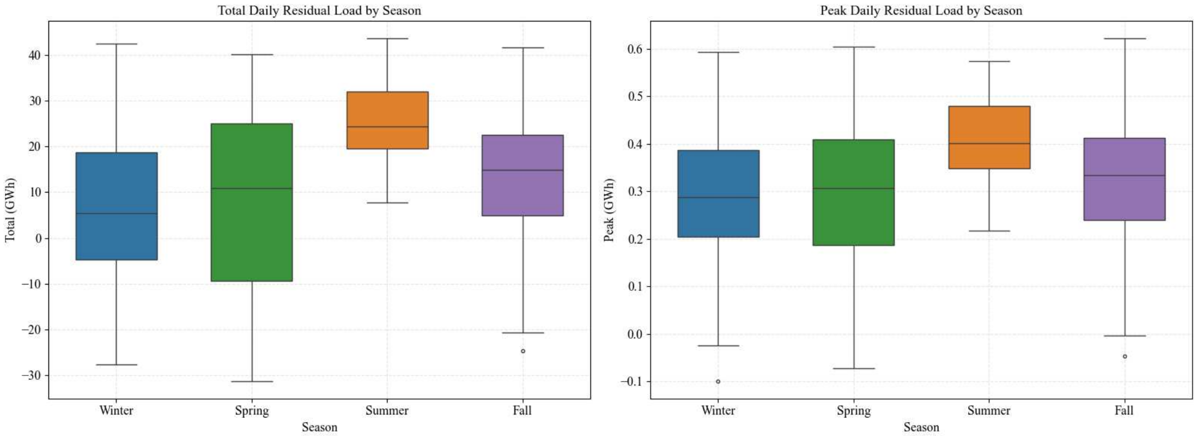


Figure 10: Distribution of Total / Peak Daily RL’s by Season

A seasonal analysis reveals significant variability in RL, with the highest magnitude and greatest volatility consistently observed during the summer months. This pattern emphasizes systemic vulnerabilities, which are particularly pronounced during periods of low wind production combined with reduced hydrological availability. These findings closely align with nationwide patterns identified in the descriptive analysis.

Table 6 quantifies variability using two metrics: the standard deviation (STD) in GWh and the capacity-normalized coefficient of variation (MaxCap CV). This CV metric defines variability by comparing actual production variability against theoretical maximum outputs based on installed capacities. This gives a sense of how "intermittent" the source really is and through scaling to capacity, apples-to-apples comparisons of variability are possible. Results indicate that Hydropower exhibits lower short-term volatility but is less reliable long-term. PV is relatively consistent. Last but not least wind energy offers moderate reliability but experiences significant volatility during shorter intervals, especially in winter and spring.

Source	**15min**	**1h**	**4h**	**8h**	**24h**	**48h**	**1w**	**30d**	**1y**
Hydro	0.23 (0.18)	0.92 (0.18)	3.37 (0.16)	6.38 (0.15)	16.27 (0.13)	31.80 (0.13)	106.63 (0.12)	433.88 (0.12)	2660.80 (0.06)
Wind	0.08 (0.25)	0.30 (0.25)	1.16 (0.24)	2.22 (0.23)	5.69 (0.20)	10.06 (0.17)	23.84 (0.12)	59.72 (0.07)	937.65 (0.09)
Photovoltaic	0.02 (0.16)	0.08 (0.16)	0.32 (0.15)	0.61 (0.14)	0.67 (0.05)	1.28 (0.05)	4.24 (0.05)	17.26 (0.04)	198.23 (0.04)

Table 6: Variability of VRE from 2020-2025 as measured in STD (MaxCap CV)

Overall, RL does not display a declining trend over time but instead follows a distinct seasonal pattern, with pronounced volatility in winter and spring. On a further note, the hottest 5 % of hours (≥ 95th percentile), both total electricity consumption and RL rise sharply compared to baseline conditions, with non-overlapping 95 % confidence intervals (CI) confirming statistical significance. Mean RL increases from 0.1278 GWh (95 % CI [0.1246, 0.1310]) to 0.3446 GWh ([0.3366, 0.3526]), and consumption from 1.4727 GWh ([1.4687, 1.4767]) to 1.5299 GWh ([1.5195, 1.5403]). In the coldest 5 % of hours (≤ 5th percentile), RL and consumption both decline slightly—by about 0.03 GWh each—again with non-overlapping CIs. However, the changes are much smaller than under extreme heat, likely due to higher winter hydro and wind output buffering demand. Analysis of ramp rates (changes in RL within intervals) shows that most 15-minute fluctuations fall between ±0.1 GWh, whereas hourly fluctuations mainly lie between ±0.25 GWh. These findings underscore the necessity of available pumped hydro storage / other forms of storage, particularly during high-volatility periods in winter and spring. RL ramp rates exhibit a strong negative correlation (~ -0.7) with production-driven changes, but a positive correlation with consumption-driven fluctuations, notably during extreme temperature events. Peaks typically occur when production declines coincide with consumption surges. RL duration analysis shows positive RL approximately 74% of the time, but surplus energy generation has been relatively limited, amounting to only 5,152 hours since 2020.

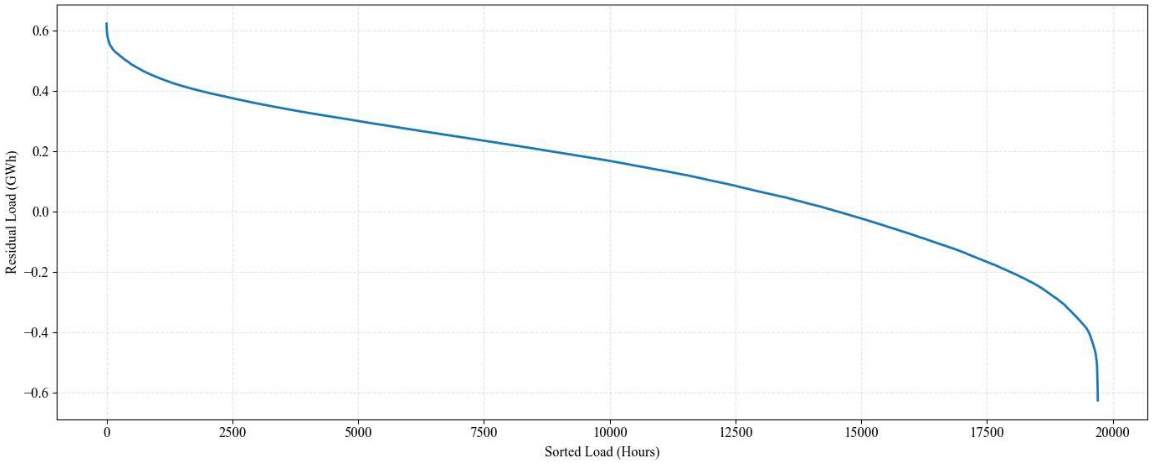


Figure 11: RL Duration Curve (2020 - 03/2025)

From a financial perspective, purchasing energy at market prices to cover RL cost EDP approximately €732 million in 2023 and €303 million in 2024—equating to on average roughly €1.4 million per day. During positive RL periods, as already shown, market prices are typically elevated (€87.3/MWh) compared to surplus sales prices (€59.3/MWh), underscoring the inefficiency and high costs of current market-driven strategies. Had RL's been covered equally by market purchases and EDP's thermal plants, with an emission intensity of approximately 500 tons of CO_2/GWh, EU ETS carbon costs alone would have reached €174 million in 2023 and €85 million in 2024, excluding fuel and maintenance costs.

Further I conducted an optimization analysis to evaluate the return on investment (ROI) of various potential expansions of VRE capacities and battery storage. The results, which are detailed in Table 7, clearly show that expanding PV capacity is more economically advantageous than investing in wind and storage technologies, primarily due to the higher projected ROI. The ideal investment allocation of €1 billion at current prices determined by my greedy hill climb algorithm should favors the addition of approximately 1,716 MW of PV and 0.4 GWh of storage, reducing total RL (GWh) by over 30%.

Scenario	**PV MW**	**Wind MW**	**Storage GW**	**Σ RL GWh**	**Savings GWh**
Actual	0	0	0	14.132	0
Optimized	1.716	0	0.44	**10.093**	**4.039**
100% PV	1.833	0	0	10.159	3.972
100% Wind	0	574	0	11.882	2.250
100% Battery	0	0	6.3	12.771	1.360

Table 7: Optimization Problem - Portfolio Additions - €1 billion

Further simulations show that the benefits of storage alone are limited because periods of surplus generation are rare. For example, a 1 GWh storage facility costing about €227 million could have reduced RL costs by about €3 million in 2023 and €4 million in 2024, while reducing imports by 173 GWh in 2023 and 305 GWh in 2024 (~4% of total imports on average). Expanding storage beyond 1 GWh shows diminishing returns due to the current limited surplus available.

Bitcoin mining simulations conducted alongside the 1GWh storage scenario show significant additional economic potential. Bitcoin mining is lucrative in times of excess energy, with low market prices and storage operating at full capacity. An investment of €500 million in mining hardware (priced at €25 per TH/s and with an energy efficiency of 0.025 kW per TH/s) would have generated additional revenues of approximately €28 million in 2023 and €127 million in 2024. This strategy significantly reduced import dependency by 56 GWh in 2023 and 83 GWh in 2024, with mining equipment active for 513 hours in 2023 and 1.758 hours in 2024. By early 2025, elevated bitcoin prices would have reduced Q1 RL costs to approximately €0.5 million-about €5 million less than the no storage and mining scenarios. Keeping the approximately 3.398 mined bitcoins would yield approximately €315 million by May 17, 2025.

More detailed technical descriptions of the optimization algorithm, the storage simulation and the Bitcoin mining simulation can be found in Appendix A.

In conclusion, my historic analysis suggests a phased investment strategy for EDP: first prioritizing PV expansion to significantly reduce summer RL's, followed by investment in battery storage systems to improve energy utilization during periods of surplus and reduce the dependency on stored hydro capacity. Once these expansions were conducted, integrating bitcoin mining could further diversify revenue streams and maximize the economic utility of excess energy.

4.2 Forecasting Residual Load and Implications for EDP's Portfolio Resilience

This second analysis chapter provides a comprehensive assessment of projected future RL scenarios and evaluates their impact on EDP's portfolio resilience under different RCP’s and a constant / slight growth consumption increase. Using my predicted energy outputs for the different VRE sources based on the climate model CORDEX and the consumption forecasts, the analysis provides strategic insight into EDP's future energy landscape.

To make it short: Ceteris paribus (no growth, no additions) under all scenarios the RL would increase, while especially from 2039 on the gap widens between RCP 8.5 and the other scenarios, primarily caused by reduced hydrological outputs over time. Excluding hydro production one can see that RL volatility is slightly higher in RCP 8.5 while experiencing lower RL most of the years, due to increases in PV production, and EDP having their highest RL typically in the summer.

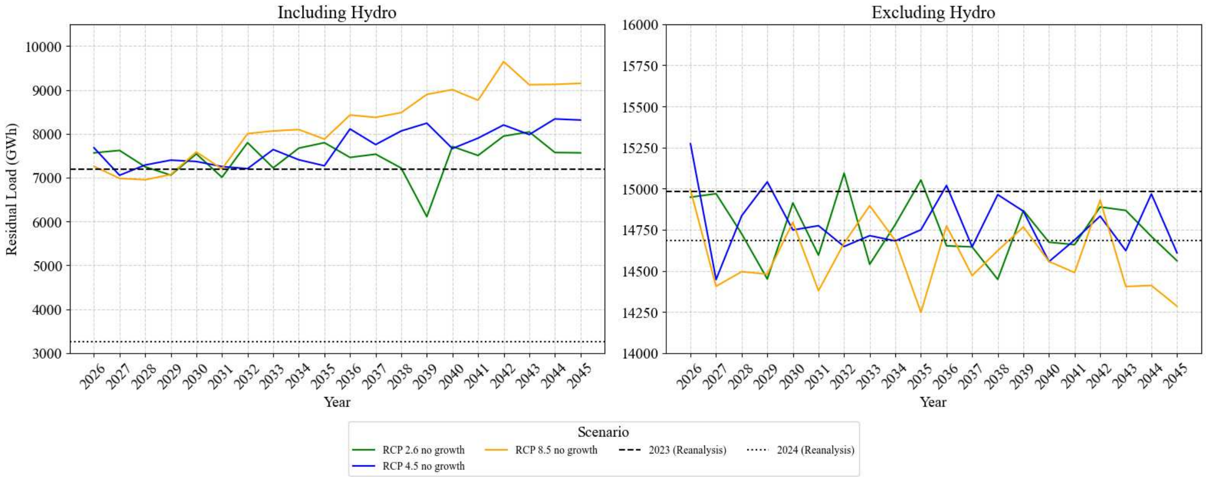


Figure 12: Development RL - Ceteris Paribus (incl. Hydro + excl. Hydro)

It has to be considered that EDP’s portfolio expansion foresees investing both further in PV and wind, with the plan to add another 1000 MW of PV capacity by the end of 2026. 2030, Portugal's national wind capacity will reach approximately 10.4 GW. Maintaining its current market share (19%), EDP's onshore wind capacity would grow to about 2 GW. Including approximately 0.4 GW of offshore wind (Gonçalves, 2025), EDP's total wind capacity could approach 2.4 GW. Accounting for that by adjusting the production values linearly by the new capacity relative to the old capacity, the RL levels decrease substantially. As I only have knowledge of planned additions until 2030, RL’s are increasing again n from 2031 on as consumption growth requires more additions, given EDP wants to keep their market share.

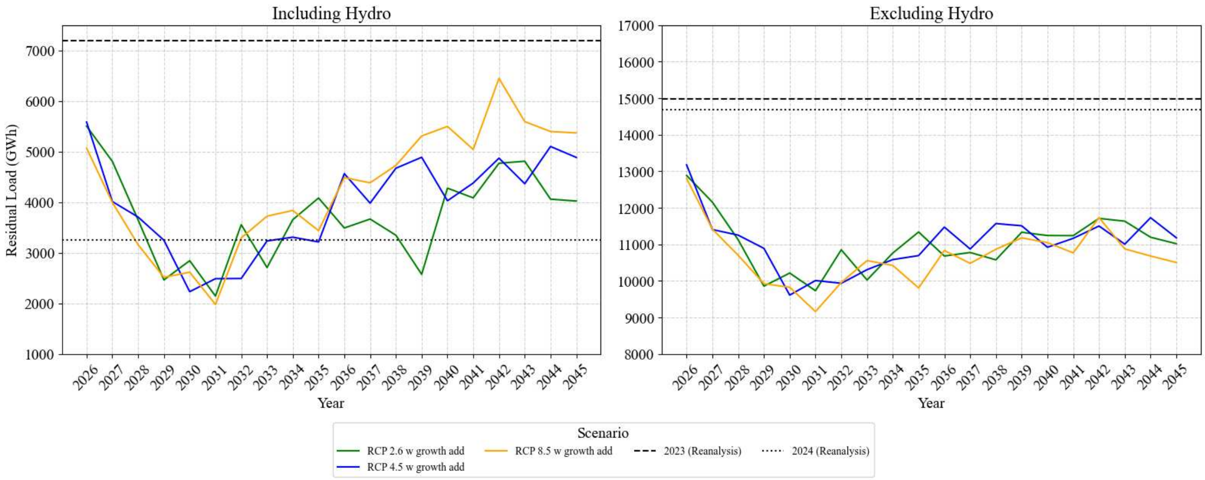


Figure 13: Development RL - Accounting for Portfolio Expansion and Consumption Growth

The most critical scenario, the "perfect storm", in my data visible for 2042 – having a reduction in hydropower generation of 31% until then, maximum average temperatures, and minimum wind generation - could push average daily RL above 17 GWh. This would represent an increase of 30% over historical averages and amount to daily costs of €1.3 million. This estimate is likely conservative as the inadequate temporal resolution (3/6 hourly) of the CORDEX climate data likely generally under-represents the volatility inherent in VRE generation, suggesting that actual volatility-and thus associated risks-are underestimated. The reduction of 2,601 GWh until 2045 in hydropower generation (RCP 8.5) corresponds to a value at risk of yearly €195 million at its peak, assuming an average market price of €75 per MWh for the underproduction. The value of risk at its peak for RCP 2.6 amounts to €29 million, in RCP 4.5 to €97 million.

On a yearly average, RL would be at 8025 GWh (RCP 2.6), 7570 GWh (RCP 4.5), and 8512 GWh (RCP 8.5) in 10-15 years, ceteris paribus, compared to the historical average of 5,360 GWh (without portfolio expansion/consumption growth). At RCP 8.5, this represents an increase of almost 60%.

Scenario	**Hydro**	**% RL**	**Peak 15min RL**	**Peak 4h RL**	**Peak DailyRL**	**Avg. Yearly RL**
RCP 2.6	yes	68.98%	0.63	9.48	45.35	3726
RCP 4.5	yes	70.71%	**0.64**	**9.60**	**46.88**	3963
RCP 8.5	yes	**72.25%**	0.63	9.36	46.60	**4295**
RCP 2.6	no	91.98%	**0.92**	**14.47**	**68.69**	11018
RCP 4.5	no	**92.33%**	**0.92**	14.46	68.22	**11040**
RCP 8.5	no	91.17%	0.90	14.21	67.23	10678

Table 8: KPI's by Scenario –Consumption Growth & Additions – Average 2026-2045

Assuming linear capacity growth from 2026 under no-growth scenarios, EDP could reduce times of RL by approximately 20% (RCP 2.6 and RCP 4.5) and 24% (RCP 4.5 and RCP 8.5). Also, levels achieved would not exceed RL’s already observed in the last years. Interestingly, while the time of RL is the highest in RCP 8.5, the inherent volatility as measured in RL peaks is most elevated in RCP 4.5, due to inferior PV performance compared to RCP 8.5.

Excluding hydropower, RL’s remain relatively consistent across climate scenarios, with slightly lower RLs in the RCP 8.5 scenario due to higher average wind and PV power. Under consumption growth, these deficits would increase by about 9% on average.

No matter CORDEX's limitations in temporal resolution, variability analyses show slightly increased volatility, in comparison to ERA5 (Table 9). Wind power demonstrates the highest volatility, with intramonthly / intrayearly increases under more severe climate scenarios. PV, less sensitive to climate variations, show stable volatility across scenarios. This was expected as *ssrd* and *strd*, which have the highest impact on power output didn’t show much variation between the three scenarios even though the temperature showed a clear increase over the years especially within RCP 8.5. Hydropower volatility is reduced due to methodological limitations in capturing variability through my forecast effectively cutting extreme scenarios.

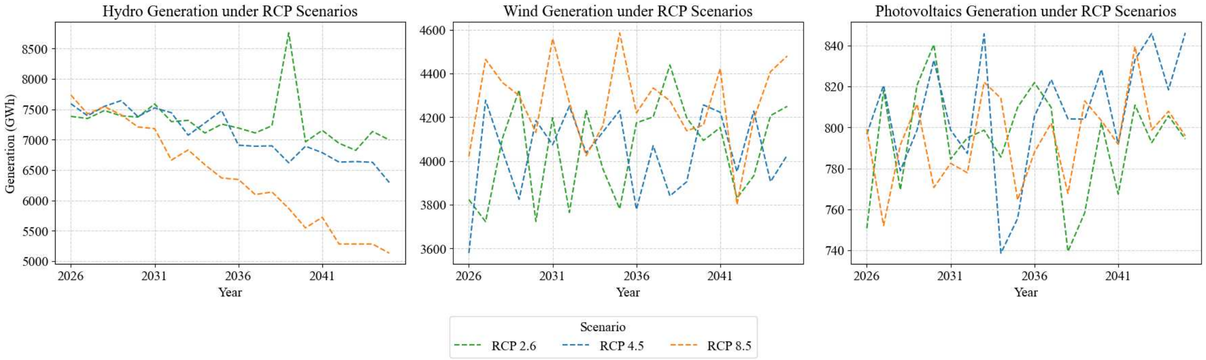


Figure 12: Expected VRE Generation 2026-2045

Although Russo et al. (2023) report a 30-45% increase in winter solar radiation under SSP5-8.5, this is not reflected in my RCP 8.5 PV outputs, which only increases by ~4.6% over two decades. Further, the increases happen more in spring than in winter. This could be due to the model's learned associations - e.g. winter conditions typically yielding low output - so it may not respond accurately to unprecedented high radiation winters. Manual corrections would be required to address this limitation.

Plant-level observations for PV show either stable or slightly increasing power output from 2025 to 2045 under all scenarios. This is aligned with the literature review in which it was assessed that PV poses the least physical climate risks.

Conversely, several wind farms show small to significant declines in output under severe climate scenarios, notably Alagoa de Cima (12 MW), highlighting potential regional vulnerabilities and differences, also confirming the findings in the literature review. Overall wind generation is most elevated in RCP 8.5 and is similar in RCP 2.6 and 4.5 both in terms of volatility and volume.

The financial implications of RL are significant; without capacity expansions and constant consumption, RL costs could range from €548 million per year under RCP 2.6 to €638 million under RCP 8.5 in 10 to 15 years, assuming expected average energy prices of €75/MWh (Energy Brainpool). Strategic capacity additions in VRE coupled with storage solutions, could significantly reduce these costs, underscoring the need for targeted investments to strengthen portfolio resilience.

The investment optimization again shows an initial preference for expanding PV capacity throughout all scenarios, primarily due to its low cost per kWh and strong correlation with elevated RL profiles during typical business hours - when PV generation closely matches consumption patterns.

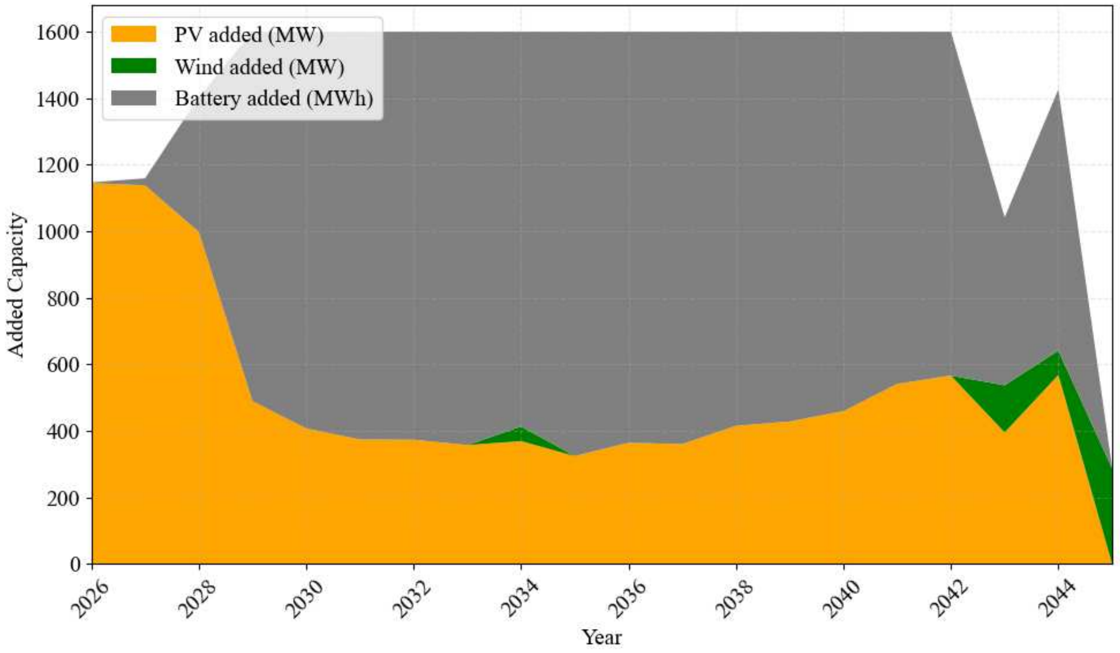


Figure 14: Optimized Annual Capacity Additions - RCP 4.5 - With Consumption Growth - €500 million annual investment

The optimization was performed again using a greedy hill-climbing algorithm, this time modified to give equal weight to both volatility reduction and absolute RL reduction over the entire planning horizon from the current point (t) to the end of the planning horizon (T) (see Appendix A). After adding roughly 2.2 GW of PV capacity, the algorithm then favors adding over 1 GW annually in parallel with further extending PV capacity. This makes sense as when PV approaches saturation, investment in energy storage becomes increasingly relevant, although currently storage solutions should primarily be attributed to wind and hydro sources rather than PV. This is because wind and hydro generation can often lead to periods of high energy production with relatively low immediate consumption, creating clear use cases for storage. Conversely, PV generation tends to occur during business hours when energy demand is naturally high, limiting significant storage needs to weekends or holidays. Marginal utility first decreases significantly after the PV additions and again after 2034. While expanding the consumption market share after the initial additions could increase future marginal utility gains, it would also likely alter the investment profile, shifting the focus from storage to production. Toward the later stages of the optimization horizon, minor additional wind capacity also becomes beneficial, supporting greater grid stability and diversification of the overall generation portfolio.

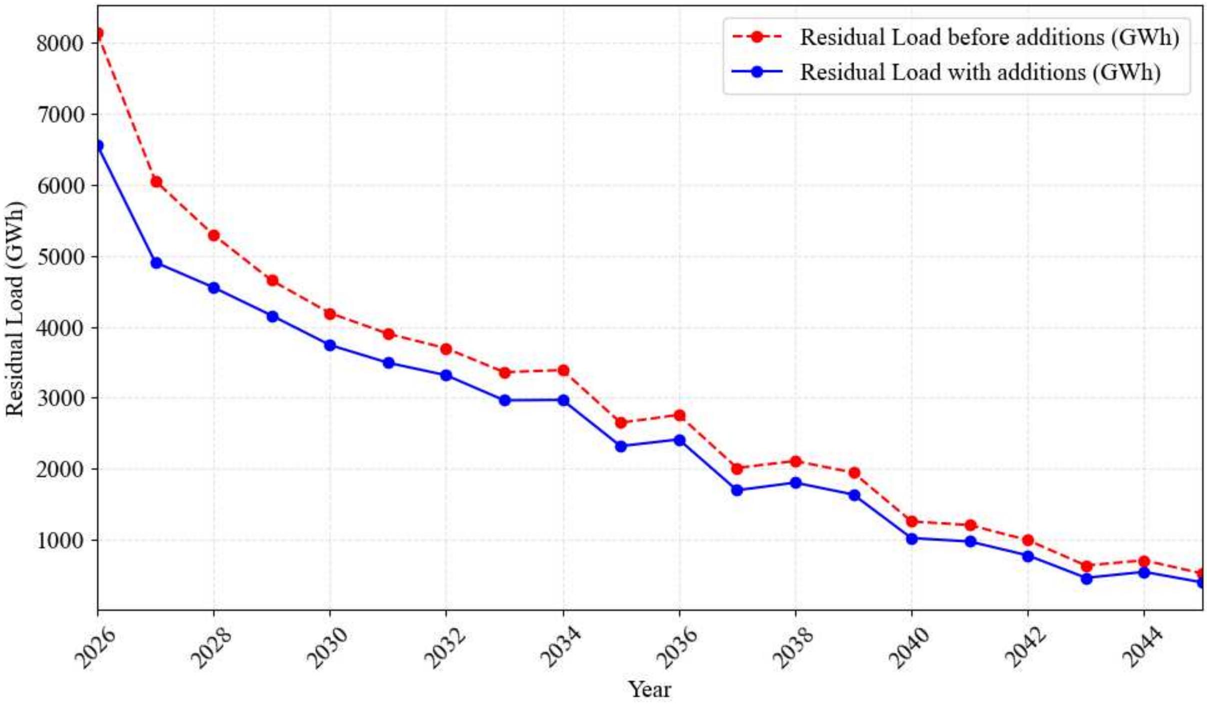


Figure 15: RL Reductions over time - RCP 4.5 - With Consumption Growth - €500 million annual investment

EDP’s current strategy of massively expanding their PV capacity and investing in storage is therefore in line with my recommendations. However, EDP should put more emphasis on expanding storage as the volatility in this assessment is likely underestimated and their strong dependence on hydro storage coupled with the reduced outputs will make them vulnerable. It has to be said that I only consider battery storage here, as this is the only storage type I can model properly. However, conceptual this is still applicable to other forms of storage as outlaid in the mitigation measures.

Last but not least practical limitations also need to be considered. Significant expansion of PV capacity requires adequate land availability, as PV installations require significantly more space than wind. In addition, additional operational constraints - such as permitting, local infrastructure conditions and grid integration factors - also play a critical role but are not explicitly captured in this optimization.

Extreme weather events, such as floods, heat waves or forest fires - which EDP has explicitly recognized as a financial risk in the range of €50 million to €100 million – could not be adequately modeled due to methodological, data and time constraints. In addition, additional operational risks identified by EDP, including energy loss, reduced efficiency, turbine failure, and asset damage from wildfires or extreme temperatures, were also beyond the scope of measurable or estimable impacts within the scope of this thesis.

Overall EDP's primary forecasted climate risks come from its significant dependence on hydropower. This dependence results in elevated expected risk levels over time and under increasingly severe climate scenarios. PV is the most promising addition to EDP’s existing portfolio. Once PV capacity reaches approximately 2.9 GW, the ideal strategy is to expand energy storage solutions to manage surplus energy production in parallel to expanding further PV and later also some wind capacity.

5 Conclusion

In conclusion, this thesis has thoroughly examined the potential impacts of climate change on EDP’s RL from 2023 to 2045, highlighting critical strategic insights that are essential for improving portfolio resilience in an increasingly renewable energy landscape. The analysis emphasizes the importance of proactive climate risk management, particularly considering EDP's substantial reliance on VRE.

My thesis strongly advocates prioritizing the expansion of PV capacity for EDP. PV’s growth potential, combined with its lower sensitivity to climate variability, low cost and consistent performance, as evidenced both by my analysis and literature, makes it an ideal candidate for strategic investment. Wind energy retains significant strategic value due to its complementary production profile. However, increased volatility in wind patterns underscores the necessity for greater geographic diversification and improved forecasting capabilities.

The thesis acknowledges limitations in the methodology, particularly regarding distributed PV generation, hydro power outputs and the assumption of full plant availability. These limitations likely lead to an underestimation of the true RL and especially its volatility and associated financial risks. This highlights the urgent need for more sophisticated, high-resolution reanalysis and climate projection datasets and studies that focus more on the variability of RL. Furthermore, the constraints posed by limited time and data access imply that more sophisticated forecasting models and optimization algorithms, especially for hydro assets, could substantially improve the accuracy and usefulness of future results.

Despite the constraints, my predictive models using reanalysis climate data produced promising results. The reanalysis benefits from high temporal resolution and robust validation processes. Advancements in artificial intelligence and ML methodologies likely significantly enhance the accuracy of climate modeling, enabling a better representation of volatility and variability - critical components for effective portfolio management and planning.

Financially, the thesis clearly illustrates the substantial economic implications of renewable energy management. Strategic investments in expanding renewable capacity, particularly PVs, and the timely integration of storage solutions are essential. Furthermore, incorporating flexible demand-side innovations, such as bitcoin mining, could provide additional economic benefits by efficiently curtailed renewable energy during periods of unfavorable market conditions.

Given the uncertainties in climate projections and the limitations of current modeling, EDP's immediate strategic priorities should emphasize developing more flexible generation assets, employing robust demand-side management strategies, and effective hedging mechanisms.

Future research should extend this analysis by optimizing grid efficiency and refining investment strategies based on improved data quality, particularly actual production outputs to evaluate the models on. Although PV investments currently appear to be the least risky option, it is important to acknowledge the potential underrepresentation of volatility in existing climate datasets and the decreasing reliability of hydroelectric storage in the face of projected drought conditions. Consequently, EDP's investment strategy should initially prioritize VRE expansion, gradually shifting towards balanced investment in storage solutions as VRE capacities stabilize.

Ultimately, this thesis introduces a novel, data-driven framework for RL management strategies tailored to EDP’s asset portfolio yet flexible enough to be generalized and applied by other utilities. This framework provides actionable financial insights and data-driven strategic solutions to improve resilience and profitability in a climate-uncertain future.

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Appendix A: Appendix

Technical Description – Storage Simulation:

Purpose: Models charging and discharging of a lossless battery over a net-load time series, respecting capacity limits and preserving state-of-charge (SoC).

Algorithm (vectorized/Numba versions):

1. Surplus Handling: When net load < 0, charges the battery up to its remaining capacity; any excess is exported.
2. Deficit Handling: When net load > 0, discharges the battery to meet demand; any remaining shortfall is imported.
3. State Tracking: Updates SoC at each timestep; returns the post-storage net-load series (for further aggregation) and, in fast variants, per-interval cost, SoC, and optimized exchange (rl_opt – residual load optimized).

Technical Description – Optimize Investment Mix – Historical Data:

Purpose: Greedily allocates a fixed investment budget across photovoltaics, wind, and battery capacity to minimize cumulative unmet demand (residual load) over a given time horizon.

Key Steps:

1. Cost Conversion: Converts USD-based cost schedules from World Energy Outlook 2024 stated policies scenarios to EUR, scaling per-unit (e.g. EUR/MW for PV and wind, EUR/kWh for battery).
2. Profile Assembly: Builds per-scenario, per-year supply (hydro, PV, wind) and demand time-series.
3. Marginal Benefit Calculation: For each candidate incremental investment (ΔMW of PV or wind, ΔGWh of battery), re-computes unmet demand across remaining years and divides demand reduction by cost to get a €/GWh "benefit rate."
4. Greedy Selection: Iteratively invests in the technology with the highest marginal benefit until the annual budget is exhausted or no positive returns remain.
5. Cumulative Tracking: Updates baseline capacities at each year's end and records additions and resulting deficits and volatility.

Technical Description – Bitcoin Mining Simulation:

Purpose: Integrates battery operation with opportunistic Bitcoin mining to maximize profit. Surplus energy is either stored, used to mine (if mining revenue > market sale), or sold; deficits are met via discharge or grid purchase.

Core Assumptions - Bitcoin:

1. Hashrate Proxy
   - Company Hashrate: assumed equal to equipment_budget / rig_cost_per_ths.
   - I take a per-TH/s cost of $24.56 per TH/s, based on the Bitmain Antminer S21 XP Immersion's market price of $7,368 for 300 TH/s ⇒ $7,368 ÷ 300 ≈ $24.56/TH/s
   - Network Hashrate (network_ths): Daily updated Total Hash Rate taken from blockchain.com
2. Power Efficiency
   - Rig Power Consumption (rig_power_per_ths): assumed 0.025 kW per TH/s (25 W/TH), which is conservative relative to leading ASICs like the Antminer S21+ at 16.5 W/TH and the S21 XP Immersion at 13.5 W/TH. This ensures that I consider that in the past two years these efficiencies were slightly lower than today's state of the art miners.
3. Block Rewards & Fees & Prices
   - Initial Block Reward: 50 BTC in 2009, halved every 210,000 blocks (~4 years).
   - Average Transaction Fees: set to 0.05 BTC per block, approximating long-term network averages.
   - Block Time: 600 s per block (10 min on average).
   - Prices: Hourly Bitstamp Euro Prices taken from cryptodatadownload.com

Core Assumptions – Energy Management:

1. Surplus Usage Decision:
   - Charge battery when price < average.
   - Mine using available hash rate if projected BTC revenue (based on network share, block reward, fees) exceeds sale value at current price.
   - Otherwise sell surplus on the market.
2. Deficit Management:
   - Discharge storage during high-price intervals to avoid expensive imports.
   - Purchase from grid at prevailing €/MW price for any remaining shortfall.

Technical Description – Optimize Investment Mix – Forecast

Purpose: Extends the historical-data optimizer to a multi-year planning framework. Allocates annual investment budgets in photovoltaics, wind, and battery capacity to minimize unmet demand and volatility across a defined future horizon, accounting for evolving costs and scenario-specific generation and demand profiles.

Key Steps:

1. Cost Interpolation & Conversion
    - Ingests USD-based cost schedules (e.g. from World Energy Outlook projections) for PV, wind, and battery.
    - Reindexes to cover every decision year, interpolates missing values, and converts to EUR unit costs (EUR/MW for PV & wind, EUR/kWh for battery).
2. Scenario & Profile Preparation
    - Parses sub-hourly time series into per-scenario, per-year arrays for hydro, PV, wind, and demand forecast (“no growth” vs. “with growth”) times average historical market share (37.7%)
    - Organizes these into a nested dictionary keyed by scenario name and year.
3. Yearly Budget Scheduling
    - Sets an annual investment that may grow at a specified rate.
    - For each decision year, uses that year’s budget to purchase capacity additions.
4. Deficit & Volatility Metrics
    - Defines a local helper deficit_for_year (f, cap_pv, cap_wind, cap_batt) that:
        - Scales generation profiles by current capacities.
        - Computes net-load (demand minus supply) at 15-minute resolution, applies storage dispatch via a Numba-accelerated routine, then sums remaining deficits.
        - Computes initial-year unmet demand and raw volatility (standard deviation of net deficits).
5. Multi-Year Marginal Benefit Calculation
    - For each candidate ΔMW (PV, wind) or ΔGWh (battery), simulates its impact on unmet demand across all remaining years.
    - Aggregates total demand reduction and divides by incremental cost to derive a €/GWh marginal benefit.

6. Greedy Investment Loop
   - Iteratively invests in the technology with the highest marginal benefit per euro.
   - Updates the remaining budget and current capacities, stopping when the budget is exhausted or no positive-benefit investments remain.
7. Cumulative Tracking & Results Assembly
   - At the end of each decision year:
   - Commits additions to the baseline capacity.
   - Records year-end residual deficits, volatility, percentage reductions, and cumulative capacities.

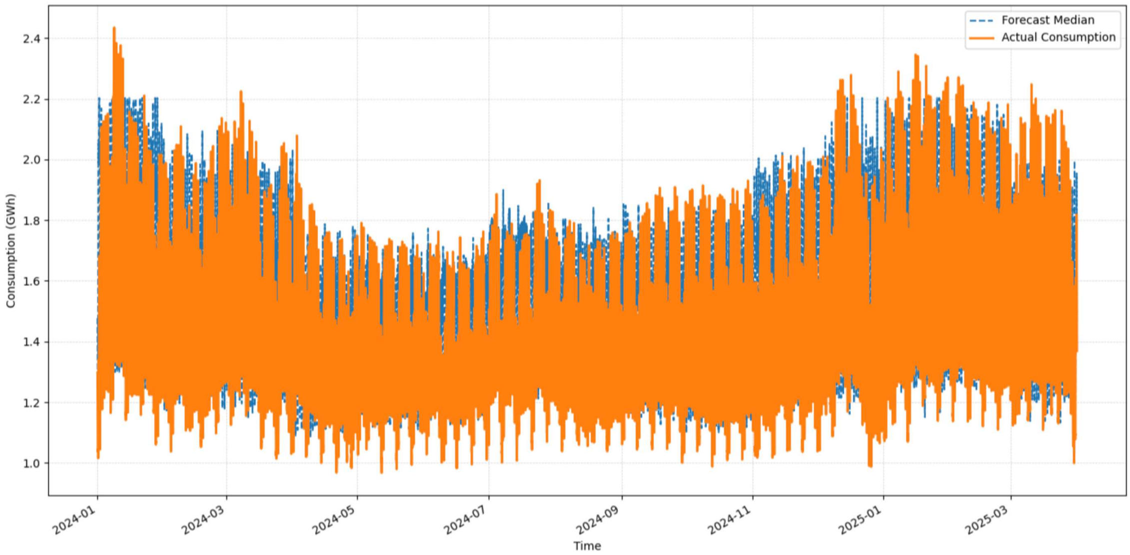


Figure 16: Consumption Forecast – Top-Down w. Montecarlo

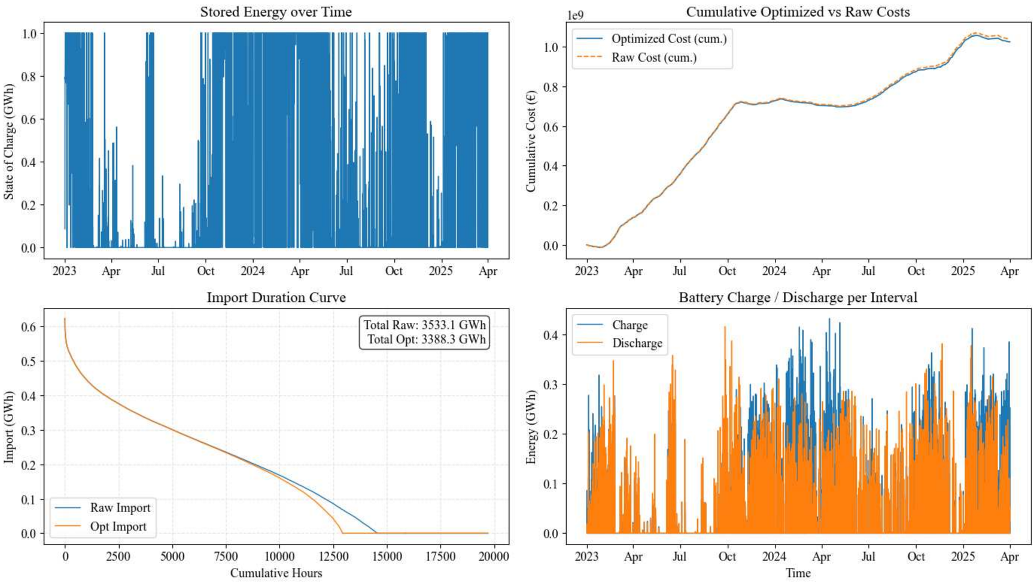


Figure 17: Graphic Summary of 1 GWh Simulated Storage

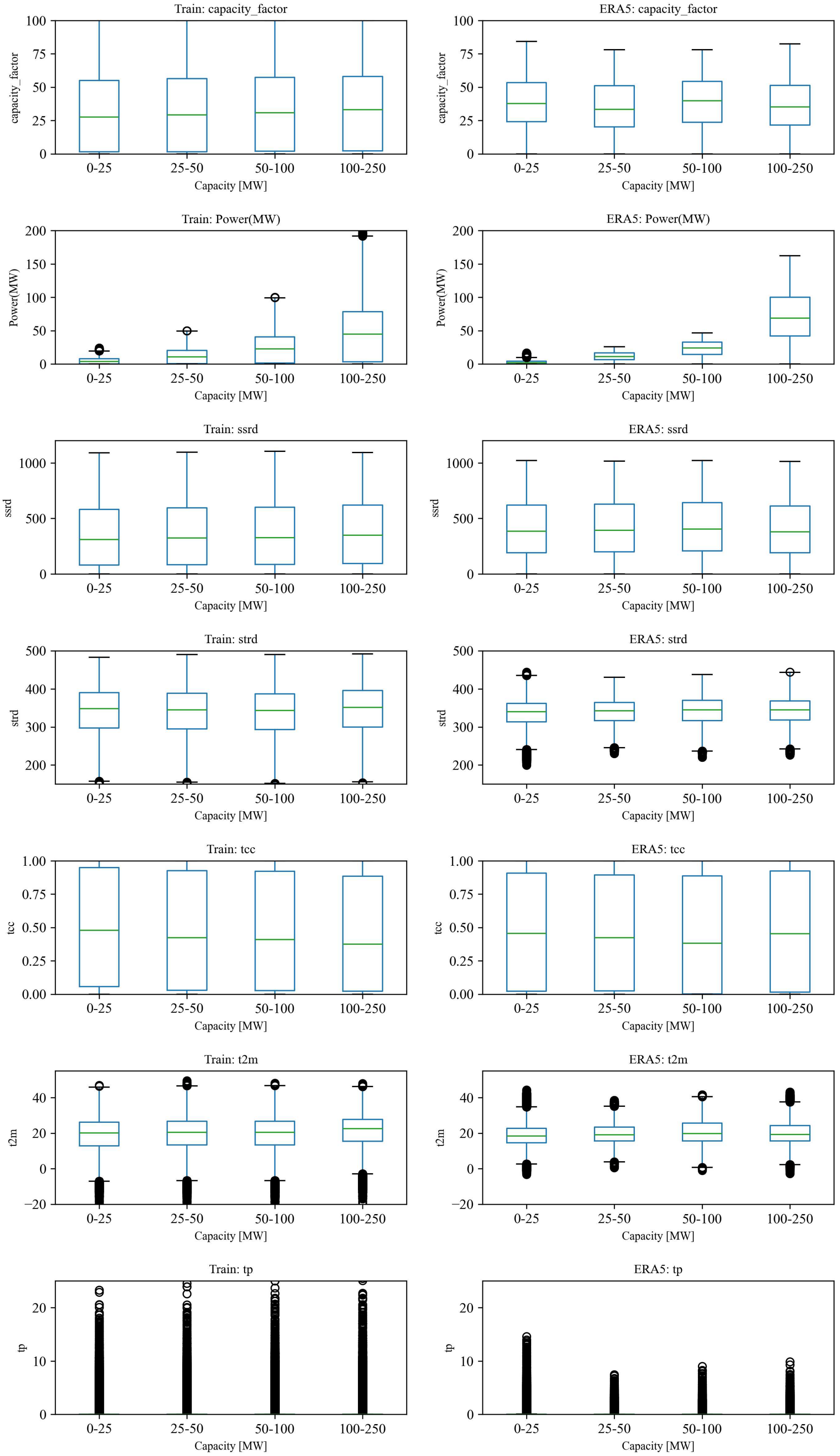


Figure 18: Variables Distributions Train & ERA5 Data Portugal

Figure 19: Variables Distributions CORDEX Data Portugal

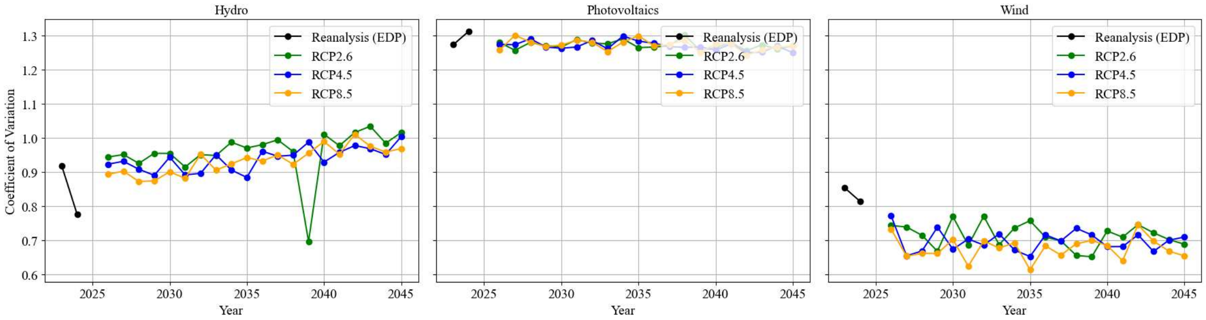


Figure 20: Annual Coefficient of Variation CORDEX by VRE Source

Source	Scenario	15min	1h	4h	8h	24h	48h	1w	30d	1y
Hydro	ERA 5	**0.23 (0.18)**	**0.92 (0.18)**	**3.37 (0.16)**	**6.38 (0.15)**	**16.27 (0.13)**	31.80 (0.13)	106.63 (0.12)	**433.88 (0.12)**	**2660.80 (0.06)**
	RCP 2.6	0.20 (0.15)	0.79 (0.15)	2.98 (0.14)	5.83 (0.14)	16.14 (0.13)	**31.99 (0.13)**	**109.96 (0.13)**	450.54 (0.12)	2205.61 (0.05)
	RCP 4.5	0.19 (0.14)	0.74 (0.14)	2.77 (0.13)	5.42 (0.13)	14.96 (0.12)	29.67 (0.12)	102.00 (0.12)	419.43 (0.11)	2036.13 (0.04)
	RCP 8.5	0.16 (0.12)	0.64 (0.12)	2.37 (0.11)	4.63 (0.11)	12.75 (0.10)	25.29 (0.10)	86.94 (0.10)	357.92 (0.10)	1764.05 (0.04)
Wind	ERA 5	0.08 (0.25)	0.30 (0.25)	1.16 (0.24)	2.22 (0.23)	5.69 (0.20)	10.06 (0.17)	23.84 (0.12)	59.72 (0.07)	937.65 (0.09)
	RCP 2.6	**0.08 (0.28)**	**0.33 (0.28)**	**1.30 (0.26)**	**2.50 (0.26)**	**6.29 (0.22)**	**11.07 (0.19)**	**26.63 (0.13)**	66.29 (0.08)	1232.69 (0.12)
	RCP 4.5	0.08 (0.27)	0.32 (0.27)	1.26 (0.26)	2.42 (0.25)	6.07 (0.21)	10.75 (0.19)	25.96 (0.13)	**70.67 (0.08)**	1225.43 (0.12)
	RCP 8.5	0.08 (0.27)	0.33 (0.27)	1.29 (0.27)	2.48 (0.26)	6.24 (0.22)	10.96 (0.19)	26.59 (0.13)	67.84 (0.08)	**1290.95 (0.12)**
Photo voltaic	ERA 5	0.02 (0.16)	0.08 (0.16)	0.32 (0.15)	0.61 (0.14)	0.67 (0.05)	1.28 (0.05)	4.24 (0.05)	17.26 (0.04)	198.23 (0.04)
	RCP 2.6	0.03 (0.21)	0.11 (0.21)	0.43 (0.20)	0.82 (0.19)	**0.87 (0.07)**	**1.67 (0.06)**	5.44 (0.06)	**22.16 (0.06)**	239.21 (0.05)
	RCP 4.5	**0.03 (0.22)**	**0.12 (0.22)**	**0.44 (0.20)**	**0.84 (0.19)**	**0.87 (0.07)**	**1.67 (0.06)**	5.46 (0.06)	22.06 (0.06)	**244.07 (0.05)**
	RCP 8.5	0.03 (0.21)	0.11 (0.21)	0.43 (0.20)	0.82 (0.19)	**0.87 (0.07)**	**1.67 (0.06)**	**5.49 (0.06)**	21.99 (0.06)	239.66 (0.05)

Table 9: Variability of VRE from ERA 5 2020-2025 vs. RCP 2035-2045 as measured in STD (MaxCap CV) in GWh

Your request	
Request ID	4784e9ae-36fc-4f55-997b-b813f3f2fd84 Open request form
Domain	Europe
Experiment	RCP 8.5
Horizontal resolution	0.11 degree x 0.11 degree
Temporal resolution	6 hours
Variable	10m u-component of the wind, 10m v-component of the wind
Global climate model	CNRM-CERFACS-CM5 (France)
Regional climate model	CNRM-ALADIN63 (France)
Ensemble member	r1i1p1
Start year	2023
End year	2024

Figure 21: Cordex Request Form

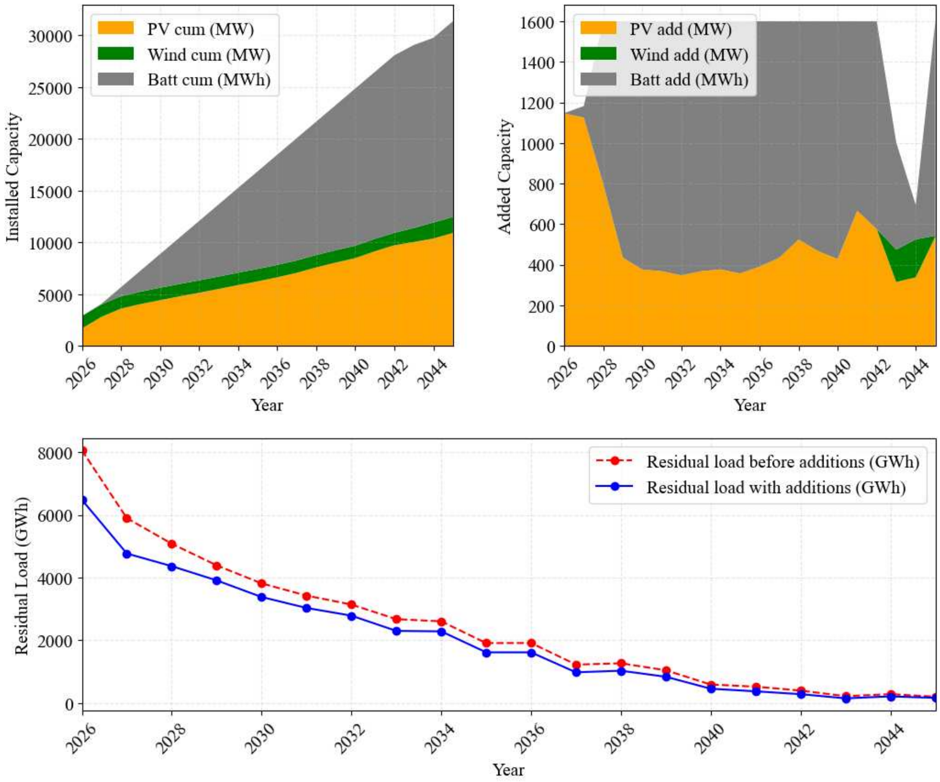


Figure 22: Optimization on Forecasted RL (RCP 4.5, No Growth, 500 million annually, Constant Market Share)

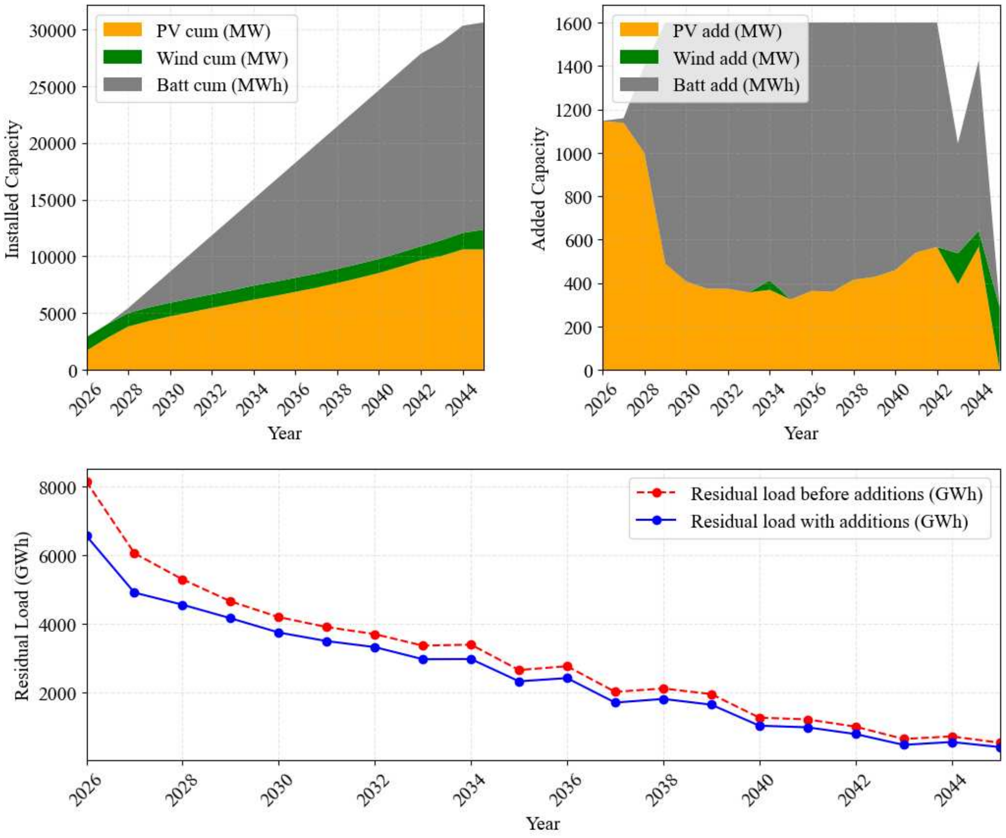


Figure 23: Optimization on Forecasted RL (RCP 4.5, With Growth, 500 million annually, Constant Market Share)

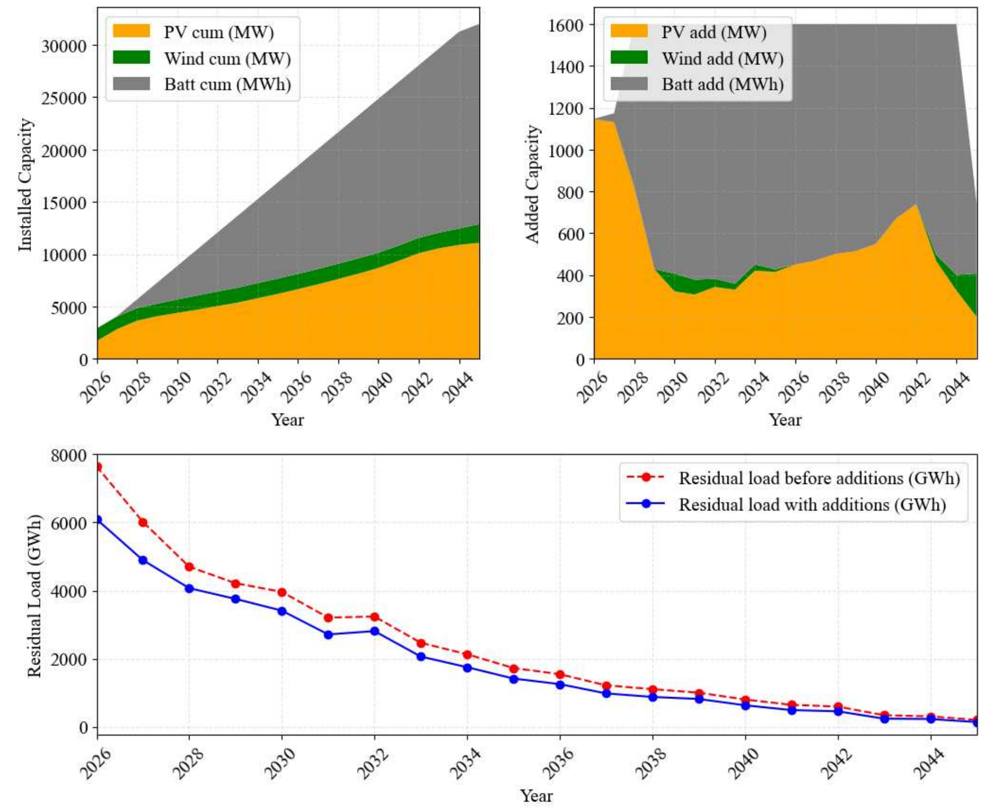


Figure 24: Optimization on Forecasted RL (RCP 8.5, No Growth, 500 million annually, Constant Market Share)

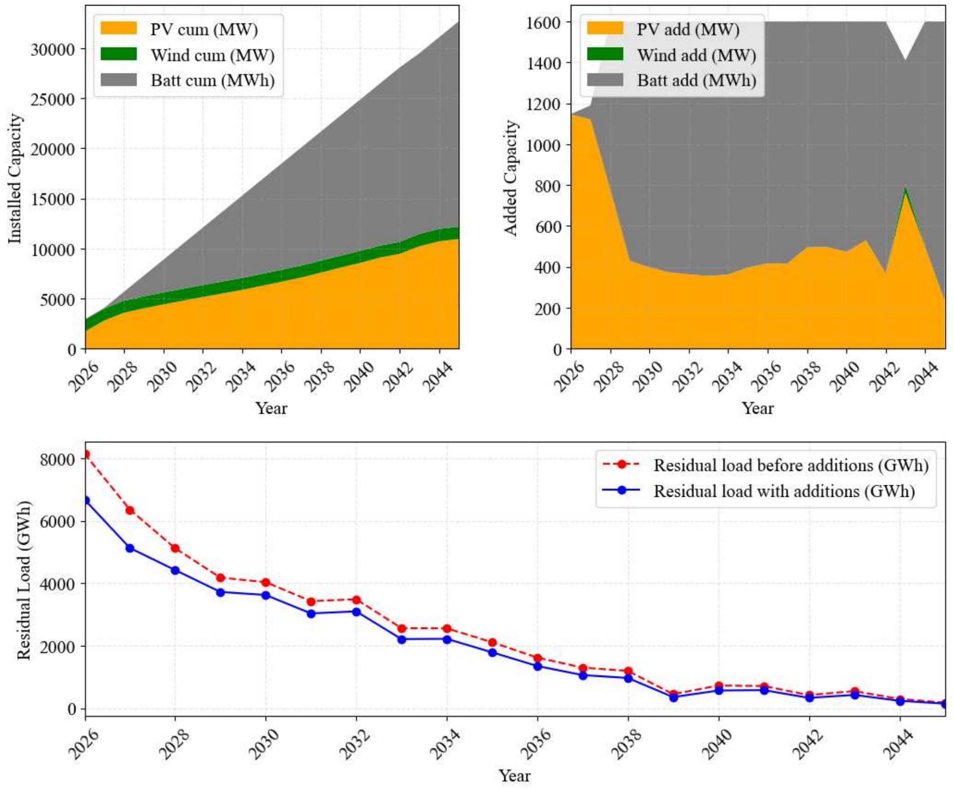


Figure 25: Optimization on Forecasted RL (RCP 2.6, No Growth, 500 million annually, Constant Market Share)

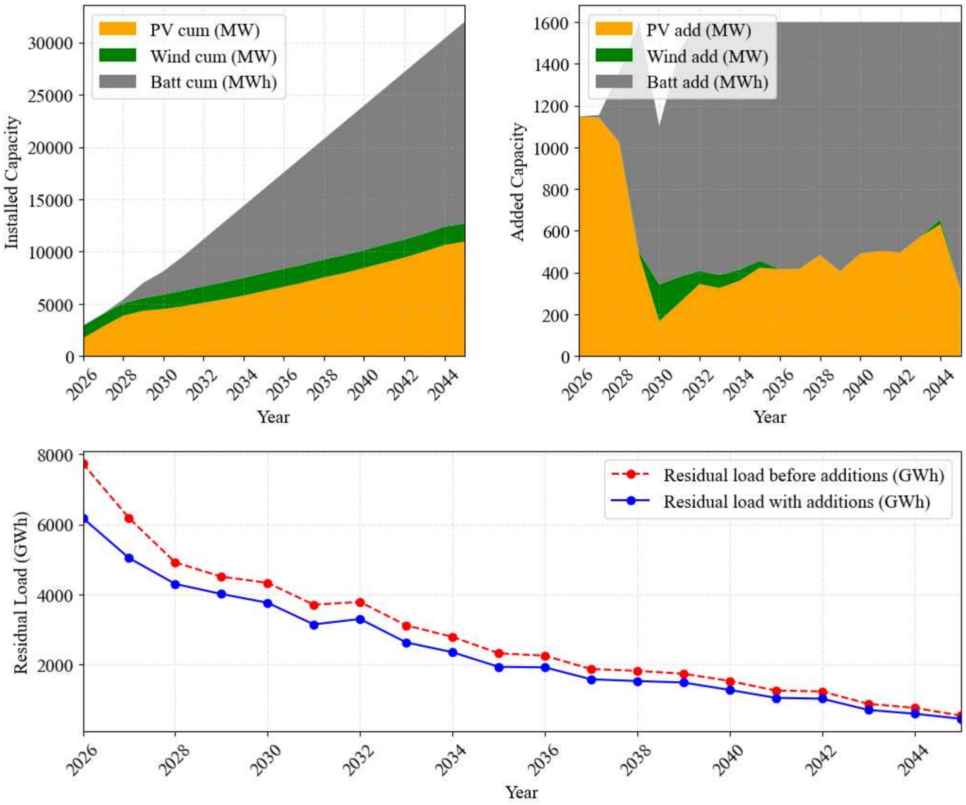


Figure 26: Optimization on Forecasted RL (RCP 8.5, With Growth, 500 million annually, Constant Market Share)

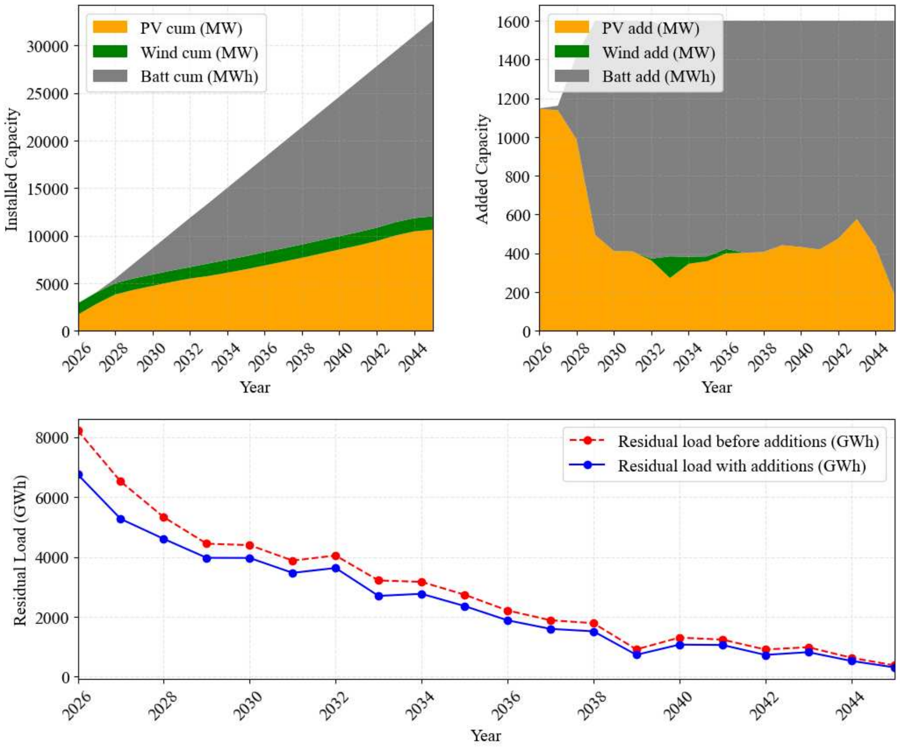


Figure 27: Optimization on Forecasted RL (RCP 2.6, With Growth, 500 million annually, Constant Market Share)

Breakdown of Production_20100101_20250331.xlsx

Data sourced from REN, required as check and balance / verification of exports & imports

Variable	Description
Date and Time	Current Date and Time in yyyy-mm-dd hh:mm:ss ~ 15min
Hydro	Nationwide Hydro Output in MW
Wind	Nationwide Wind Output in MW
Solar	Nationwide Solar Output in MW
Biomass	Nationwide Biomass Output in MW
Wave	Nationwide Wave Output in MW
Natural Gas	Nationwide Natural Gas Output in MW
Coal	Nationwide Coal Output in MW
Other Thermal	Nationwide Other Thermal Output in MW
Imports	Energy Imports in MW
Exports	Energy Exports in MW
Pumping	Pumped Hydro in MW
Battery Injection	Injected Battery Capacity in MW
Battery Consumption	Consumed Battery Capacity in MW
Consumption	Consumption in MW

consumo-total-nacional.xlsx

15min consumption data to estimate EDP's share of consumption from E-Redes

Variable	Description
Date/Time	Current Date and Time in dd Month yyyy hh:mm
Day	Current day (dd)
Month	Current month (mm)
Year	Current year (yyyy)
Date	Current Date in dd Month yyyy
Hour	hh:mm
Low Voltage (kWh)	Low Voltage Consumed Power
Medium Voltage (kWh)	Medium Voltage Consumed Power
High Voltage (kWh)	High Voltage Consumed Power
Very High Voltage (kWh)	Very High Voltage Consumed Power (Industrial Clients)
Total (kWh)	Sum of Low, Medium, High & Very High Voltage

energia-injetada-na-rede-de-distribuicao.xlsx

15min energy injected into the distribution network from E-Redes

Variable	Description
Date/Time	Current Date and Time in dd Month yyyy hh:mm
Day	Current day (dd)
Month	Current month (mm)
Year	Current year (yyyy)
Date	Current Date in dd Month yyyy
Hour	hh:mm
Other Technologies (kWh)	Output of other Technologies than VRE
Hydro (kWh)	Hydro Output in kWh
Photovoltaics (kWh)	Photovoltaics Output in kWh
Wind (kWh)	Wind Output in kWh
Cogeneration (kWh)	Combined Heat and Power Plant Power Output

produzida-total-nacional.xlsx

Shows the amount energy bought at the market / produced within the country from E-Redes

Variable	Description
Date/Time	Current Date and Time in dd Month yyyy hh:mm
Total (kWh)	Sum of Market (kWh) & Special Regime (kWh)
Day	Current day (dd)
Month	Current month (mm)
Year	Current year (yyyy)
Date	Current Date in dd Month yyyy
Hour	hh:mm
Market (kWh)	Amount of Energy bought at the Market
Special Regime (kWh)	Special regime production (SRP) production activity subject to special legal regimes, such as the production of electricity through co-generation and renewable resources in kWh

Plants_EDP.xlsx

Aggrecated, collected data of EDP's plants

SOURCES:

Sheet containing the sources

ALL:

Sheet containing all plants

Variable	Description
Plant Name	Name of Production Site
Type	hydro, solar or wind
Total Capacity (MW)	Total Plant Capacity in MW
latitude	Exact Latitude of Plant
longitude	Exact Longitude of Plant

Hydrogen:

Sheet containing the planned Hydrogen plants

Variable	Description
Plant Name	Name of Production Site
Type	hydrogen
Total Capacity (MW)	Total Plant Capacity in MW
COD	Commercial Operation Date

Hydro:

Sheet containing all obtained Hydropower Plants

Variable	Description
Plant Name	Name of Production Site
Type 1	hydro
Type 2	hydro - water-pumped-storage or hydro - water-storage or hydro - run-of-the-river or hydro- small-hydro
Sold	Plant sold to different energy provider (6)
Total Capacity (MW)	Total Plant Capacity in MW
Average Annual Productivity (GWh)	Average annual output as stated by EDP
Total Storage (hm3)	Storage in hm3 if available for storage, pumped storage plants
latitude	Exact Latitude of Plant
longitude	Exact Longitude of Plant
Link	Link to Plant on openstreetmap

Wind:

Variable	Description
ID	Unique Identifier of Windfarm for simplified later processing
Area	Area in which the Windfarm is located
Plant Name	Name of Production Site
latitude	Exact Latitude of Plant
longitude	Exact Longitude of Plant
Total Capacity (kW)	Total Plant Capacity in kW
Total Capacity (MW)	Total Plant Capacity in MW
Number of Turbines	-
Hub Height (m)	Height of the wind turbine
Turbine Model	Specifying the Type and Manufacturer
Commissioning Date	Year specifying the commercial operation date
Link	Link to Plant on openstreetmap

Photovoltaic:

Variable	Description
Plant Name	Name of Production Site
Type 1	solar
Type 2	solar - photovoltaic
Sold	Plant sold to different energy provider (0)
Activated	Exact Activation Date if available
capacity_MW	Total Plant Capacity in MW
Estimated Annual Production GWh	-
latitude	Exact Latitude of Plant
longitude	Exact Longitude of Plant
Link	Link to Plant on openstreetmap

icap-graph-price-data-2020-01-01-2025-02-13.csv

Data containing the daily ETS prices, obtained from ICAP

Variable	Description
Date	Current Date in yyyy-mm-dd
Exchange rate EUR/EUR	-
Exchange rate EUR/USD	solar - photovoltaic
Market Currency	EUR
Primary Market	Price in EUR

Day-ahead Market Prices_20230101_20250331.csv

Data required to quantify historical residual load in financial terms from REN

Variable	Description
Date	Current Date in yyyy-mm-dd
Hour	Hour of the day (1-24)
Portugal	Market Price in €/MW
Spain	Market Price in €/MW

Hash-Rate.json

Hashrate required for the Bitcoin mining simulation (blockchain.com)

Variable	Description
timestamp	-
Metric1: hash-rate	Current Date in yyyy-mm-dd
Metric2: market-price	Current Market Price of Bitcoin in US$

Bitstamp_BTCEUR_1h.csv

Bitcoin data required to quantify the bitcoins mined in EUR if sold directly at the market. Price used for calculations is the average of open/close. cryptodatadownload.com

Variable	Description
unix	Date unix as number
date	Current Date in mm/dd/yy hh:mm (hourly)
symbol	BTC/EUR
open	Opening Price
high	Session High
low	Session Low
close	Closing Price
Volume BTC	Volume BTC traded
Volume	BTC Volume measured in EUR

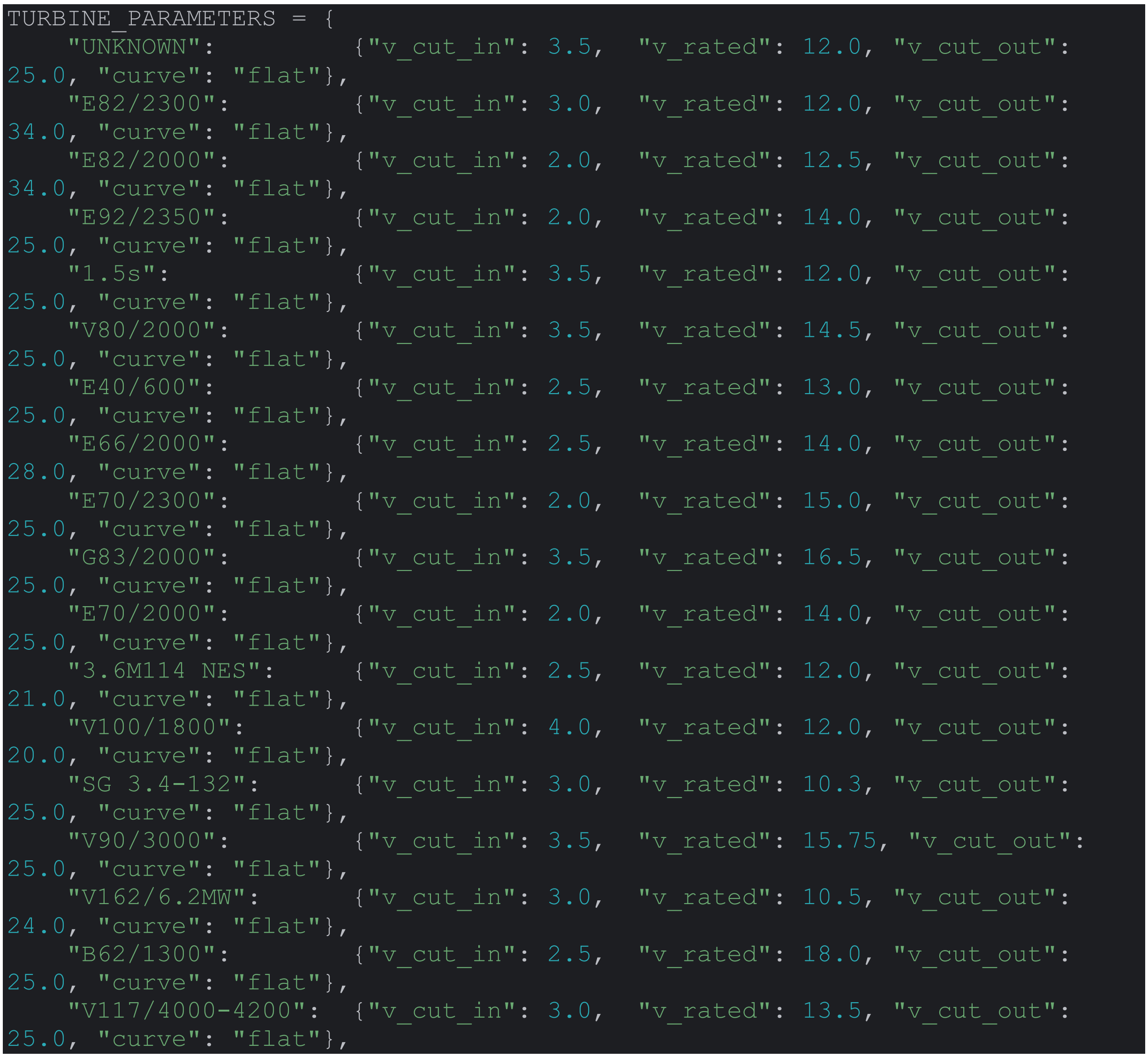
ML_Consumption_Data.csv

Consumption shares tabularized as obtained from 25 ERSE PDF's (Boletim do Mercado Liberalizado de Eletricidade - mes yyyy).

Variable	Description
Month	Month yyyy (e.g Jan 2023)
ML Consumo (GWh)	Country Wide Monthly Electricity Consumption
Overall EDP (%)	EDP Market Share e.g 40.4
Δ to month of previous year (%)	Change y-o-y

Collected Wind Turbines Data:

Wind Turbine Power Output Curve data obtained from respective manufacturers.



```
TURBINE_PARAMETERS = {
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    "E82/2300":        {"v_cut_in": 3.0,  "v_rated": 12.0, "v_cut_out":
34.0, "curve": "flat"},
    "E82/2000":        {"v_cut_in": 2.0,  "v_rated": 12.5, "v_cut_out":
34.0, "curve": "flat"},
    "E92/2350":        {"v_cut_in": 2.0,  "v_rated": 14.0, "v_cut_out":
25.0, "curve": "flat"},
    "1.5s":            {"v_cut_in": 3.5,  "v_rated": 12.0, "v_cut_out":
25.0, "curve": "flat"},
    "V80/2000":        {"v_cut_in": 3.5,  "v_rated": 14.5, "v_cut_out":
25.0, "curve": "flat"},
    "E40/600":         {"v_cut_in": 2.5,  "v_rated": 13.0, "v_cut_out":
25.0, "curve": "flat"},
    "E66/2000":        {"v_cut_in": 2.5,  "v_rated": 14.0, "v_cut_out":
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    "E70/2300":        {"v_cut_in": 2.0,  "v_rated": 15.0, "v_cut_out":
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    "G83/2000":        {"v_cut_in": 3.5,  "v_rated": 16.5, "v_cut_out":
25.0, "curve": "flat"},
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    "SG 3.4-132":      {"v_cut_in": 3.0,  "v_rated": 10.3, "v_cut_out":
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    "V90/3000":        {"v_cut_in": 3.5,  "v_rated": 15.75, "v_cut_out":
25.0, "curve": "flat"},
    "V162/6.2MW":      {"v_cut_in": 3.0,  "v_rated": 10.5, "v_cut_out":
24.0, "curve": "flat"},
    "B62/1300":        {"v_cut_in": 2.5,  "v_rated": 18.0, "v_cut_out":
25.0, "curve": "flat"},
    "V117/4000-4200":  {"v_cut_in": 3.0,  "v_rated": 13.5, "v_cut_out":
25.0, "curve": "flat"},
```

```
    "MM92/2050":       {"v_cut_in": 3.5,  "v_rated": 13.0, "v_cut_out":
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    "G80/2000":        {"v_cut_in": 3.5,  "v_rated": 15.0, "v_cut_out":
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    "E48/600":         {"v_cut_in": 2.0,  "v_rated": 13.0, "v_cut_out":
25.0, "curve": "flat"},
    "E40/500":         {"v_cut_in": 2.5,  "v_rated": 13.5, "v_cut_out":
25.0, "curve": "flat"},
    "V42/600":         {"v_cut_in": 4.5,  "v_rated": 16.0, "v_cut_out":
25.0, "curve": "flat"},
    "Ecotecnia 74":    {"v_cut_in": 3.0,  "v_rated": 13.0, "v_cut_out":
25.0, "curve": "flat"},
    "80 1.6":          {"v_cut_in": 3.0,  "v_rated": 12.5, "v_cut_out":
25.0, "curve": "fade_out", "fade": 0.05}
}
```

Solar Train Data

Solar Power Data for Integration Studies from the National Renewable Energy Laboratory (NREL).

5-minute solar power output data for approximately 6,000 UPV/DPV (Utility scale PV) simulated PV plants used to train PV machine learning models. Only UPV Actual was used.

The naming convention of the state-wise solar power data (.csv files) from the Solar Integration Studies is as follows:

Data Type_Latitude_Longitude_Weather Year_PV Type_CapacityMW_Time Interval _Min.csv

Data Type:

- Actual: Real power output
- DA: Day ahead forecast

HA4: 4 hour ahead forecast

Weather Year: The PV data is based on the particular year's known weather condition.

PV Type:

- UPV: Utility scale PV
- DPV: Distributed PV

Note: The practical difference between UPV and DPV is in the configurations (UPV has single axis tracking while DPV is fixed tilt equaling to latitude) and the smoothing (both are run through a low-pass filter, the DPV will have more of the high frequency variability smoothed out).

Capacity: Installed capacity in MW

Time Interval: PV generation data reading interval in minutes.

Variable	Description
LocalTime	Current Time in mm/dd/yy hh:mm
Power (MW)	Power Output in MW

Appendix B: Code

All the manual obtained data & the full code, including the analysis, data pipeline and Jupyter Notebooks can be found here

https://github.com/DanielRauser/EDP-Thesis-Daniel-Rauser

Exemplary CDO Homebrew Code to merge Wind Data

```
cdo cat \

  uas_EUR-11_CNRM-CERFACS-CNRM-CM5_rcp85_r1i1p1_CNRM-ALADIN63_v2_6hr_202301010600-202401010000.nc \

  uas_EUR-11_CNRM-CERFACS-CNRM-CM5_rcp85_r1i1p1_CNRM-ALADIN63_v2_6hr_202401010600-202501010000.nc \

  uas_cat.nc

cdo cat \

 vas_EUR-11_CNRM-CERFACS-CNRM-CM5_rcp85_r1i1p1_CNRM-ALADIN63_v2_6hr_202301010600-202401010000.nc \

 vas_EUR-11_CNRM-CERFACS-CNRM-CM5_rcp85_r1i1p1_CNRM-ALADIN63_v2_6hr_202401010600-202501010000.nc \

 vas_cat.nc

cdo merge uas_cat.nc vas_cat.nc wind_2023_2024_rcp_8_5.nc
```