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PRICE FORECASTING FOR GREEK ELECTRICITY MARKET

D I P L O M A T H E S I S

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PREFACE

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ABSTRACT

PRICE FORECASTING FOR GREEK ELECTRICITY MARKET

AIKATERINI BAMPAGIOURI **PANAGIS, VOVOS**

Peak price forecasting in the balancing energy market is vital for modern power systems. This dissertation addresses the challenge of predicting the timing and magnitude of daily peak imbalance prices in the Greek electricity market. The motivation stems from the Greek system's increasing volatility due to high renewable penetration and the need for system operators and market participants to anticipate extreme balancing costs. A regression-based forecasting methodology was developed, leveraging physically meaningful predictors such as net load forecast changes, wind and solar forecast errors etc to estimate when the highest balancing energy price will occur each day and how high that price will be. The model was implemented in MATLAB and produces 15-minute interval price forecasts, effectively capturing the daily price spike dynamics. Over a full year of testing, the tool demonstrated promising accuracy: it could predict approximately 58% of the variability in peak price timing ($R^2 \approx 0.58$) and achieved a normalized mean absolute error (nMAE) of about 25% in peak price magnitude predictions. In practical terms, the typical forecast error was on the order of 100 €/MWh for peak prices that averaged 400 €/MWh, with the median error around 90 €. The model reliably pinpointed the peak's timing, often exact to the hour or 15-minute block and provided a reasonable estimate of the peak price's value. These results confirm that a relatively interpretable regression model can yield foresight in the highly volatile balancing market.

The findings are useful for both market participants and system operators. Traders, generators, and energy storage or demand response operators can utilize the forecast to optimize their bids and operational schedules, ensuring they either capitalize on price spikes or hedge against costly imbalances. For the transmission system operator (IPTO), better anticipation of peak balancing prices means improved reserve scheduling and risk mitigation, contributing to overall system reliability and cost efficiency. An innovative aspect of this work is its integrated view of the balancing arena: the study not only forecasts energy market spikes (mFRR) but simultaneously considers the aFRR reserve market. By examining reserve capacity deployment and its relationship to price surges, the dissertation offers a holistic perspective – aligning with the fact that in Greece's balancing mechanism, energy and reserve markets are interlinked. This combined analysis enhances the robustness of the approach, as forecasting the energy spike inherently aids in understanding reserve stress conditions.

Future development possibilities emerging from this research include incorporating advanced machine learning models to capture non-linear patterns, using real-time data feeds for dynamic forecast updates, and extending the framework to probabilistically predict extreme events with confidence intervals. Additionally, expanding the scope to forecast other related metrics (such as separate upward/downward prices) would further increase the tool's value to the market.

The very chapter of the dissertation contributed to this comprehensive study is detailed below. Chapter 1introduced the balancing market context in Greece and formulated the forecasting problem, emphasizing its importance for market efficiency and stability. Chapter 2 detailed the design and operation of the Greek electricity markets (day-ahead, intraday, and balancing), providing foundational knowledge of how imbalance pricing works and highlighting historical challenges. Chapter 3 reviewed relevant literature on electricity price forecasting and imbalance markets, drawing lessons from previous studies and identifying gaps addressed by this work. Chapter 4 presented the methodology and model development, describing the regression approach, the selection of predictors, and the rationale for focusing on peak price timing and magnitude. Chapter 5 focused on how the forecasting model was implemented and assessed using real historical data. It presented results across several statistical measures, including R^2, RMSE, and nMAE, and examined specific cases that illustrated the model's strengths and limitations. The concluding chapter, chapter 6, drew together the main conclusions, outlined how this work might be extended and offered some personal reflections on the research methodology followed. Overall, this dissertation has shown that forecasting extreme balancing prices, especially their timing, is meaningful and achievable in the Greek electricity market. The approach delivers insights that can help market participants and system operators anticipate costly balancing prices and operate more effectively in an increasingly complex energy landscape.

ΕΚΤΕΤΑΜΕΝΗ ΕΛΛΗΝΙΚΗ ΠΕΡΙΛΗΨΗ

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Η πρόβλεψη των τιμών αιχμής στην αγορά ενέργειας εξισορρόπησης είναι ζωτικής σημασίας για τα σύγχρονα συστήματα ηλεκτρικής ενέργειας. Η παρούσα διατριβή ασχολείται με την πρόκληση της πρόβλεψης του χρόνου και του μεγέθους των ημερήσιων τιμών αιχμής εξισορρόπησης στην ελληνική αγορά ηλεκτρικής ενέργειας. Το κίνητρο προκύπτει από την αυξανόμενη μεταβλητότητα του ελληνικού συστήματος λόγω της υψηλής διείσδυσης των ανανεώσιμων πηγών ενέργειας και την ανάγκη των διαχειριστών του συστήματος και των συμμετεχόντων στην αγορά να προβλέπουν το ακραίο κόστος εξισορρόπησης. Αναπτύχθηκε μια μεθοδολογία πρόβλεψης με βάση την παλινδρόμηση, η οποία αξιοποιεί φυσικώς σημαντικούς προγνωστικούς δείκτες όπως αλλαγές στις προβλέψεις του καθαρού φορτίου, σφάλματα πρόβλεψης παραγωγής αιολικών και φωτοβολταικών κ.α για να εκτιμηθεί πότε θα εμφανιστεί η υψηλότερη τιμή ενέργειας εξισορρόπησης κάθε μέρα και πόσο υψηλή θα είναι αυτή η τιμή. Το μοντέλο υλοποιήθηκε σε MATLAB και παράγει προβλέψεις τιμών σε διαστήματα 15 λεπτών, αποτυπώνοντας αποτελεσματικά τη δυναμική της ημερήσιας αιχμής των τιμών. Κατά τη διάρκεια ενός ολόκληρου έτους δοκιμών, το εργαλείο επέδειξε πολλά υποσχόμενη ακρίβεια: μπορούσε να προβλέψει περίπου το 58% της μεταβλητότητας του χρονισμού των τιμών αιχμής ($R^2 \approx 0,58$) και πέτυχε κανονικοποιημένο μέσο απόλυτο σφάλμα (nMAE) περίπου 25% στις προβλέψεις του μεγέθους των τιμών αιχμής. Σε πρακτικούς όρους, το τυπικό σφάλμα πρόβλεψης ήταν της τάξης των 100 €/MWh για τιμές αιχμής που ήταν κατά μέσο όρο 400 €/MWh, με το διάμεσο σφάλμα γύρω στα 90 €. Το μοντέλο προσδιόρισε αξιόπιστα το χρόνο της αιχμής, συχνά με ακρίβεια ώρας ή 15λεπτου μπλοκ, και παρείχε μια λογική εκτίμηση της τιμής αιχμής. Τα αποτελέσματα αυτά επιβεβαιώνουν ότι ένα σχετικά ερμηνεύσιμο μοντέλο παλινδρόμησης μπορεί να αποδώσει πρόβλεψη στην εξαιρετικά ευμετάβλητη αγορά εξισορρόπησης.

Τα ευρήματα είναι χρήσιμα τόσο για τους συμμετέχοντες στην αγορά όσο και για τους διαχειριστές συστημάτων. Οι έμποροι, οι παραγωγοί και οι διαχειριστές αποθήκευσης ενέργειας ή απόκρισης ζήτησης μπορούν να αξιοποιήσουν την πρόβλεψη για να βελτιστοποιήσουν τις προσφορές και τα επιχειρησιακά τους προγράμματα, διασφαλίζοντας ότι είτε αξιοποιούν τις αιχμές των τιμών είτε αντισταθμίζουν τις δαπανηρές ανισορροπίες. Για τον διαχειριστή του συστήματος μεταφοράς (IPTO), η καλύτερη πρόβλεψη των τιμών εξισορρόπησης αιχμής σημαίνει βελτιωμένο προγραμματισμό των εφεδρειών και μετριασμό των κινδύνων, συμβάλλοντας στη συνολική αξιοπιστία του συστήματος και στην αποδοτικότητα του κόστους. Μια καινοτόμος πτυχή αυτής της εργασίας είναι η ολοκληρωμένη θεώρηση του πεδίου εξισορρόπησης: η μελέτη δεν προβλέπει μόνο τις αιχμές της αγοράς ενέργειας (mFRR) αλλά εξετάζει παράλληλα και στην αγορά εφεδρειών το aFRR. Εξετάζοντας την ανάπτυξη εφεδρικής ικανότητας και τη σχέση της με τις αιφνιδιασμούς των τιμών, η διατριβή προσφέρει μια ολιστική προοπτική - ευθυγραμμιζόμενη με το γεγονός ότι στον ελληνικό μηχανισμό εξισορρόπησης, οι αγορές ενέργειας και εφεδρείας είναι αλληλένδετες. Αυτή η συνδυασμένη ανάλυση ενισχύει την ευρωστία της προσέγγισης,

καθώς η πρόβλεψη της ενεργειακής αιχμής βοηθά εγγενώς στην κατανόηση των συνθηκών πίεσης της εφεδρείας.

Κάθε κεφάλαιο της διατριβής συνέβαλε σε αυτή την ολοκληρωμένη μελέτη: Το Κεφάλαιο 1 παρουσίασε το πλαίσιο της αγοράς εξισορρόπησης στην Ελλάδα και διατύπωσε το πρόβλημα πρόβλεψης, τονίζοντας τη σημασία του για την αποτελεσματικότητα και τη σταθερότητα της αγοράς. Το Κεφάλαιο 2 περιέγραψε λεπτομερώς το σχεδιασμό και τη λειτουργία των ελληνικών αγορών ηλεκτρικής ενέργειας (ημερήσια, ενδοημερήσια και εξισορρόπησης), παρέχοντας θεμελιώδεις γνώσεις για τον τρόπο λειτουργίας της τιμολόγησης ανισορροπίας και υπογραμμίζοντας τις ιστορικές προκλήσεις. Το Κεφάλαιο 3 εξέτασε τη σχετική βιβλιογραφία σχετικά με την πρόβλεψη των τιμών ηλεκτρικής ενέργειας και τις αγορές ανισορροπίας, αντλώντας διδάγματα από προηγούμενες μελέτες και εντοπίζοντας τα κενά που αντιμετωπίζει η παρούσα εργασία. Στο κεφάλαιο 4 παρουσιάστηκε η μεθοδολογία και η ανάπτυξη του μοντέλου, περιγράφοντας την προσέγγιση παλινδρόμησης, την επιλογή των προβλεπτικών παραγόντων και το σκεπτικό για την εστίαση στο χρόνο και το μέγεθος των τιμών αιχμής. Το κεφάλαιο 5 επικεντρώθηκε στον τρόπο με τον οποίο το μοντέλο πρόβλεψης εφαρμόστηκε και αξιολογήθηκε με τη χρήση πραγματικών ιστορικών δεδομένων. Παρουσιάστηκαν τα αποτελέσματα σε διάφορα στατιστικά μέτρα, όπως το R^2, το RMSE και το nMAE, και εξετάστηκαν συγκεκριμένες περιπτώσεις που καταδεικνύουν τα πλεονεκτήματα και τους περιορισμούς του μοντέλου. Το συμπερσματικό κεφάλαιο, το κεφάλαιο 6, συνόψισε τα κύρια συμπεράσματα, περιέγραψε τον τρόπο με τον οποίο η εργασία αυτή μπορεί να επεκταθεί και προσέφερε κάποιες προσωπικές σκέψεις σχετικά με την ερευνητική μεθοδολογία που ακολουθηθήκε. Συνολικά, η παρούσα διατριβή έδειξε ότι η πρόβλεψη των ακραίων τιμών εξισορρόπησης, και ιδίως ο χρονισμός τους, έχει νόημα και είναι εφικτή στην ελληνική αγορά ηλεκτρικής ενέργειας. Η προσέγγιση παρέχει γνώσεις που μπορούν να βοηθήσουν τους συμμετέχοντες στην αγορά και τους διαχειριστές συστημάτων να προβλέπουν δαπανηρές τιμές εξισορρόπησης και να λειτουργούν αποτελεσματικότερα σε ένα ολοένα και πιο σύνθετο ενεργειακό τοπίο.

Πίνακας περιεχομένων

1. Introduction 17

1.1 Historical Context: Evolution of Energy Markets 17

1.2 The energy transition 17

1.3 The Role of the Energy Market today 20

1.4 Economic and Technical Importance of the Balancing market 21

1.5 Research Focus 22

1.6 Conclusion 24

2.Electric Power System 27

2.1 The Greek Electric Grid 27

2.2 Electricity generation units 30

2.2.1 Thermal Power Plants 34

2.2.2 Hydroelectric power plant 34

2.2.3 Renewable Energy Sources 35

2.3 Interconnections 35

2.4 Projects under development 38

2.4.1 Tranmission grid 38

2.4.2 Storage 39

2.4.3 Conclusion 40

3. Electricity markets in Greece 41

3.1 Structure 41

3.2 The Day ahead market in Greece 43

3.2 The Intraday market 48

3.3 The balancing market 52

3.4 Balancing market reforms 59

3.5 Conclusion 60

4. Forecasting in the energy market 61

4.1 Forecasting Methodologies 61

4.2 Predictors used 63

4.3 Impementation 64

4.4 Forecasting Model for the Greek Balancing Market 66

4.4.1 Forecasting the point in time for Peak Price of activated energy 69

4.4.2 Forecasting the magnitude of the peak price of activated energy 69

4.5 Evaluation metrics 71

4.6 AFRR reserve markets forecasting 74

4.7 Conclusion 75

5.Results 77

5.1 Data retrieval and preprocessing 79

5.2 Forecasting Peak Price Timing (mFRR Balancing Energy) 80

5.3 Forecasting Peak Price Magnitude (mFRR Balancing Energy) 85

5.6 AFRR (capacity) peak price forecast 89

5.7 Conclusion 91

6. Conclusions 93

6.1 Contributions of this dissertation 93

6.2 Future Work 94

6.3 Personal reflections 95

References 97

Appendices 103

Appendix A 103

Appendix B 111

Appendix C 117

Acronym	Full Form
IPTO	Independent Power Transmission Operator (Greece)
BESS	Battery Energy Storage Systems
DAM	Day-Ahead Market
DSR	Demand-Side Response
ENEX	Hellenic Energy Exchange
ETSS	Energy Trading Spot System
EU	European Union
EV	Electric Vehicle
FCR	Frequency Containment Reserve
FM	Forward Market
GDP	Gross Domestic Product
IDM	Intra-Day Market
IPTO	Independent Power Transmission Operator
ISO	Independent System Operator
MCP	Market Clearing Price
mFRR	Manual Frequency Restoration Reserve
aFRR	Automatic Frequency Restoration Reserve
RES	Renewable Energy Sources
RTO	Regional Transmission Organization
RAE	Regulatory Authority for Energy
RAAEY	Regulatory Authority for Waste, Energy, and Water

1. Introduction

1.1 Historical Context: Evolution of Energy Markets

The liberalization of energy markets has been a transformative process, driven by competition, efficiency and social welfare. Historically, energy markets were vertical monopolies where generation, transmission and distribution were all under one entity. This structure was very reliable, but lacked competitive incentives, often leading to inefficiencies and higher consumer costs. The liberalization movement started in the 90's in Europe and parts of the US and aimed to dismantle these monopolies and introduce competition and market based mechanisms. In EU, the Target Model was adopted in 2009 to facilitate the harmonization of energy markets across member states, cross border trade and market efficiency [1]. This model has 4 separate markets: day ahead market, intraday market and balancing market, each serving specific functions in maintaining grid stability and market efficiency. In the US, electricity markets evolved differently with regional transmission organizations (RTOs) and independent system operators (ISOs) managing market operations. These entities are responsible for market functions, reliability and efficiency determining different degrees of market liberalization. The differences in market structures have influenced the development of balancing markets and price forecasting in each region of Greece followed the European path, liberalized its energy market in line with EU directives. The implementation of the Target Model in Greece introduced structured markets including the balancing market. This plays a critical role in maintaining grid stability especially with the country's increasing reliance on renewable energy sources (RES) [2]. The liberalization process in Greece was not without challenges. Early stages were marked by market concentration, limited competition and regulatory hurdles. Successive reforms, though, especially the adoption of the European Target Model in 2020, brought significant improvements. The introduction of day ahead market, intraday market and balancing market made market operations more efficient and better integration with European markets [1].

The historical evolution of energy markets also reflects broader economic and policy changes. As environmental concerns became more prominent, markets are increasingly prioritizing RES. This shift posed new challenges to market stability and price forecasting, further highlighting the importance of balancing markets. In this thesis, although the main focus will be on the balancing market, we will also look at the structure and operation of all energy markets in Greece, day ahead and intraday markets, in order to have a full picture of the energy markets regulatory framework.To contextualize this analysis, the following section will explore the ongoing global energy transition and its implications for electricity markets.

1.2 The energy transition

The global energy transition refers to the structural shift from fossil fuel-based energy systems to low-carbon and renewable energy sources. This transformation is originated by the urgent need to reduce greenhouse gas emissions and mitigate the impacts of climate change as much as. According to Julien Jomaux's insights on energy transitions [7], energy production and consumption account for approximately three-quarters of

global emissions as shown in figure 1. This means the decarbonization of energy systems is of critical priority.

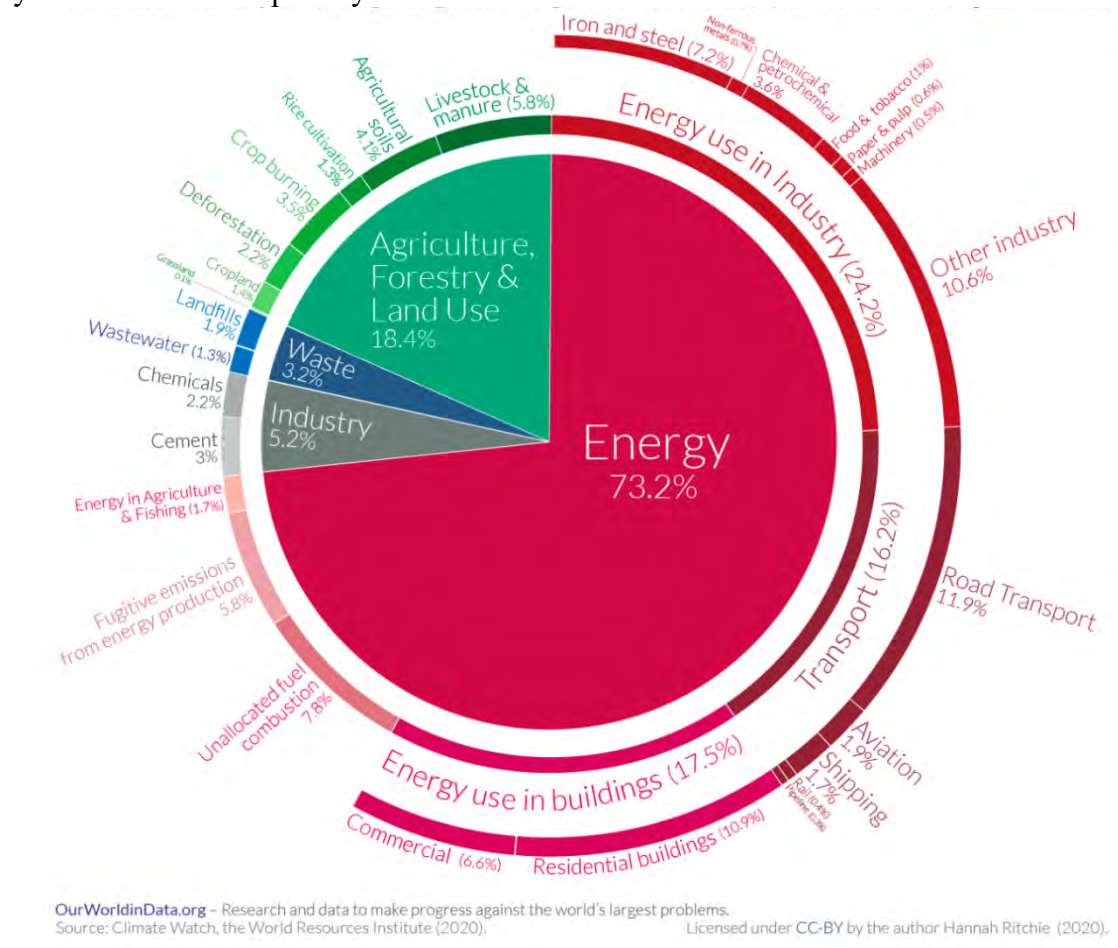


Figure 1 Global CO2 Emissions by Sector [7].

Historically, energy transitions have been characterized by shifts from one dominant energy source to another, such as from biomass to coal during the Industrial Revolution or from coal to oil and natural gas in the 20th century. However, this ongoing transition is unique due to its scale, speed, and the environmental imperatives. Unlike previous transitions that were primarily driven by economic and technological factors, the present shift is related to sustainability and environmental stewardship. Of course, there are underlying financial motives and penalties urging the countries towards energy transition. One of the most critical challenges is balancing economic growth and emission reductions. This has recently turned out to be a formidable challenge for Europe, as achieving stringent environmental regulations is difficult compared to other economies like China or Russia where environmental regulations are weak or poorly defined. Decoupling carbon emissions from GDP growth has been lagging despite monumental progress in the technology of renewable energy. The use of fossil fuels keeps on increasing around the world, making it difficult to remain within the 1.5°C level of warming increase as agreed in the Paris Agreement. The second challenge is the unequal share of emissions and energy consumption in the world. While developed nations emit most of the emissions, developing nations experience energy poverty and do not have access to clean and secure energy sources. This disparity necessitates a tailored reaction to energy transitions based on the different starting points and needs of each country. Favorable developments in the energy transition include the steadily declining cost of renewable energy technology, particularly solar and wind power, and

the advancement in energy storage technologies. This will continue because more companies produce them, so they become cheaper through competition. The cost of solar modules has fallen more than 99% over the last three decades, allowing for historically unprecedented deployment levels. Battery prices are also coming down, increasing the viability of incorporating variable renewable energy sources into the grid.

In Greece, a lot of work is in progress to include battery energy storage systems (BESS) into the national grid. New legislation, such as the Energy Framework Law No. 4001/2011, has initiated licensing schemes for electricity storage, promoting investment in the sector [8]. The initial stage of the scheme introduced in 2024 aims to deploy between 1.5 GW and 2 GW of battery capacity, with additional 500 MW expected via business support programs [9]. These initiatives are predicted to bring Greece's total battery capacity to approximately 3.5 GW by 2030. The Ministry of Environment and Energy launched the "Storage Systems in Businesses" program in January 2025 with a budget of €153.7 million, providing incentives for battery storage systems integrated with photovoltaic systems [10].

All these efforts, of course financed by the European Union, demonstrate Greece's commitment to enhancing grid stability and supporting renewable energy integration. This effort aligns with the European mission and already show some success as it can be shown in figure 2, demonstrating the decarbonization efforts in the country the last decade. The transport model is being revolutionized too, as more electric vehicles (EVs) are used and there is growing development of charging stations. Heat pumps, LEDs, and other energy-efficient technologies are also contributing to lowering emissions in commercial and building sectors. There are still major issues, however, in the transition to energy. Rebound effect (Jevons Paradox) suggests that greater energy efficiency will see overall energy usage rise [8]. It becomes harder, therefore, to lower the amount of emissions because greater efficiency gains will be overtaken by added demand. Increased demand is a characteristic of economic growth in an economy. Policy action and change in consumer behavior mainly pave the way for speeding up the energy transition. Investments in public transport, carbon pricing instruments, and government subsidies reinforce the decarbonization effort. Meanwhile, individual actions such as energy saving, clean technology shifts, and sustainable preferences—can all together make a significant difference. For Greece, energy transition involves integrating high penetrations of renewable power into the grid, modernizing its infrastructure, primarily through subsidization, and increasing cross-border energy trade. Greece is favored by vast resources of sun and wind which make the transition to a low-carbon power system lavier, though there are issues of stability to the grid as well as to the market during this transition.

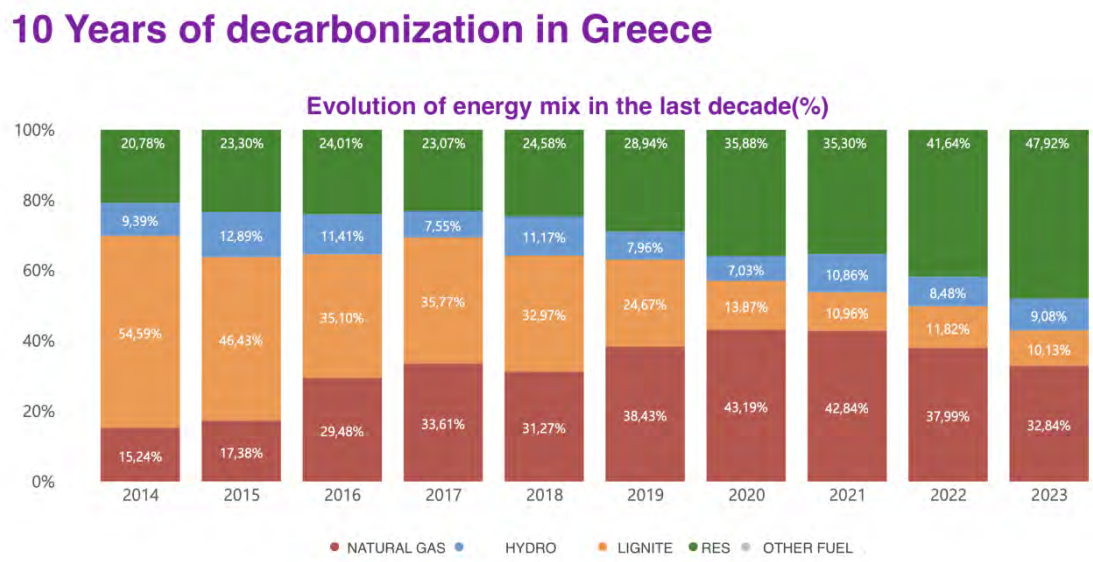


Figure 2 Decarbonization in Greece over the past decade. 2023 marked a historic milestone in Greece's clean energy production, with 57% of the energy mix being supplied by Renewable Energy Sources (wind and solar) and hydroelectric units, surpassing 25 TWh [2].

1.3 The Role of the Energy Market today

The Greek power market follows the European Target Model, a model designed to harmonize energy markets across EU member states and allow for more efficient energy trading. The end goal is to achieve a single European energy market that allows electricity to flow freely across borders, enhancing competition and stability. The Target Model structures the market into four principal pillars: the forward market, day-ahead market, intraday market, and the balancing market [1]. These are connected to each other, operating sequentially as shown in figure 3. Each plays a distinct role in the reliability and efficiency of the electricity system. The forward market allows the possibility for the participants to hedge against future price uncertainty by acquiring contracts for future electricity deliveries. The majority of electricity trading takes place in the day-ahead market. Prices are set based on forecasts of supply and demand for the following day, which helps to ensure generation is matched to expected consumption [6]. The intraday market offers flexibility, allowing traders to modify their positions as real-time conditions evolve, leaving space for unexpected changes in energy generation or demand [6]. Finally, the balancing market addresses real-time imbalances between supply and demand. It deploys reserves when needed to balance the grid and maintain frequency stable. This market is increasing in importance as higher percentages of renewable energy sources (RES)—wind and solar, for example—enter the mix, bringing variability and uncertainty to electricity generation [3].



Figure 3 Energy Markets in Greece [17].

The liberalization of energy markets across Europe, endorsed by the implementation of the Target Model, has brought significant benefits. It has increased competition, improved market transparency, and reduced electricity prices in many regions. Moreover, market integration has facilitated cross-border electricity flows, optimizing resource utilization and enhancing energy security across the continent [1].

1.4 Economic and Technical Importance of the Balancing market

The previous section briefly described the role of the energy market as part of the larger European system for energy. This section elucidates more profoundly the economic and technical relevance of the balancing market. It dissects the prospects and difficulties arising from the integration of the balancing market in the market mechanism and clarifies the reason why exact prognosis of balancing market prices and especially their peaks and when they occur is essential.

The balancing market has a fundamental role to maintain the stability and effectiveness of electricity supply. Being a real-time market, it balances the real-time electricity supply and demand to provide a reliable power grid. In its strategy to build a single energy market, the European Union devised the Target Model which is designed to harmonize member states' electricity markets. This initiative promotes cross-border electricity trading and enhances market efficiency in general [1]. From the economic perspective, a sound balancing market ensures the reduction of the operational cost by concentrating resources on an international level. This organized system reduces the need for expensive local reserves, and thus the energy market becomes competitive and less expensive. Studies suggest that introducing balancing resources across regions can significantly cut the costs of maintaining grid reliability [13].

Technically, the balancing market is pivotal when the grid contains great amount of renewable energy sources (RES). Since renewables like wind and solar are intermittent, they generate variability that destabilizes the grid. The balancing market provides the flexibility to absorb these variations in real-time and ensure overall grid stability [7]. Switzerland is a prime example of demonstrating the complexity of grid stability. Although it is well connected to the European grid through 41 cross-border high-voltage lines, it still faces potential electricity shortages. The lack of a comprehensive electricity agreement with the EU has generated coordination issues, and therefore unscheduled cross-border electricity flows have taken place. Such unscheduled power transfers often require rapid intervention by Swissgrid—the national transmission system operator—to prevent blackouts and ensure grid stability [14].

In Greece, the balancing market is managed by the Independent Power Transmission Operator (IPTO), while the Hellenic Energy Exchange (ENEX) runs the forward, day-ahead, and intraday markets. This setup allows IPTO to be solely responsible for real-time grid management, allowing a system operator to pay full attention on system reliability and security instead of transactions in the market. Greece's integration into the Target Model, though, hasn't been a smooth ride. The country has witnessed a significant rise in the cost of electricity, which has been triggered by a range of factors. Low capacity of cross-border interconnections, market imbalances, and the absence of competitive forces are some of them. The above issues and others will be explained in greater detail in the following chapters. In this context, the Greek authorities have called for broader EU regulation reforms and new cross-border investment projects with a view to enhance market efficiency as well as energy security [1]. Some significant interconnections are underway to address these concerns. A good example is the Crete-Attica interconnection, the largest transmission within Greece, to go into operation in spring 2025. While these new interconnections and the recent legislation in favor of storage units have significant benefits, they do add complexity to the balancing market. Their control requires accurate forecasting of how much energy the grid will need to supply to avoid imbalances that would compromise grid stability. The growing diversity of energy sources, specifically that of intermittent renewables, further underscores the need for more advanced forecasting tools to accommodate different output and the constantly fluctuating character of the energy market.

Accurate forecasting of prices, peak and energy that will be supplied through the balancing market is vital for several key reasons:

- **Grid Stability:** Forecasting helps maintain the delicate balance between supply and demand, preventing frequency deviations and minimizing the risk of blackouts.
- **Economic Efficiency:** Reliable predictions reduce reliance on expensive reserve power, helping to lower costs and mitigate the financial risks associated with market volatility.
- **Renewable Integration:** Effective forecasting supports the smooth integration of RES into the grid by anticipating variability in energy production.

In conclusion, the balancing market is a pillar of European and Greek energy systems that ensures stability for operation thus supporting economic efficiency. The Swiss case points out problems that can be generated by non-perfect market integration and coordination. The importance of good forecasting within the balancing market is even more critical for maintaining stability in the grid, it the long-term goal of decarbonization is to be achieved.

1.5 Research Focus

This research focuses on the balancing market, highlighting its central position in the provision of grid stability and its economic importance. The real-time balancing market reflects the physical condition of the power grid at a great extent rather than relying solely on market mechanisms like the Day-Ahead Market. This aspect underscores the importance of accurate forecasting in realizing grid stability and economic efficiency.
As mentioned already, an inherent feature of the balancing market is that it is highly tied to the physical dynamics of the grid. Unlike the Day-Ahead Market, which is

mostly determined by economic bids and forecasts, the balancing market must track the real-time operational constraints of the grid. This implies that knowledge of the physics of the grid, load flows, frequency deviations, and voltage stability is key to improving forecasting accuracy. This dissertation aims to enhance the predictive power for balancing market peak prices by analyzing the physical drivers of grid stability and integrating them into forecast models. This will allow market participants and system operators to prepare for potential imbalances sooner, allocate resources more efficiently, and minimize economic exposures.

The financial impact of the balancing market cannot be overstated. Its price, in terms of activated energy units, is comparable to that of the day ahead market (mcp), which is the biggest and most important market in terms of volume and revenues [ipto]. This is typical in months we have taken on this paper but in figures 4 and 5 day ahead price (mcp) vs balancing energy prices (mfrr) for November 2023 are shown for illustration purposes.

Title	Market Clearing Price (MCP)
Scope	Day Ahead Market (DAM)
Analysis	Daily

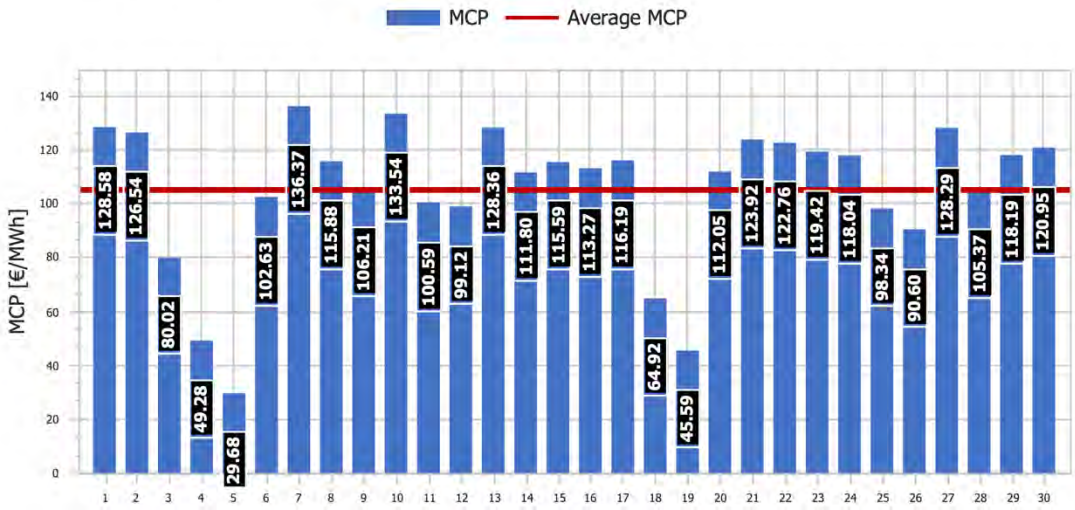


Figure 4 MCP for November 2023 [18].

Title	mFRR & Imbalance Prices
Scope	Imbalance Settlement Procedure
Analysis	Daily

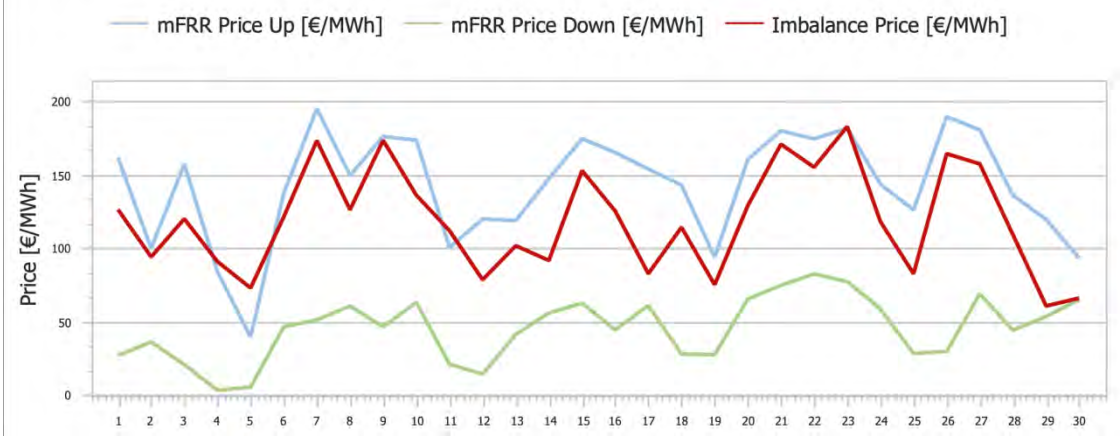


Figure 5 Mfrr up for November 2023 [18].

Moreover, price volatility during grid stress or spontaneous imbalances can have severe economic effects on both market participants and operators. As mentioned in recent studies these are generally worsened by the increasing penetration of renewables, which introduces further variability into the system [11]. System demand variability, RES penetration levels, cross-border interconnection capacities, and market rules are other parameters influencing prices and peak occurrences. All these need to be examined in an effort to construct credible forecasting models. It is now clear how valuable these models are, not only to guarantee grid stability but also to mitigate economic risks and strengthen the energy market.

The following chapters will delve deeper into the methodologies employed for balancing market forecasting, explore the relevant market dynamics, and present the results and implications of the developed models.

1.6 Conclusion

This chapter provided a general overview of the balancing market, starting with the historical evolution of electricity markets and moving through the global energy transition, the role of energy markets, and the specific economic and technical importance of the balancing market in Europe and Greece. It highlighted how market deregulation and the integration of renewable energy resources have transformed the electricity sector so that it is now more complex to provide grid stability and market efficiency.

Balancing market's dual role in ensuring real-time grid stability as well as the economic management of energy imbalances is also discussed. This chapter emphasized the important role of accurate forecasting in the balancing market due to its dependency on the physical characteristics of the grid rather than market-based schemes. This puts emphasis on accurate forecasting models considering real-time operating constraints and variability caused by renewable energy sources.

Price forecasting in balancing markets relies on the detection of the underlying parameters influencing the electricity system, which include grid physics, penetration

of RES, and fluctuating demand. An understanding of such parameters is of paramount importance for system stability, but also alleviates the fiscal risks associated with price volatility.

In the next chapter, we will perform a more in-depth discussion of the structure and operational characteristics of the Greek electricity system, discussing its basic structure and most critical elements. This discussion will provide the technical basis for understanding their influence on energy markets initially and, later, developing sound forecasting models that can handle the complexities of the modern electricity grid.

2.Electric Power System

2.1 The Greek Electric Grid

Understanding the technical structure of the Greek power grid is important in understanding the function and conduct of various market mechanisms most importantly, the balancing market. A good idea of how electricity is being transmitted and distributed allows us to analyze the technical worth and operational capability of different market products. Furthermore, technical characteristics of the system such as generation mix, flexibility, interconnection strength, and storage availability impact frequency and energy imbalance and consequently the price and size of balancing energy required by the grid. Since this dissertation aims to forecast price peaks on the balancing market, it is necessary first to study the physical underpinnings of the grid that constitute such peaks. This technical foundation also allows us to understand better how the systemic constraints translate possibly into economic indicators in the energy markets.

The Greek electric grid is as a complex and interconnected system designed to ensure the efficient, reliable, and continuous transmission and distribution of electricity across the country. It is structured into two primary components: the Hellenic Transmission System and the Hellenic Distribution Network, each with distinct roles, responsibilities, and infrastructure. A simplistic representation of the electric grid is shown in figure 6[20].

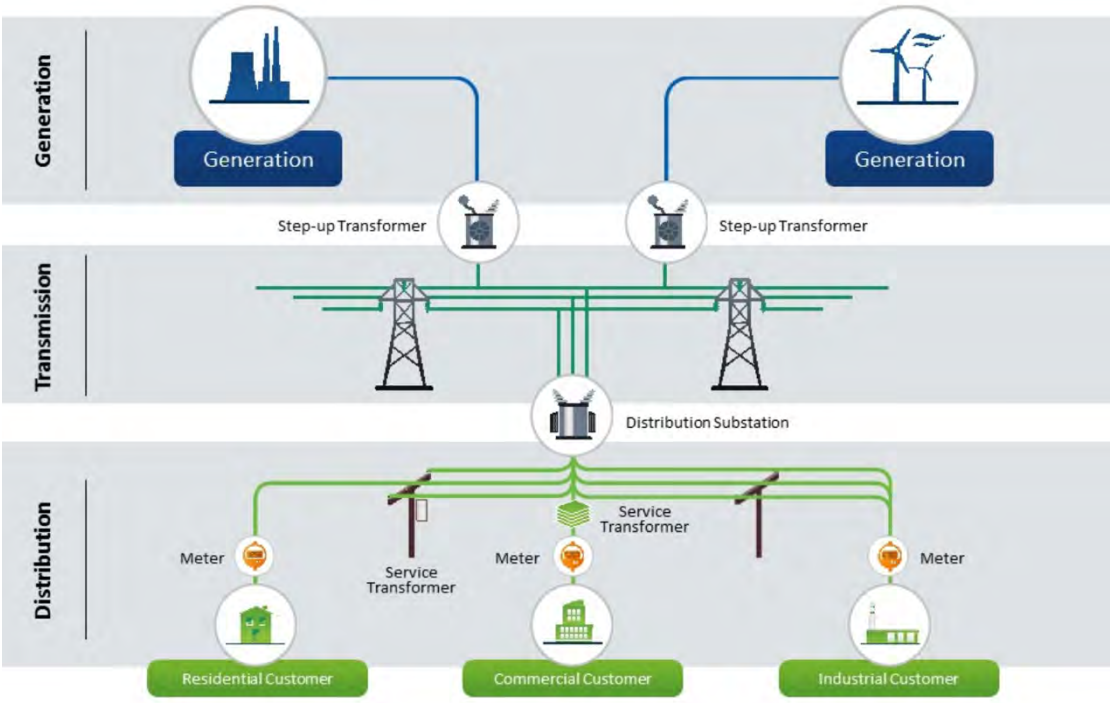


Figure 6 The electric grid [20].

The Hellenic Transmission System is owned and operated by the Independent Power Transmission Operator (IPTO). The transmission system comprises (Law No. 4001/2011):

- High-voltage lines (primarily 150 kV),
- Ultra-high voltage lines (mainly 400 kV),
- International interconnections, and
- All infrastructure and equipment necessary to transport electricity safely and reliably from generation units to distribution networks or directly to large consumers [1].

The primary function of the transmission system is to facilitate the long-distance transmission of electricity at high voltages, minimizing energy losses and supporting quality of supply, but considering at the same time the financial viability of the suggested implementations. It serves as the backbone of the national grid, connecting power plants, substations, and major load centers, while enabling cross-border electricity exchanges through international interconnections. The transmission system also includes critical infrastructure for the interconnection of Non-Interconnected Islands (NIIs). These islands, which were traditionally reliant on local power generation, are now increasingly being integrated into the mainland grid through submarine interconnections using High Voltage Alternating Current (HVAC) or High Voltage Direct Current (HVDC) technologies. This integration enhances grid stability, reduces generation costs as the old oil-fired local power plants become redundant, and supports the transition to cleaner energy sources [19]. However there are certain facilities that are excluded from the transmission system, mainly the Electricity generation units, any high voltage lines along with its infrastructure incorporated in the Hellenic Distribution Network and high voltage lines and infrastructure if the NIIs that again fall into the Distribution Network.

The Hellenic Distribution Network is managed by the Hellenic Electricity Distribution Network Operator (HEDNO) which corresponds to the Greek title "*Διαχειριστής Ελληνικού Δικτύου Διανομής Ηλεκτρικής Ενέργειας – ΔΕΔΔΗΕ Α.Ε.*". This network is responsible for the final stage of electricity delivery from transmission substations to residential, commercial, and smaller industrial consumers. This is the part of the grid that brings electricity to our homes. The distribution network consists of:

- Medium voltage lines (typically 20 kV),
- Low voltage lines (230V/400V for end-users),
- Distribution substations and transformers,
- High voltage lines that have been integrated into the distribution system for specific purposes [19].

These high voltage lines, although typically part of the transmission network, have been incorporated into the distribution system to serve specific purposes such as supplying large industrial consumers, feeding remote substations, enhancing grid reliability, or addressing legacy infrastructure arrangements.
It also includes the infrastructure necessary for local energy distribution in areas not connected to the mainland grid, particularly on Non-Interconnected Islands. These islands operate autonomous grids, often relying on a combination of conventional and

renewable energy sources, though many are being gradually integrated into the mainland network through new interconnections. The distribution network connects to the transmission system through high-to-medium voltage substations (HV/MV), where voltage levels are stepped down to accommodate consumer needs. This multi-level infrastructure ensures the safe and reliable delivery of electricity across urban, suburban, and rural regions [19].

Greece, with its numerous islands, experiences significant seasonal fluctuations in energy demand, particularly during the summer months when tourism reaches its peak. The influx of visitors during this period leads to a substantial increase in electricity consumption on the islands, resulting in a much different profile when compared to the winter season. As tourism continues to grow, effectively managing this heightened and variable demand has become increasingly critical, not only for ensuring the stability and reliability of the national grid but also for maintaining the efficiency and balance of the energy market. This seasonal variability underscores the importance of understanding how these islands are incorporated into the grid, as their integration plays a pivotal role in managing demand, ensuring energy security, and supporting the overall resilience of the electricity system. The responsibility for managing the Electrical Systems of these islands, including generation, market operation, and system management, rests as mentioned earlier with the Hellenic Electricity Distribution Network Operator (HEDNO). This management is governed by the "Non-Interconnected Islands Electrical Systems Management Code" (Law No. 4001/2011) [19].

How electricity is supplied to NIIs has significantly evolved over the past decade. In March 2018, the completion of Phase A of the Cyclades Interconnection Project linked some of the most touristic islands, such as Syros, Mykonos, Paros, and Naxos to the mainland grid. This development marked a fundamental shift in how these islands are powered, reducing their reliance on local, oil-fired power plants. The subsequent completion of Phases B and C, which connected the rest of the Cyclades islands, further strengthened the reliability and stability of the Cyclades' electricity supply. Despite these advances, a significant number of NIIs, mostly in the southeastern Aegean, still rely on local oil-fired power plants (mazut and diesel) operated by the Public Power Corporation (PPC). Lately, Renewable Energy Sources (RES**)** have also begun to play a more substantial role in the energy mix of these islands, with wind farms and photovoltaic (PV) stations contributing significantly to local electricity production.

The electricity market in the NIIs is highly decentralized and consists of 29 autonomous electrical systems, each one with each own local market. Some of these systems cover more than one island, forming island clusters that operate as single, integrated networks. The scale and characteristics of these systems vary significantly, and they are categorized based on peak electricity demand:

- Nineteen "small" autonomous systems have peak demand levels of up to 10 MW
- Eight "medium-sized" autonomous systems experience peak demand ranging from 10 MW to 100 MW
- Two "large" autonomous systems—Crete and Rhodes—exceed peak demand levels of 100 MW [19].

The annual electricity demand in the NIIs also varies widely, from just a few hundred MWh in the smallest islands to several GWh in the bigger ones.

Having explored the structure and operation of Greece's transmission and distribution networks, as well as the unique challenges posed by the Non-Interconnected Islands, it is essential to delve into the backbone of the electricity system, the generation units. The efficient functioning of the national grid, along with the integration of remote islands, depends heavily on the diversity, capacity, and geographical distribution of these generation facilities.

2.2 Electricity generation units

Greece's power generation landscape comprises a mix of conventional plants (such as natural gas, lignite, and oil-fired stations) and an increasingly significant share of Renewable Energy Sources (RES), including wind, solar, and hydroelectric power. Understanding how these generation units are distributed, their operational characteristics, and their role in balancing supply and demand is crucial for evaluating the resilience, sustainability, and efficiency of the Greek electricity system. This section will explore the various types of generation units, their contribution to the energy mix.

The total installed capacity of an electricity system serves as a key indicator of a country's ability to meet its energy demands under peak conditions. In Greece, the current installed capacity reflects the nation's evolving energy landscape with a growing shift towards Renewable Energy Sources (RES) alongside conventional power plants. As of 2024, Greece's total installed electricity generation capacity is estimated at approximately 23 to 24 GW as shown in figure 7, highlighting the significant strides the country has made in diversifying its energy mix [21]. It is essential to distinguish between installed capacity and actual electricity generation. Installed capacity refers to the maximum potential output of all power plants in the system under ideal operating conditions. In contrast, actual generation is influenced by numerous factors, including fuel availability, weather conditions, operational efficiency, system demand and market mechanisms.

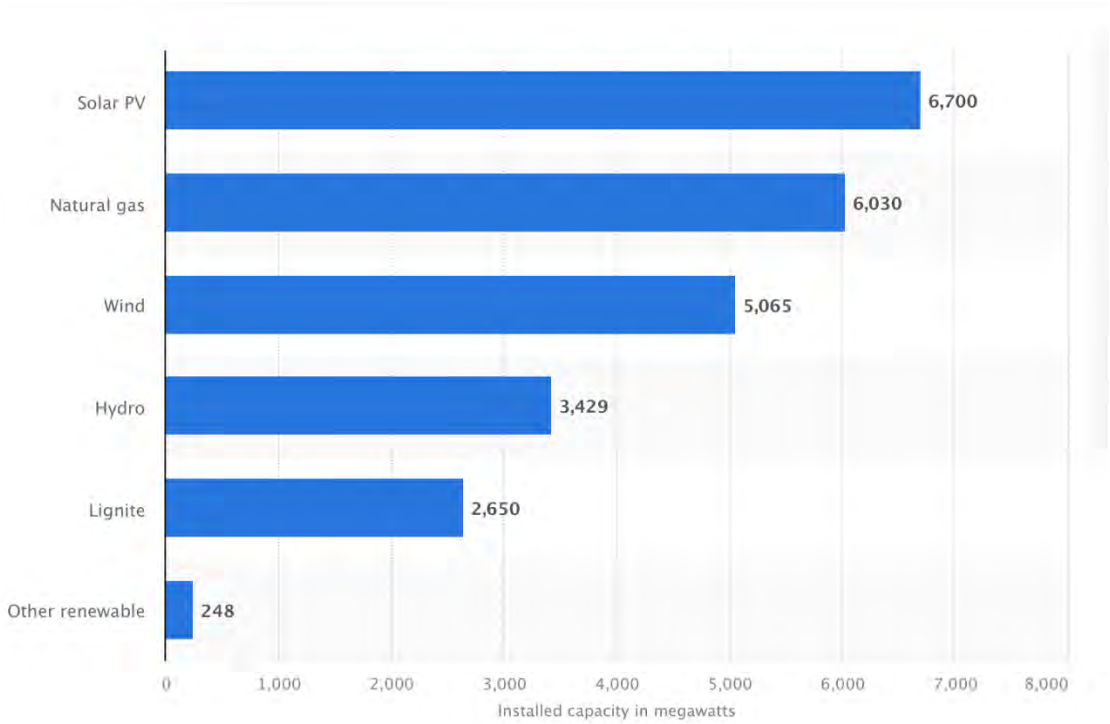


Figure 7 Installed capacity in Greece 2024 [22].

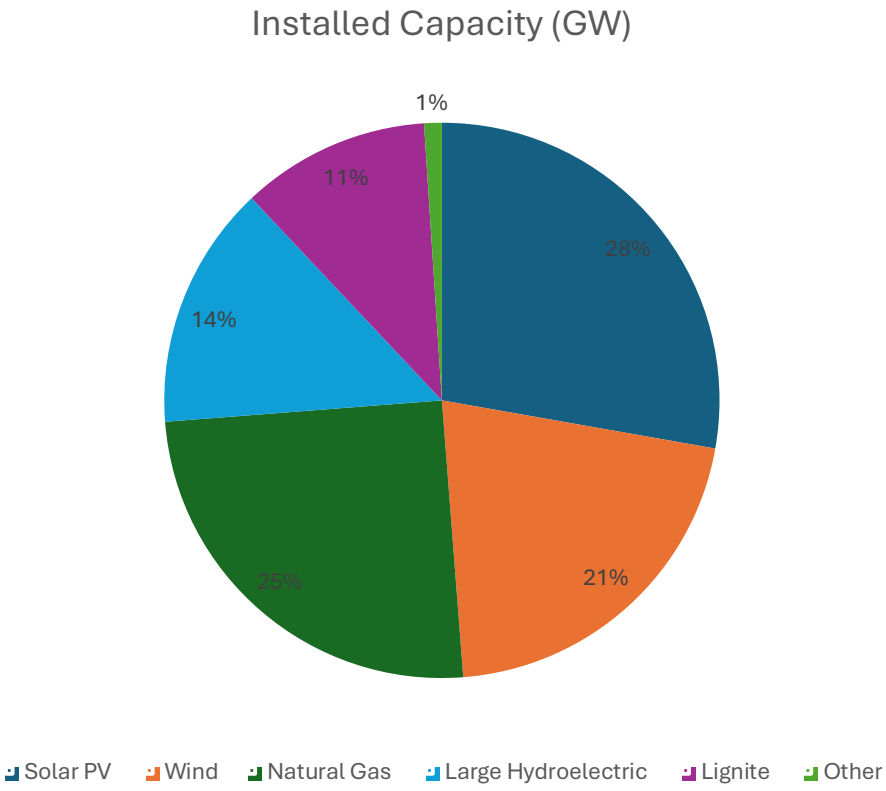


Figure 8 Installed capacity as a percentage in Greece 2024 [22].

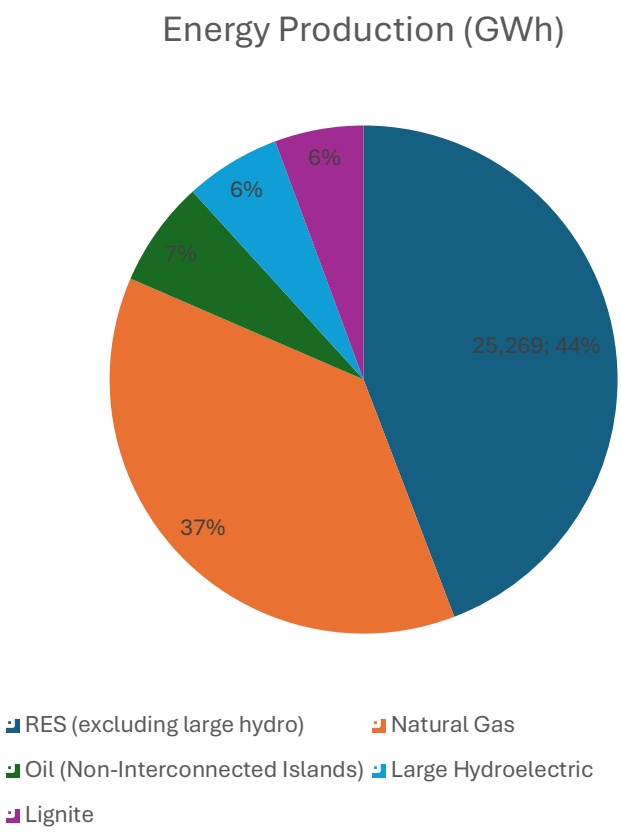


Figure 9 Energy Production in Greece in 2024 [31].

Greece's electricity generation landscape has undergone significant transformations in recent years, driven by the dual imperatives of decarbonization and energy security. The national focus on expanding Renewable Energy Sources, reducing reliance on fossil fuels, and enhancing grid integration has reshaped the country's power generation mix. As of 2024**,** clean energy sources contributed approximately 55% to Greece's total electricity generation mix, highlighting the country's progress towards its renewable energy goals. The allocation of generation for Greece for 2024 can be shown in figure 8. Specifically, RES which include solar**,** wind, and biomass accounted for 48.3% of total generation, while hydroelectric power contributed an additional 6.7%. This marks a significant milestone, as nearly half of the nation's electricity demand is now met by RES, with clean energy production reaching a record 25.2 TWh, an 18% increase from the previous year as shown in figure 9[23]. As it can be easily understood, this increased penetration of RES in the energy mix, although very desirable, it increased volatility and increases the share of balancing market in the whole energy market.

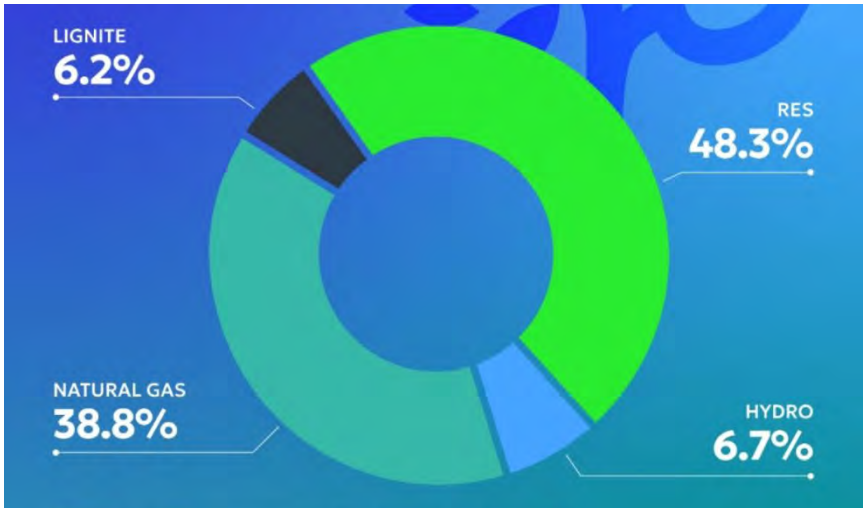


Figure 10 Generation mix in Greece 2024 (ipto) [23].

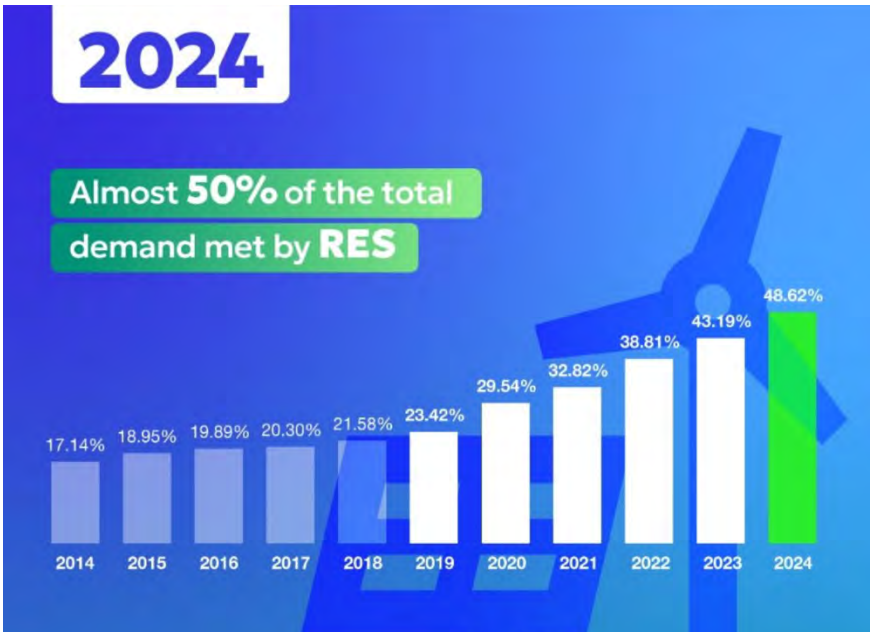


Figure 11 RES generation in recent years [23].

On the conventional generation side, natural gas remains a major contributor, supplying 38.8% of the electricity mix, while lignite once the backbone of Greek power generation has declined sharply, representing just 6.2% of total production in 2024 [23]. This decline aligns with Greece's broader decarbonization strategy and the planned phase-out of lignite-fired plants in the coming years. However, something worth mentioning is that lignite is a local product, allowing Greece to develop a cost effective and energy independent electricity generation strategy throughout much of the 20th century. The low extraction and transportation costs associated with lignite compared to imported natural gas or oil traditionally made it one of the cheapest sources of electricity in the country. Despite its historical economic advantages, lignite-fired power generation faces challenges due to environmental concerns and the European Union's decarbonization policies. The introduction of stricter carbon pricing mechanisms under the EU Emissions Trading System (EU ETS) has increased the operational costs of lignite plants, making them less competitive compared to cleaner energy sources. Consequently, Greece has initiated plans to phase out lignite-fired

plants, aiming to retire most by 2028, as part of its broader strategy to reduce greenhouse gas emissions and transition to sustainable energy systems [24]. This transition along with the increased share of RES has introduced new challenges, particularly regarding grid reliability and the need for enhanced flexibility in real-time electricity balancing.

The power plants operating within the Greek electricity market exhibit distinct technical characteristics that determine their role in energy production and their ability to participate in different segments of the electricity market**.** Some power plants, such as lignite-fired and large combined-cycle gas turbines, has been developed for covering the base load, operating continuously with minimal fluctuations. In contrast, open-cycle gas turbines, hydropower plants provide the necessary flexibility and rapid response capabilities, making them crucial for the balancing market. This role is expcted to be shared with battery systems when they will be integrated in the electric grid, because they have even faster response and they are able to provide power within seconds. The operational differences between these generation units influence electricity prices, market participation strategies, and overall system efficiency, reinforcing the need for a well-coordinated generation portfolio**.**

2.2.1 Thermal Power Plants

Thermal power plants are the backbone of the country's electricity production, utilizing fossil fuels such as lignite, natural gas and oil. These plants generate electricity by converting heat energy into mechanical energy, which then drives a turbine connected to a generator producing ac voltage. Lignite power plants operate on the Rankine cycle, where fuel combustion produces steam that drives a steam turbine. These plants have long start up times and slow load adjustment making them suitable for base load units. Their efficiency ranges from 35% to 40%. Their capacity has significantly decreased over the last years and is expected to become zero by the end of the decade due to all the reasons explained earlier.

Natural Gar Power Plants are classified into Open Cycle Gas turbines and Combined Cycle Gas turbines. The first operate on a Bratton cycle, where compressed natural gas is burned to produce high pressure exhaust gases that directly drive a turbine. They have high operational flexibility, enabling rapid response to demand fluctuations. However, their efficiency is quite low, ranging from 30% to 40%. Combined cycle gas turbines improve efficiency by integrating one or more gas turbines with a steam turbine in a two-stage process. The waste heat from the gas turbines is used to generate steam, which then drives a steam turbine. They achieve efficiency up to 50% and they are mostly used for both base load and varying load generation. Oil fired power plants primary operate in Non-Interconnected Islands, where they serve as the main power source, mainly due to the lack of transmission interconnections and the high energy density provided by oil. They use diesel or heavy fuel oil and their high fuel cost make them less competitive compared to other technologies.

2.2.2 Hydroelectric power plant

The way power is produced by hydro power plants is categorized into run of river plants and reservoir-based plants. The first generate electricity based on the continuous flow of water from a river. They provide stable output, but lack the ability to store energy for peak demand periods. The second use water storage reservoirs allowing them to regulate output based on demand fluctuations when there is excess of water. During winter and rain seasons they cover the base load while during summer time they cover peak demand. There are also the pumped storage plants that act as a hybrid between reservoir plants and energy storage systems. These plants have two reservoir tanks, operating as simple reservoir plants when water is flowing from the upper tank to the lower reservoir via a hydro turbine and pumping water from the lower tank to the upper tank when operating as storage. Such plants usually generate power (consume water) at times of high demand/prices and store energy (pump water) at time of low demand/prices. This operation makes them important for balancing supply and demand in the grid.

2.2.3 Renewable Energy Sources

Renewable energy generation is expanding rapidly in Greece, driven by decarbonization policies and favorable weather conditions. Wind turbines convert kinetic energy from wind into electricity by allowing wind to move their blades which put a turbine in motion producing ac current through a generator. Their variability, due to their dependence to weather conditions, makes them difficult to forecast. Solar panels (also known as photovoltaics, PVs) generate electricity by converting sunlight into direct current (dc), which is then converted to ac. Solar energy production peaks during midday, but may present excessive and unpredictable fluctuations during days of unsettled weather conditions.

Another, less exploited RES is Biomass. Biomass power generation, one of the oldest energy sources, converts organic material (agricultural waste, forestry residues manure, etc.) into electricity. The process involves combustion, where biomass is burned to produce steam that drives a turbine, or gasification, where biomass is converted into syngas for power generation. Alternatively, anaerobic digestion produces biogas, which fuels gas engines [24].

2.3 Interconnections

The interconnection of the any power system with neighboring systems plays a pivotal role in ensuring energy security, market integration, and grid stability. Greece's geographic location makes it a critical link in the broader European electricity network, facilitating cross-border energy exchanges that enhance market efficiency and promote regional energy cooperation. The Hellenic Transmission System, operated by the Independent Power Transmission Operator (IPTO), is synchronously connected to the European grid under the coordination of ENTSO-E. Greece's interconnections enable both the import and export of electricity, balancing supply and demand fluctuations while contributing to grid stability and price formation in the electricity market. For many years Greece has been a net importer of electricity and 2024 was the first year that Greece transformed into a net exporter of electricity as shown in figure 12.

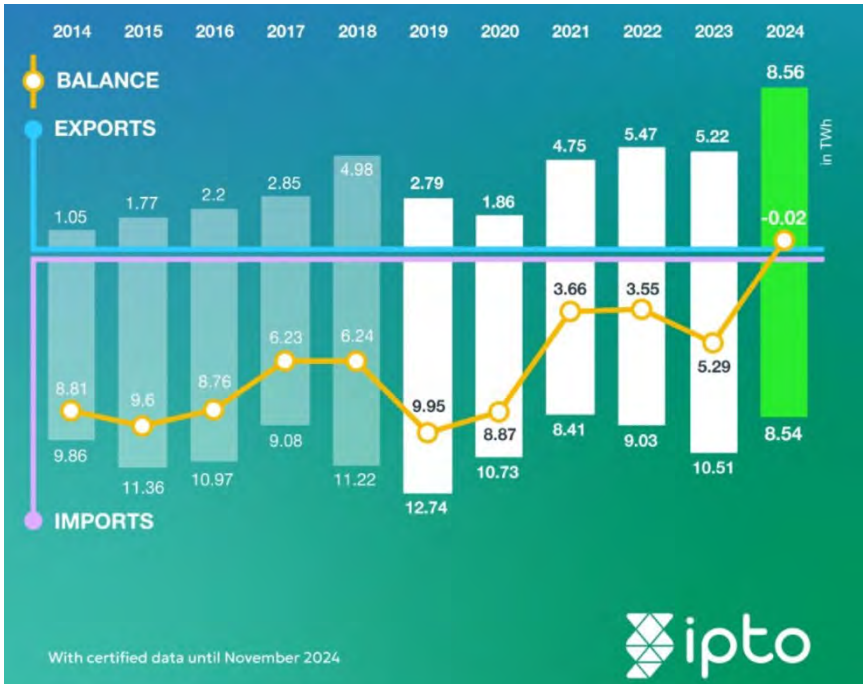


Figure 12 Net import export balance of Greece through the years.

The Greek electricity system currently operates with five international interconnections, all of them at a 400kV voltage level. A 1GW connection facilitates energy trade between Greece and Albania, allowing power exchanges depending on market conditions and system needs. Another key interconnection is that with Bulgaria of 1.2GW with an additional line of 500MW capacity activated in 2023, enabling significant energy flows given Bulgaria's surplus electricity production from nuclear and coal plants. North Macedonia is also connected to the Greek grid via 2 500-60MW lines, securing stability in the Balkan region. Another important interconnection is that with Turkey via a 600MW line. Last, there is an interconnection with Italy via a submarine cable with 500 MW capacity. Unlike the other connections, which operate synchronously with the ENTOSE system, the Greece-Italy interconnection is a High Voltage Direct Current (HVDC) link and it provides vital energy corridor between Greece and Western Europe [17]. These interconnections and their future expansion is shown in figure 13 [17].

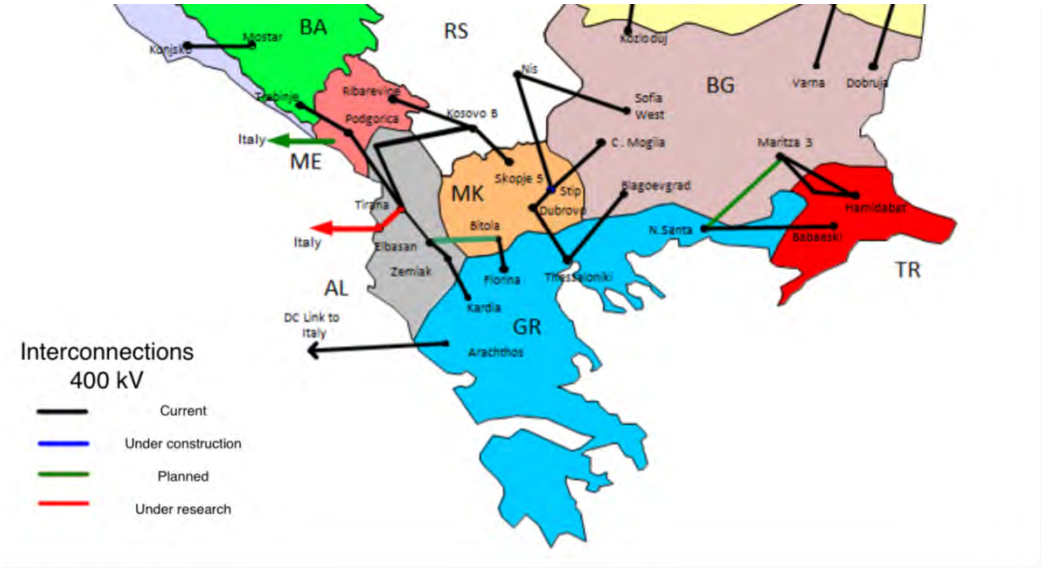


Figure 13 Balkan Interconnections [17].

The ability to import and export electricity ensures flexibility in responding to seasonal demand variations, supply shortages, and market fluctuations. The European Target Model has significantly influenced Greece's approach to energy trading and interconnections. The country participates in market coupling mechanisms, aligning electricity market operations with those of neighboring countries to optimize cross-border trade. This enhances liquidity, price convergence and the efficient utilization of resources [17]. The interconnections enable arbitrage opportunities, where Greece can import cheaper electricity when domestic prices are high and export surplus electricity when local prices are low. This tendency is expected to reduce overall energy costs and supports grid balancing by leveraging the diverse energy mixes of neighboring countries.

Despite the significant benefits offered by Greece's interconnections, several challenges must be addressed to maximize their efficiency and reliability. One of the primary limitations is transmission capacity constraints, as the physical infrastructure of the existing interconnections often restricts the volume of electricity that can be exchanged. The expansion of capacity will permit even higher cross-border electricity flows and will enhance Greece's integration with neighboring energy markets [18]. Additionally, market volatility and regulatory differences between Greece and the interconnected countries present further challenges. Variations in pricing mechanisms, energy policies, and grid regulations can lead to inefficiencies in cross-border electricity trading, limiting the full potential of interconnections [23]. Furthermore, while interconnections improve energy security, they also introduce system reliability risks, particularly during periods of high demand or extreme weather events, when neighboring countries may face supply shortages and restrict exports. This dependence on external energy flows necessitates a comprehensive risk management strategy to ensure grid stability under all conditions [18]. Addressing these challenges will require continued investment in transmission infrastructure, enhanced regulatory coordination with neighboring markets, and the development of advanced forecasting tools to optimize electricity exchange across borders.

2.4 Projects under development

The continuous development and modernization of Greece's electricity infrastructure play a vital role in ensuring the reliability, efficiency, and sustainability of the national grid. The projects currently under development focus on expanding transmission capabilities, integrating renewable energy sources (RES), enhancing cross-border interconnections, and reinforcing grid stability in response to evolving energy demands. Overall, these projects represent a strategic investment in Greece's electricity system, enabling a smoother transition to a more sustainable and resilient energy sector. By modernizing its grid infrastructure, Greece is enhancing system flexibility, supporting higher RES penetration, and aligning with the broader European energy transition goals.

2.4.1 Tranmission grid

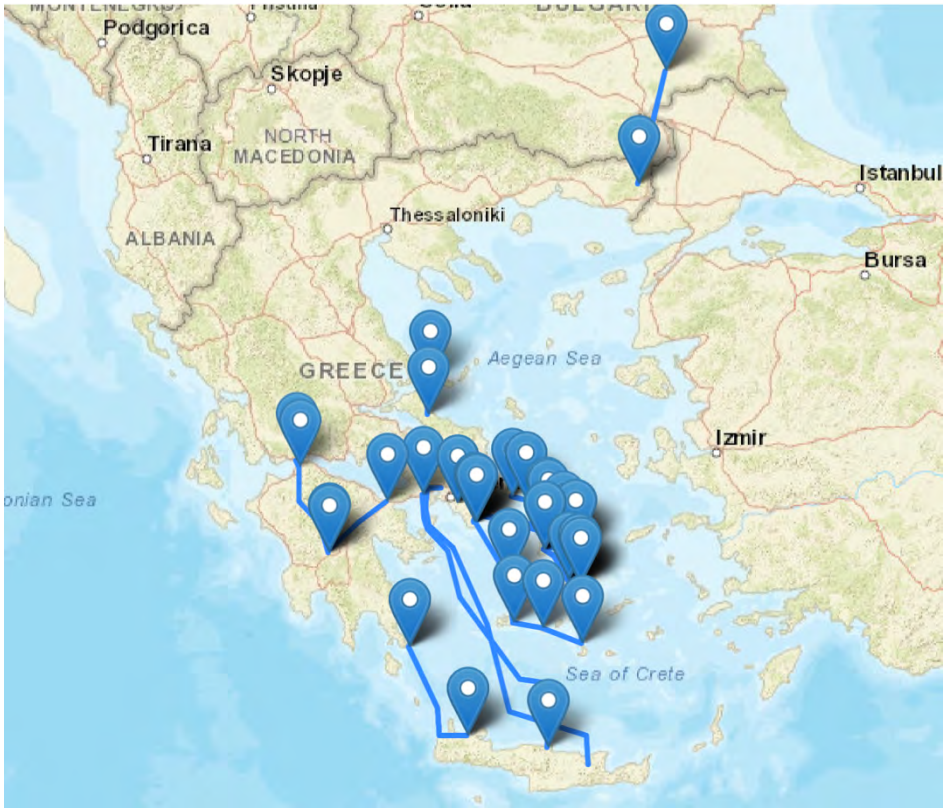


Figure 14 Interconnections under development [29].

The Independent Power Transmission Operator (IPTO) has launched multiple projects to strengthen the high-voltage network, enhance inter-regional energy exchanges, and support the increasing share of RES in the energy mix. The ongoing interconnections are shown in figure 14 [29]. Among the most significant upgrades is the expansion of the 400 kV transmission backbone grid, which aims to facilitate the efficient transfer of electricity across different regions while ensuring system stability [17]. A central priority of Greece's energy strategy is the integration of Non-Interconnected Islands (NIIs) into the mainland grid. The Cyclades interconnection project, which has already completed its initial phases, continues with further expansions to link more islands to the national grid. The Crete-Attica interconnection, Greece's largest electricity transmission project, is another milestone, expected to be fully operational by 2025.

This project will significantly reduce Crete's reliance on oil-fired power plants, enhance energy security, and allow for greater RES penetration [17].

At the same time, grid reinforcement projects are being implemented to accommodate the growing capacity of renewable energy. With Greece committed to achieving its ambitious decarbonization targets, additional grid infrastructure is required to support the connection of new wind farms, photovoltaic installations [17].

Furthermore, plans are underway to upgrade and modernize cross-border interconnections. One of the most significant projects currently under development is the Crete-Attica interconnection, Greece's largest electricity transmission initiative. This €1.1 billion project consists of two 500 kV DC submarine cables spanning 335 km,expected to become operational by mid-2025. It aims to stabilize Crete's power supply, reduce reliance on oil-fired generation, and facilitate the seamless integration of renewable energy sources into the national grid [27]. Another key project is the Great Sea Interconnector, which will connect the power grids of Greece, Cyprus, and Israel through a 1,240 km HVDC submarine cable, expected to be operational by 2030. With an estimated cost of €2.4 billion, this interconnection will be one of the longest and deepest subsea electricity links globally. It is designed to improve regional energy security and enable large-scale renewable electricity trade between the Eastern Mediterranean and mainland Europe [28]. Additionally, Greece has reinforced its cross-border interconnection with Bulgaria by electrifying a second 400 kV ultra-high voltage transmission line in 2023. This upgrade significantly increases the capacity for energy exchanges between the two countries. In parallel, plans for a new 400 kV interconnection with Albania are underway. Through these projects, Greece is not only enhancing its energy security but also positioning itself as a key energy hub within the Mediterranean and European electricity markets.

2.4.2 Storage

Greece has recently started the process of enhancing the flexibility of its generation and demand by integrating Battery Energy Storage Systems (BESSs). The National Energy and Climate Plan (NECP) outlines a target of installing 4.3 GW of energy storage capacity by 2030. To achieve this, the Greek Ministry of Environment and Energy has unveiled a plan to deploy initially 3.55 GW of standalone BESSs that enolnved in 4.GW until May 2025 [30], granting these projects priority access to the grid. BESSs will also integrate into the energy market.

In addition to large-scale installations, Greece is promoting energy storage at the commercial and industrial levels. In January 2025, the government launched the "Storage Systems in Businesses" program, allocating €153.7 million to subsidize battery systems paired with new or existing photovoltaic installations. This initiative aims to encourage businesses across various sectors to adopt energy storage solutions, thereby enhancing energy efficiency and resilience. These strategic efforts underscore Greece's commitment to modernizing its energy system, facilitating the integration of renewable energy, and ensuring a reliable and sustainable power supply for the future.

2.4.3 Conclusion

This chapter explored the physical structure and operational features of the Greek electric power system, providing the necessary technical context for understanding how energy markets — and especially the balancing market — function. The analysis of the transmission and distribution networks, generation, interconnections, and ongoing infrastructure projects reveals the complexity of maintaining equilibrium between generation and demand in a system undergoing rapid decarbonization and diversification.

These insights are not merely descriptive; they are foundational to the core objective of this dissertation. The accurate forecast of balancing market prices requires more than statistical modeling — it demands a deep understanding of the physical system dynamics that drive imbalances. For instance, the high share of RES, now exceeding 50% of Greece's energy mix, introduces variability that directly affects the need for balancing actions. Likewise, limited storage capacity, seasonal demand swings, and weak interconnections between some regions add further strain to grid stability and affect pricing mechanisms.

By connecting the physical constraints of the power system — such as generation ramping limitations, reserve availability, and cross-border capacity — to market outcomes, we gain the necessary perspective to model and interpret price spikes in the balancing market. Each component analyzed in this chapter plays a role in determining when and how imbalances occur, and ultimately, what price must be paid to resolve them.

In the next chapter, we shift focus from the technical structure of the Greek power system to the institutional and regulatory framework of the Greek energy market. Understanding how markets are organized and how balancing services are traded will further complete the foundation needed to build robust forecasting models that reflect both the physical and market realities of Greece's evolving power system.

3. Electricity markets in Greece

The structure and functioning of the Greek electricity market form the institutional and regulatory framework within which all electricity trading activities take place. This chapter aims to provide a comprehensive overview of that framework, outlining how the different market segments interact, and emphasizing the role of the balancing market within the broader electricity market.

Understanding the Greek energy market is essential for several reasons. Firstly, electricity prices, especially those in the balancing market, are not shaped in isolation. They are the outcome of processes that begin well before real-time operation. Markets such as the forward, day-ahead, and intraday markets play a fundamental role in shaping expectations, allocating generation resources, and preparing the system operator to manage demand and supply. Secondly, the design, rules, and inefficiencies of these markets can introduce imbalances which trigger volatility in the balancing market, causing spikes in prices as the ones identified later in this work.

This chapter begins with a brief description of the Greek energy market as a whole, explaining day-ahead and intraday markets, as well as any mechanisms that precede them, such as the forward markets. Following that, the discussion will shift to the balancing market itself explaining its operation, underlying logic, and finally the technical and economic factors that influence its behavior. This analysis is critical, as the dissertation's primary goal is to predict price peaks within the balancing market, which requires a solid grasp of how the market is structured and why imbalances occur in the first place.

Having outlined the rationale for this chapter, a closer look at the markets preceding the clearance of the balancing market will follow. Specifically the day-ahead and intraday markets will be briefly described. They are the backbone of pre-dispatch electricity scheduling in Greece and they count for more than 90% of the traded energy volumes.

3.1 Structure

The Greek electricity market, as it operates today, is the product of a long-term transformation process driven by European Union integration goals and national legislative reforms. This transformation has been guided by the principles of the European Target Model, a harmonized framework for electricity markets that supports competition, transparency, and cross-border integration across EU member states [32]. The broader objective of this model is the creation of a single electricity market that allows energy to be traded as freely as any other commodity. Within this framework, electricity generated in one EU country can be delivered and consumed in another, thereby fostering price convergence, increasing system efficiency, and enhancing the security of supply. The implementation of the Target Model aims to deliver competitive electricity prices, efficient use of infrastructure, and environmentally sustainable practices, particularly in the context of growing renewable energy integration [32], [33].

The Target Model introduces a structured sequence of wholesale markets each corresponding to a different time horizon (figure 15) and different risk profile. It is

important to clarify that Greece is a single biding zone. This sequence includes the Forward Market (FM), the Day-Ahead Market (DAM), the Intraday Market (IDM), and the Balancing Market (BM). Together, these markets form a spectrum of participating options that begins with long-term contracting and proceeds through increased granular stages of trading until real-time system operation. In the past years, forward markets and tariff based payment for electricity production was common in Greece, especially for renewables. However the Target model transformed their structure into a more dynamic framework. Within this structure, electricity is treated as a tradable product, and all market participants -generators, suppliers, traders, and large consumers- interact through competitive, rule-based platforms. The Target Model supports efficient price formation by allowing supply and demand to meet in open markets under harmonized European rules. It also facilitates optimal scheduling of resources and cross-border flows, enhancing the resilience and flexibility of the overall system.

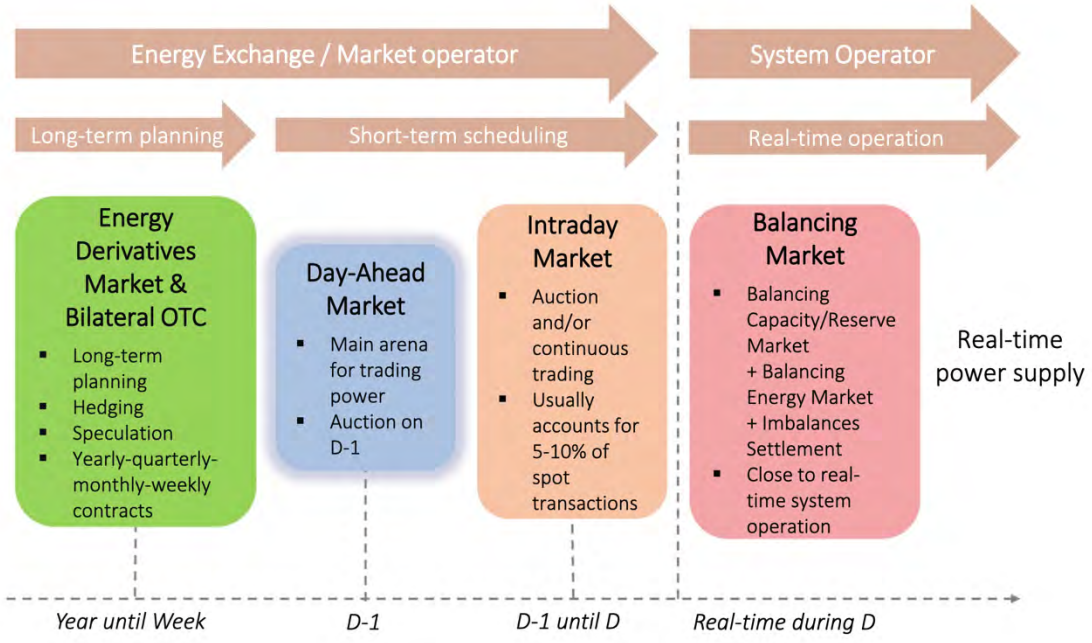


Figure 15 Energy markets time horizon.

The Greek electricity market formally adopted the Target Model framework on 1 November 2020, following years of preparatory reforms and legal harmonization. The legal foundations for this transition were laid by Laws 4425/2016 and 4512/2018, with operational responsibility for market design and clearing procedures transferred from the former market operator (LAGIE) to the Hellenic Energy Exchange (HEnEx). This marked an important moment in the liberalization of the Greek market, aligning its mechanisms with EU guidelines and establishing the necessary infrastructure for full participation in Europe's interconnected electricity system. The reform sought to address long-standing inefficiencies in the domestic market such as limited competition, insufficient transparency and restricted interconnection use [32].

The full sequence of markets now operates in accordance with European network codes and market coupling mechanisms. The Forward Market allows participants to hedge their exposure to price fluctuations months or even years ahead, though their market in Greece it remains relatively idle due to low participation. The Day-Ahead Market serves as the primary venue for energy scheduling, accounting for approximately 92%

of the traded electricity volume in 2024. The Intraday Market, in turn, offers multiple trading windows through discrete auctions and continuous trading, allowing market participants to adjust their positions based on updated forecasts or unplanned events. Finally, the Balancing Market ensures real-time system equilibrium by activating flexibility resources to respond to short-term mismatches between supply and demand, building a bridge between the markets and actual operation.

The implementation of the Target Model in Greece not only to ensures compliance with EU obligations, but also strengthens the market's ability to accommodate rising shares of RES, incorporate DSR, and reduces overall system costs. Before its adoption, the Greek electricity market operated with several structural limitations, including reliance on vertically integrated utilities, inefficient pricing signals as well as limited control and monitoring of the whole supply. Since the reform, liquidity has improved in the Day-Ahead Market, and new opportunities for cross-border trading have emerged, making Greece being a net exporter in 2024 (see section 3). Nonetheless, challenges remain, particularly in the Intraday and Balancing Markets, where limited liquidity, price volatility, and high balancing costs persist [32] and they are expected to become more challenging as the grid grows in terms of capacity and with the integration of storage systems in 2025.

As RES penetration increases, forecast errors become more frequent due to their increased volatility. The ability to trade closer to real time, so that these errors have been limited becomes essential. In this context, a well-functioning sequence of markets is not only desirable, but necessary to maintain system balance and avoid costly interventions (load scheduling).

The following sections will examine the individual markets within the Greek electricity system in greater detail. Section 3.2 and 3.3 focus on the Day-Ahead and Intraday Markets, explaining how they function within the Target Model, their respective timelines, and their impact on price formation and system flexibility. These markets are of particular relevance for understanding the short-term dynamics of the Greek electricity system and for contextualizing the balancing processes discussed in later chapters.

3.2 The Day ahead market in Greece

The DAM forms the cornerstone of short-term electricity trading in Greece and is fully integrated into the European Target Model framework. Its primary objective is to match generation and consumption forecasts for each delivery day through a centralized auction platform. Within the DAM, energy is traded with a physical delivery obligation for each hour of the following day, ensuring that commitments between market participants are met in a transparent and efficient manner [33]. The HEnEx is responsible for market operation, while RAWEW oversees compliance, transparency, and market integrity [33].



Figure 16 Coupled markets in Day-ahead.

One of the key features of the Greek DAM is its integration into the Pan-European Market Coupling mechanism, specifically through the Price Coupling of Regions (PCR) framework, where bids, offers, and network capacities and constraints are matched [32]. Coupled countries are shown in figure 16. The algorithm applied is the Pan-European Hybrid Electricity Market Integration Algorithm (EUPHEMIA). DAM coupling requires input data from all involved Nominated Electricity Market Operators (NEMOs) and TSOs. This process enables synchronized matching of orders across interconnected European countries, optimizing cross-border electricity flows. The algorithm aims to maximize total social welfare by finding a price that clears the market (figure 17), while considering both local and cross-zonal capacity constraints [34].

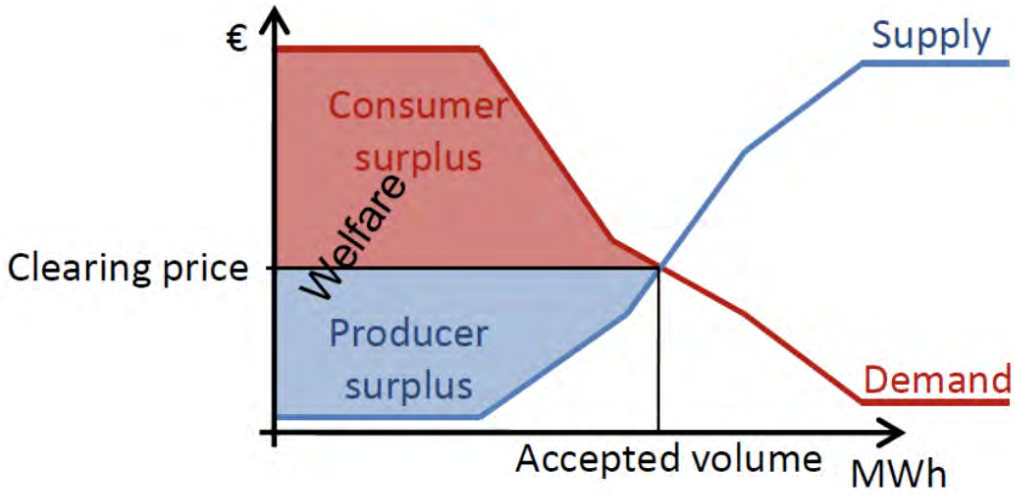


Figure 17 Euphemia algorithm clearing mechanism.

Trading in the DAM takes place daily, with buy and sell orders submitted on calendar day D-1 for the physical delivery of electricity during day D. The market follows a strict timeline, beginning with the Gate Opening Time (GOT) at 11:00 EET that market participants can begin submitting bids or offers, followed by the Validation Gate Opening Time (VGOT) when data validation processes begin, and concluding with the Gate Closure Time (GCT) at 13:00 EET as shown in figure 18 . The exact times are specified by HEnEx technical decisions, and provisions exist for extensions in cases such as partial or full decoupling of market coupling operations. It is important to clarify that the Day-Ahead Market is cleared and results are published prior to the obligation of participants to submit their reserve offers in the Balancing Market. This chronological sequence ensures that reserve bids are informed by finalized day-ahead schedules and market positions.

Currently, the Greek DAM is structured in hourly Market Time Units (MTUs), meaning prices and quantities are cleared on an hourly basis. However, starting in October 2025, MTUs will decrease in length to 15 minutes, aligning with European requirements under the Clean Energy Package. This change is expected to improve market responsiveness, enhance price signals, and support the more precise integration of flexible assets and intermittent resources into the market.

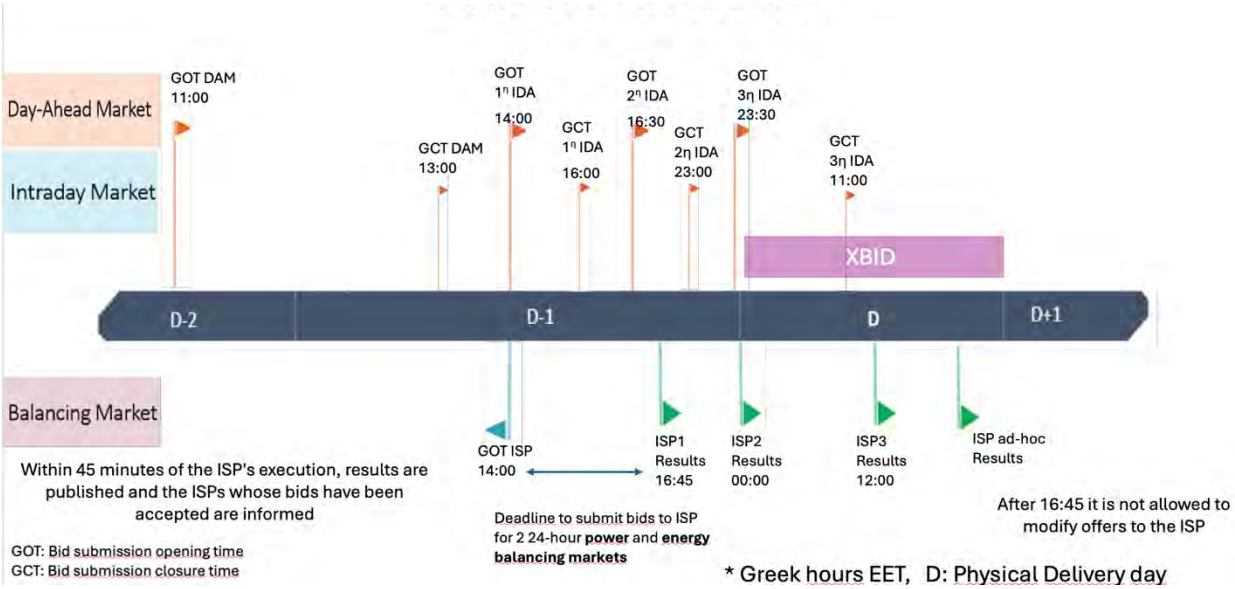


Figure 18 Market Timelines.

Market participants submit various types of orders via the Energy Trading Spot System (ETSS), including Hourly Hybrid Orders, which can include both stepwise and linear segments to reflect price-quantity preferences. These orders are validated and compiled into a Local Order Book, which is then anonymized and submitted to the Shared Order Book managed by the Market Coupling Operator (MCO) for each region. Greece is a single region [33].

The DAM operates as a centralized auction with a marginal pricing mechanism, where the market clearing price is determined by the intersection of aggregated supply and demand curves. All accepted bids are settled at the same marginal price, known as “pay as clear”, which means that all accepted bids are settled at a single market clearing price. The highest price among accepted supply offers needed to meet total demand for

each hour. This clearing mechanism incentivizes competition and transparency: generators have an incentive to bid their true marginal cost, knowing they will be paid the market price regardless of their individual offer.

In this context, RES typically bid at or near 0 €/MWh, as their marginal generation cost is minimal. The aim is to ensure dispatch priority and secure market access, especially since RES production are non-dispatchable and dependent on natural conditions. This behavior contributes significantly to price suppression effects, especially during periods of high RES penetration and low demand.

In fact, this phenomenon has become increasingly visible in Greece and across Europe, where the combination of abundant RES generation and low system load, particularly during spring weekends, has led to negative prices in some Day-Ahead Markets as depicted in figure 19. These prices reflect moments when supply exceeds demand and participants are effectively paying to remain dispatched. Negative pricing events are becoming more frequent, highlighting the challenges of balancing markets with high shares of variable RES and limited flexibility.

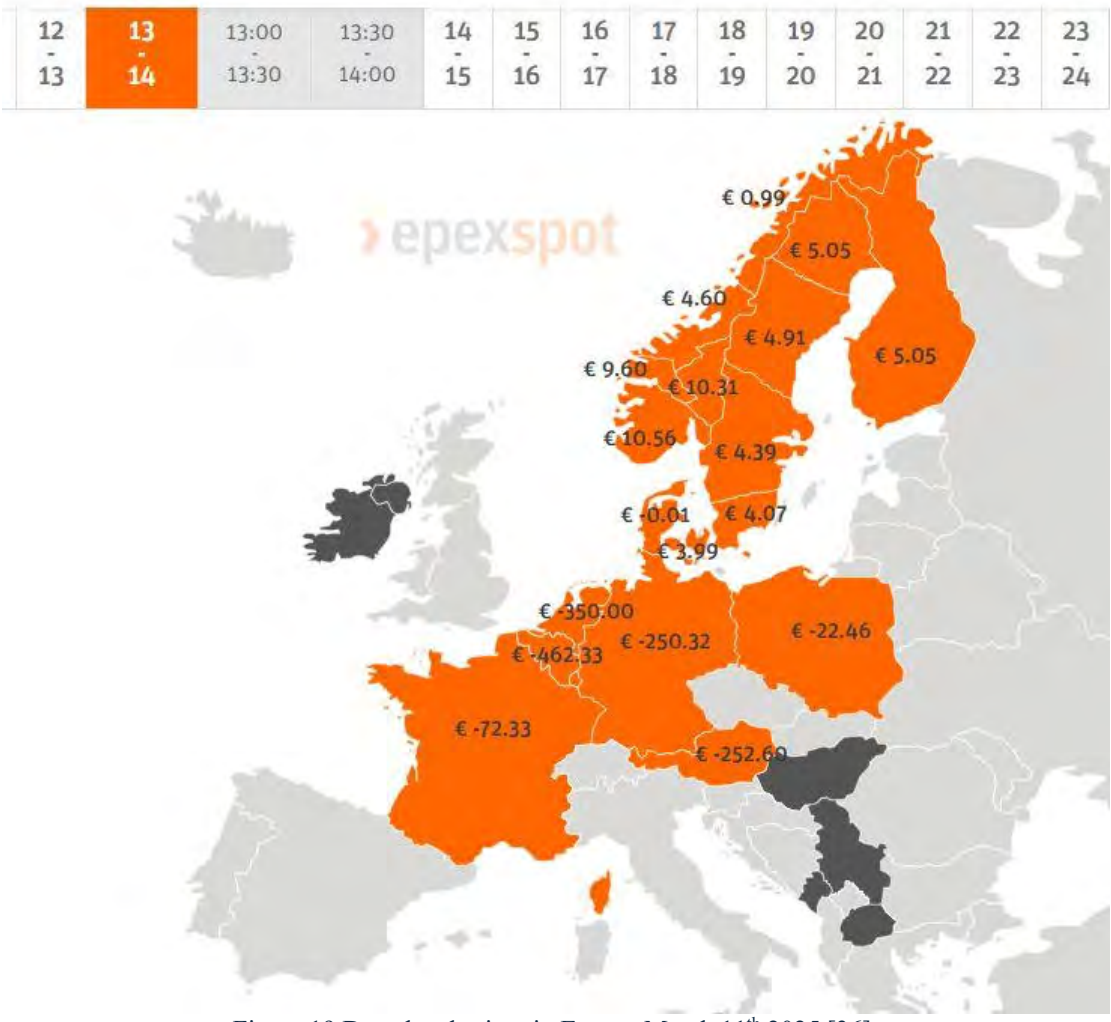


Figure 19 Day ahead prices in Europe March 11th 2025 [36].

After market closure, the clearing process is conducted by the designated Clearing House, which in Greece belongs to HEnEX. The process allocates credits and debits for each participant based on the matched trades. These results include not only pricing and energy volumes, but also settlement accounts and physical delivery obligations. The ETSS then transmits final schedules and nominations to the Transmission System Operator (TSO), which prepares the grid accordingly for the next day's dispatch. HEnEX makes results publicly available via their website, as shown in figure 20.

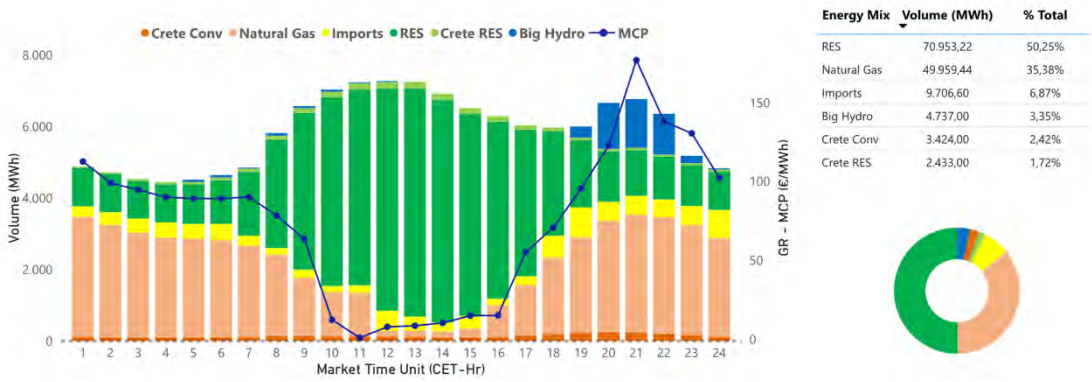


Figure 20 Day Ahead price and energy mix for March 24th in Greece [35].

The correlation between quantity and price in DAM with the energy mix in Greece is depicted in figure 21. The graph provides a summary of Greece's DAM performance in 2024, highlighting monthly energy volumes by generation source alongside Market Clearing Price (MCP) fluctuations. RES including both mainland and Crete-based assets, dominated the energy mix, contributing approximately 40.6% of total traded volume, followed by gas-fired generation at 35.5%, which continues to serve as a critical balancing resource. Imports, hydro, and lignite contributed 12.5%, 4.2%, and 3.3% respectively, with lignite maintaining a marginal role, consistent with Greece's decarbonization goals. The MCP showed clear seasonal variation—dropping steadily from January to April due to low demand and high RES availability, peaking in the summer months (June–August), when increased demand due to cooling and RES intermittency prevailed, and falling again in October due to milder weather conditions. This pattern reflects the growing volatility of electricity prices in a system increasingly reliant on RES generation, underscoring the need for strong intraday and balancing mechanisms to ensure grid stability and price efficiency.

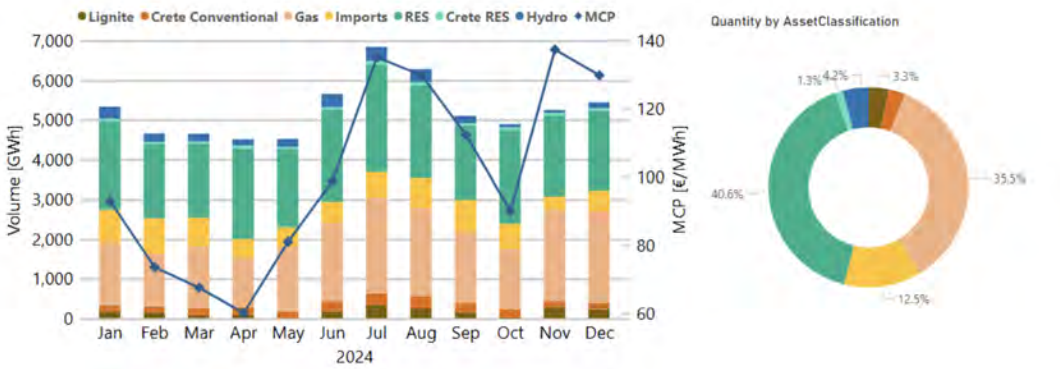


Figure 21 DAM sell side dashboard.

In conclusion, the Greek Day-Ahead Market plays a central role in price formation and short-term electricity scheduling, accounting for more than 90% of the electricity traded (figure 22). It offers transparency, competitive pricing, and strong integration with the wider European energy market. However, the Day-Ahead Market operates on forecasts submitted a day in advance, which inevitably introduce uncertainty, especially with the increasing penetration of renewable energy sources. To manage these uncertainties and allow for corrections closer to real time, the Intraday Market serves as a critical follow-up mechanism. The next section examines its structure, timing, and evolving role in maintaining system balance and supporting renewable integration in the Greek electricity market.

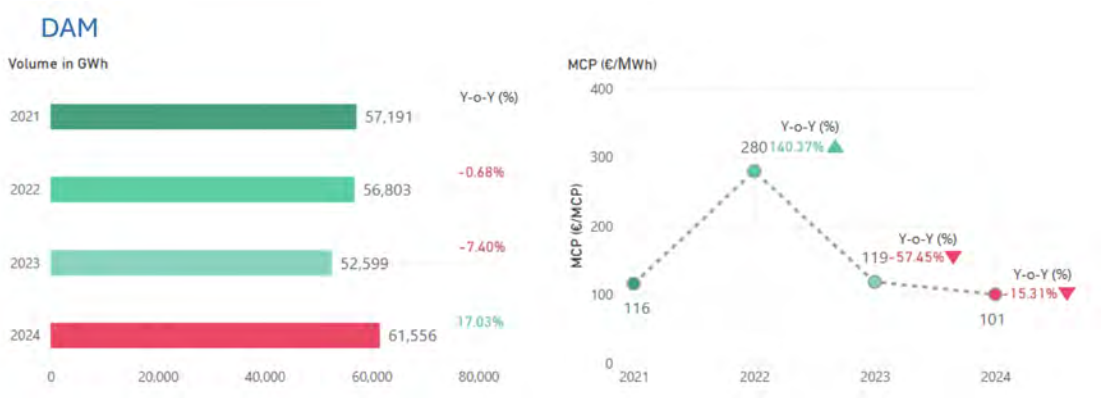


Figure 22 Day Ahead Market in Greece.

3.2 The Intraday market

The IDM complements the DAM by offering market participants the flexibility to adjust their positions closer to real-time, thereby addressing forecast deviations and improving system reliability. This flexibility becomes particularly critical in power systems with a high share of intermittent renewable energy sources, such as wind and solar. There, production forecasts can deviate significantly even a few hours ahead. In Greece, the IDM functions within the framework of the European Target Model and is operated by the Hellenic Energy Exchange (HEnEx) through two mechanisms: the Intraday Auctions (IDAs) and the Continuous Trading Platform (XBID). Both of these markets in Greece are coupled with other European markets, as shown in figure 23.

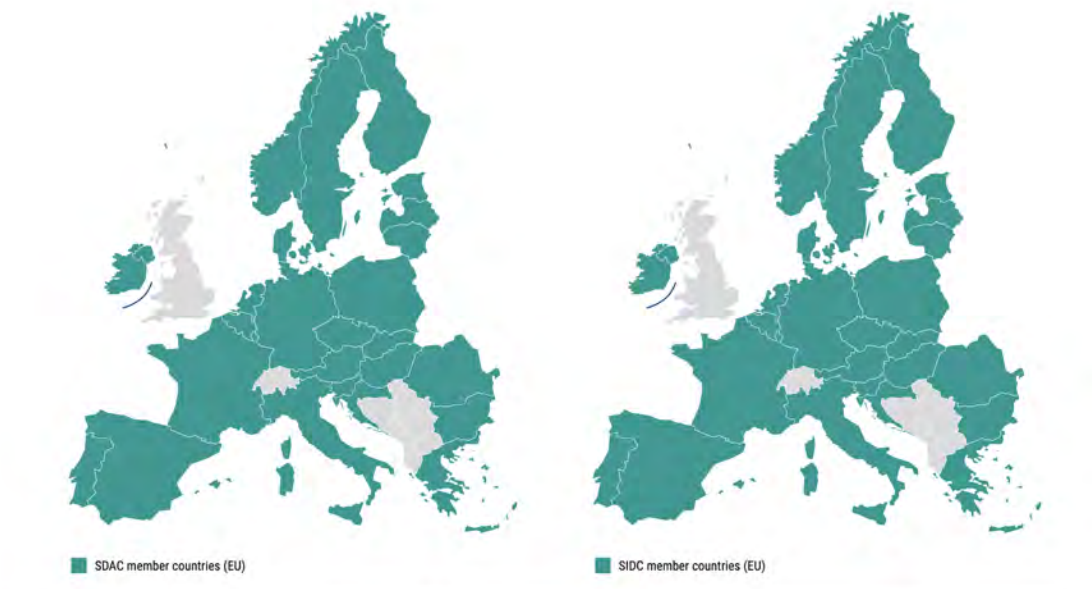


Figure 23 Coupled markets in Day-ahead (left) and Intraday (right) for coupled markets in 2024 [37].

Intraday Auctions (IDAs)

The IDAs in Greece, were originally known as LIDA (Local Intraday Auctions), and later were renamed CRIDA (Continuous Regional Intraday Auctions) reflecting their progressive integration into the European market framework and alignment with evolving terminology under the Target Model. Their market share through the last 4 years can be seen in figure 24.

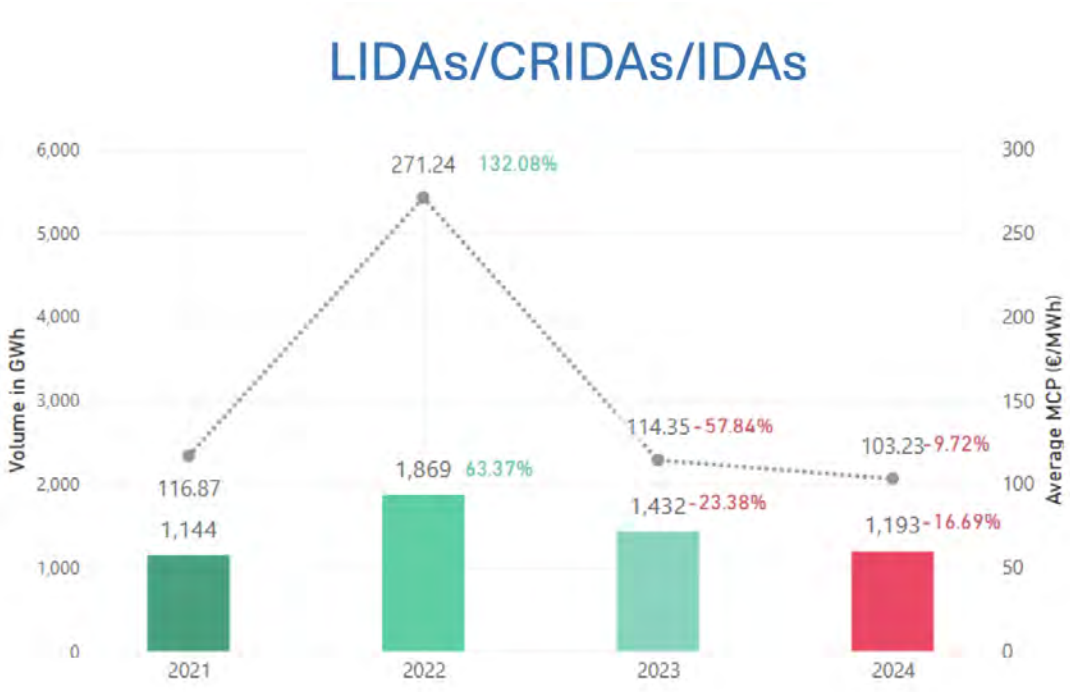


Figure 24 Intraday auctions' market in Greece through the years.

Greece currently operates three scheduled IDAs each day, enabling participants to fine-tune their positions in a structured, sequential manner. Each auction covers delivery for specific time intervals of the following or same day (Day D), depending on the time it is conducted. The timeline can be shown in figure 18.

- IDA 1 takes place on D-1, with a Gate Opening Time (GOT) at 14:00 EET and Gate Closure Time (GCT) at 16:00 EET. It allows trading for any Market Time Unit (MTU) of the delivery day. Results are published by 16:30 EET as shown in figure 25.
- IDA 2 follows, opening at 16:30 EET and closing at 23:00 EET. Results are available by 23:30 EET.
- IDA 3, conducted overnight into the day of delivery (D), opens at 23:30 EET and closes at 11:00 EET on D. This auction covers the final 12 hours of the delivery day. Results are published by 11:30 EET

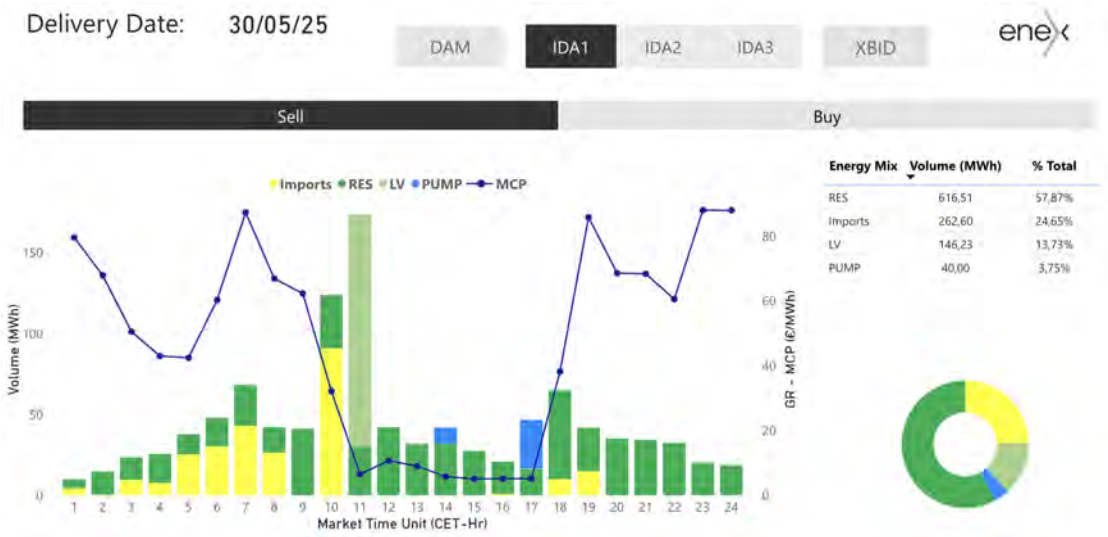


Figure 25 IDA1 for March 29th 2025 in Greece.

These auctions utilize a marginal pricing mechanism, similar to the DAM, ensuring that all accepted orders within the same MTU are settled at a uniform clearing price. This mechanism promotes transparency and economic efficiency while providing clearer incentives for demand-side flexibility and supply-side balancing. Participants in the IDAs are required to fulfill their trading commitments through physical delivery. This means that the energy quantities agreed in the auctions must be physically delivered into the grid on day D.

Continuous Intraday Market

In addition to the scheduled IDAs, Greece participates in the Pan-European XBID (Cross-Border Intraday Market) platform, which enables continuous trading across European interconnected markets. The Greek XBID session opens at 14:00 EET on D-1 and remains open until one hour before the physical delivery hour. Trades can be executed in real time via HEnEx's ETSS, and transactions are matched continuously using a first-come, first-served algorithm within available capacity limits.

The products currently traded through XBID are 60-minute contracts, but in alignment with the Clean Energy Package requirements, these are expected to transition to 15-minute segments as with the DAM, enhancing granularity and responsiveness in the

market. This shift will support better alignment between market signals and real-time system needs, especially for aggregators, demand-side participants, and flexible generation units. As it can be seen in figure 26, XBID accounts for approximately up to 10% of DAM on an average day allowing for a bigger share after the segmentation in 15' slots. The XBID markets tends to gain a bigger volume in the markets as seen in figure 27.

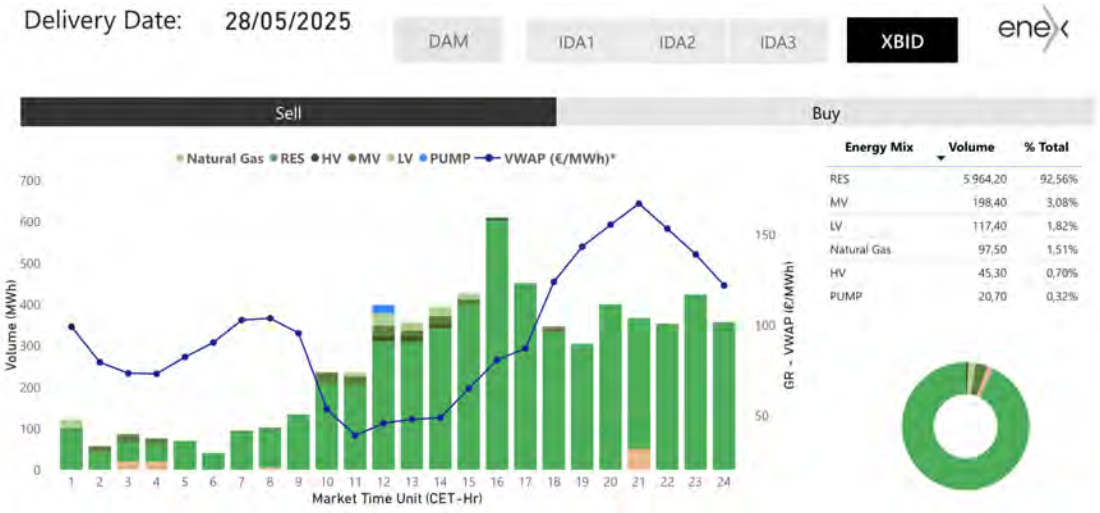


Figure 26 XBID market results for 28th of March in Greece.



Figure 27 XBID market through the years.

The IDM plays a bridging role between the Day-Ahead Market and the Balancing Market**.** By allowing market participants to revise their schedules closer to delivery, it reduces the size of real-time imbalances and mitigates the operational risk borne by the Transmission System Operator (TSO). This function becomes increasingly

important, as Greece sees rising shares of RES and as dispatch flexibility becomes a strategic requirement for grid stability.

Ultimately, while the DAM secures bulk scheduling and the balancing market addresses real-time discrepancies, the IDM serves as the adaptive layer that enhances operational accuracy and economic efficiency. In the next section, we will examine the Balancing Market, where system operators procure balancing capacity and energy in real-time, finalize system-wide schedules, and settle imbalances across all market participants.

3.3 The balancing market

The balancing market (BM) in Greece is the last component of the country's wholesale electricity market, crucial for maintaining real-time supply–demand balance and system security. It is a centralized, unit-based dispatch system operated by the IPTO on a continuous daily basis. In the BM, Balancing Service Providers (BSPs) – typically dispatchable generators and other resources – submit balancing offers per individual unit and location, while the IPTO runs optimization algorithms that select offers and issue dispatch orders to each unit as needed [32]. This centralized model ensures that balancing actions have both economic and physical effects in keeping the power system stable.

The Greek balancing market uses standard EU balancing services products, each with specific activation speeds and purposes. These balancing products are:

- Frequency Containment Reserve (FCR): FCR (often mentioned as primary reserve) is the fastest response reserve, activated locally and automatically within seconds of an imbalance measures at frequency deviation. Its role is to immediately arrest frequency changes across the synchronous area. In practice, FCR resources (governor-controlled units) begin responding almost instantaneously after a disturbance in order to recover nominal system frequency (50 Hz). FCR is procured as an upward and downward capacity for the initial handling of major imbalance or directly handle minor instantaneous imbalances.

- Automatic Frequency Restoration Reserve (aFRR): aFRR (formerly secondary reserve) is an automatically controlled centralized reserve that restores the system frequency to nominal and relieves the activated FCR. It acts on a short timescale of a few seconds up to several minutes (fully activated within roughly 5–15 minutes). In Greece, units providing aFRR receive continuous set-point signals every 8n seconds from the IPTO's AGC system in order to correct any remaining frequency error to zero. aFRR is crucial for maintaining balance after the initial containment by FCR, and it adjusts generation output quasi-continuously to follow fluctuations.

- Manual Frequency Restoration Reserve (mFRR): mFRR (often mentioned as tertiary reserve) is activated manually by dispatch instructions. It provides a slower, but much larger balancing action. It consists of generation or demand resources that can be manually instructed by the TSO to increase or decrease output. They typically become fully available within 15'. In the Greek system, mFRR is used for planned balancing interventions close to real time – for example, to address anticipated imbalances or replace aFRR. The TSO activates

upward or downward mFRR, starting with the lowest-cost bids to meet the system's needs. mFRR usually covers significant generation changes, such as starting fast-ramp units or curtailing output, and allows aFRR to return to its neutral range.

- Replacement Reserve (RR): RR (often called supplemental or tertiary reserve in a broader sense) refers to reserves with an activation time from several minutes to hours. It is used to restore the readiness of faster reserves. Replacement reserves kick in when sustained imbalances or major outages occur that aFRR/mFRR alone cannot fully address [32]. They free up the aforementioned quicker reserves, by taking over the balancing duty for the long haul. In Greece, RR capacity would typically involve slower units or offline generators that require more lead time to start but can then provide energy for extended periods, allowing FRR (aFRR/mFRR) providers to recuperate. Currently, the Greek BM procures FCR, aFRR, and mFRR as standard products. Replacement reserves are not a separately traded product in daily operations. However, Greece plans to fully integrate with the European platforms (e.g. TERRE for RR) to exchange replacement reserves, if needed in the future.

Capacity	Total BC up (MW)	Total BC DN(MW)
FCR	963	963
aFRR	3.898	3.906
mFRR	4.836	4.885

Table 1 BSPs' reserve capacity in December 2023 [41].

Each of these reserves is procured as upward (increasing generation or decreasing load) and downward (decreasing generation or increasing load) capacity. They are activated in a coordinated sequence: FCR responds first to stabilize frequency, aFRR follows to restore balance, mFRR is dispatched as needed to correct larger deviations or replace aFRR. FCR has a very small share in the market, while aFRR and mFRR have a bigger share as seen in table 1.

Participants submit offers for balancing capacity in MW and €/MW. In the Balancing capacity reserves markets FCR, aFRR and mFRR are distinguished offers. On the other hand, offers for balancing energy in the capacity market in MWh and €/MWh for aFRR and mFRR are submitted together as one energy product.

The Greek balancing market offers three stages, each with a specific role:
1. Balancing Capacity (Reserves): In this forward-looking stage, IPTO procures reserve capacity to ensure sufficient balancing resources are available for real-time operation. BSPs submit offers indicating the capacity (in MW) they are willing to hold in reserve for various balancing products (upward/downward reserves). Through an optimization process called the Integrated Scheduling Process (ISP), IPTO determines the reserve requirements for each 30-minute period and selects the least-cost offers to meet these requirements [32][38]. The ISP algorithm accounts for the day-ahead schedule (as adjusted by intraday markets), system constraints, forecasted load, and RES output to commit the necessary units and allocate reserve capacity accordingly [39]. Selected BSPs then receive a capacity payment and incur an obligation to withhold that capacity for balancing needs. Notably, capacity procurement occurs prior to real time, to guarantee the system has adequate reserve margins [32]. BSPs are paid every 30

minutes on a pay-as-bid basis for reserved capacity and must commit that capacity for real-time balancing if called upon.

2. Balancing Energy (Activation): This is the real-time (or near real-time) energy balancing operation, where IPTO activates energy from the reserves to correct imbalances and control system frequency. BSPs submit offers for upward and downward balancing energy (in MWh) based on the capacity they have reserved. They can submit improved offers up to 15 minutes before the time of physical delivery. As the delivery period approaches, IPTO runs the RTBM market which is responsible for mfrr activation and instruct units to increase or decrease output based on the cheapest available bids in order to address forecasted imbalances before real time [38] [39]. In real time, the automatic Frequency Restoration Reserves (aFRR) are activated continuously via the AGC procedure so that frequency deviations are fine tuned. Generators providing aFRR receive automatic set-point orders every 8 seconds to stabilize frequency. In other words, the TSO uses a merit order of balancing energy offers: the lowest-priced mFRR bids are deployed first for manual adjustments close to dispatch, and aFRR resources respond automatically to minute-by-minute deviations. This activation of balancing energy is essentially a redispatch process that changes generator output to maintain the supply-demand balance.

3. Imbalance Settlement: After market clearing of Reserves and activation, all real time deviations and balancing actions are financially settled in the imbalance settlement process. Balance Responsible Parties (BRPs) – typically generators and suppliers who are financially responsible for energy deviations – are charged or credited based on their imbalance volume and the imbalance price. Greece employs a 15-minute imbalance settlement period (aligned with European guidelines) since November 2020 [38]. A single imbalance price is calculated for each 15-min interval, reflecting the cost of the activated balancing energy in that period [32]. This price applies to all imbalances (whether a deficit or surplus) to incentivize market participants to be balanced. The imbalance price is based on the cost of regulation (balancing) energy deployed by the TSO, thus sending accurate economic signals: it essentially equals the marginal price of balancing energy in the dominant direction of the system imbalance, in accordance with the EU harmonization rules [38]. BRPs with a shortfall (who consumed or sold more than scheduled) will pay the imbalance price for each MWh of deficit, while those with an excess receive payment (or incur a charge for downward imbalances) at that same price, ensuring that the entities responsible for causing imbalance bear the balancing costs. This mechanism is depicted in figure 28.

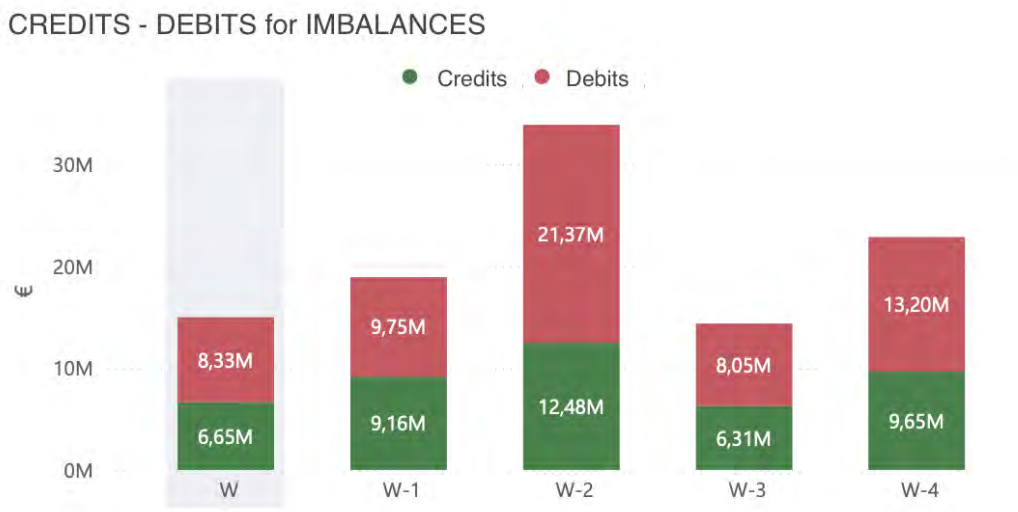


Figure 28 IMBALANCES' debits and credits [42].

The balancing market operates in close coordination with the day-ahead and intraday markets, following a strict timeline of gate closures and clearing processes as shown in figure 16:

1. Day-Ahead Market (DAM): One day before delivery, the DAM closes at 13:00 EET (D-1), producing a preliminary dispatch schedule for all generating units and expected consumption. This schedule forms the base on which reserve needs are calculated.
2. First Intraday Auction (IDA 1): On the afternoon of D-1, the first intraday market auction allows participants to adjust their positions. It closes in early afternoon (gate closure around 16:00 EET), and results are known by 16:30 EET.
3. BSPs must submit balancing capacity and energy offers for mFRR, aFRR, FCR from 14:00 EET D-1 until 16:45 EET D-1.
4. ISP1 – First Integrated Scheduling run: At 16:45 EET on D-1, right after the initial intraday results, IPTO executes the first ISP to procure reserves and commit units for the next day. ISP1 considers the updated market schedule and forecasts to optimize unit commitment for the entire next day (00:00–24:00). The results of ISP1 (unit schedules and reserve allocations) are advisory (non-binding) at this stage, they serve as an initial plan.
5. Second Intraday Auction (IDA 2): In the evening of D-1 (14:30 EET – 23:00 EET), a second intraday auction is held for additional adjustments. Participants refine their positions for the overnight and early morning hours of the delivery day.
6. ISP2 – Second Integrated Scheduling run: At 00:00 EET on D, after the evening intraday trade, IPTO runs ISP2 for the balancing market. This time, the algorithm's outcome for the first half of the delivery day (00:00–12:00) becomes binding – i.e. units are officially committed and reserve capacity awards are firm for hours 1–24 of the day's 48 half-hour periods. BSPs have the opportunity to update (improve) their offers before ISP2. After ISP2 clearing, market participants know which units must be online and what reserves are secured for the first half of the day, with associated pay-as-bid capacity payments locked in.

7. Continuous Intraday Trading: Following ISP1 at14:00 EET and through the night and morning of the delivery day, continuous intraday trading (XBID platform) is open to allow any last-minute energy adjustments up to 1 hour before delivery. This gives participants flexibility to handle forecast errors (e.g. changes in demand or renewable output) by trading energy, while the committed reserves remain in place.
8. ISP3 – Third Integrated Scheduling run: At 11:00 CET on the delivery day (D), IPTO performs ISP3 to finalize the plan for the second half of the day (12:00–24:00). BSPs again may revise their bids prior to this run. The ISP3 results (for hours 13–24 of the day) are binding for unit commitment and reserve procurement for the afternoon and evening periods. This staged clearing ensures that later hours, which have more forecast uncertainty, are committed closer to real time with updated information.
9. Real-Time Balancing Operations: As the day proceeds, IPTO continuously monitors system balance. Committed resources must follow the dispatch schedules and maintain the reserved capacity. Gate closure for balancing energy effectively occurs just before real-time dispatch: after the last ISP (or any intra-day bid update), no new bids are accepted, and the real-time balancing market (RTBM) takes over. In real time, IPTO activates balancing energy according to system needs: sending signals to aFRR units continuously and dispatch instructions to additional mFRR. Gate closure for each 15-min balancing timeframe is rolling and very short, in line with the technical limitations of sending out instructions.
10. Settlement: After delivery, the imbalance settlement process calculates each participant's deviations and settles payments for balancing capacity, balancing energy, and imbalance charges. This typically occurs on the next day or within the same week.

Having explained in detail the timeschedule of all markets above, we will now describe when participants in the Greek balancing market can implement their forecasting and submit or adapt their offers. After the IPTO announces at 09:30 on D-1 the next day's load, RES prediction production and other important forecasts about the grid, BSPs can refine their forecast about the Balancing market prices [45]. After DAM closure at 13:00 on D-1 the results are made public at 14:00. BSPs have a chance to improve these forecasts. Participants can submit their balancing capacity offers for power and energy before 16:00, so they have this time interval available to run their forecast models and form their bidding strategy. When the IPTO announces the 1st ISP results at 16:45 on D-1, with all the updated forecasts on load, generation and market schedule, participants have the possibility to update their forecast again, decide to participate or change their offers in one of the IDAS or improve their offer for balancing energy until 15' before physical delivery. In other words they can reduce their price, in case, for example, their forecasts show that the clearing price for balancing will be lower than what they had predicted and used to determine their initial offer. When the IPTO runs ISP2 at 00:00 on D, the schedules announced are binding for the first 12 hours of D so any changes before ISP2 are crucial for the first 12 hours. After ISP2 results, participants can again improve their forecasting models based on the new market schedules, load and generation forecasts. They can use these new forecasts for IDA3, XBID or to form improved offers in the balancing energy market. Accurate forecasts allow participants to choose their strategy and decide in which market to sell their enery depending on where higher prices are expected. It also allows price arbitrage, a term

which refers to the practice of buying electricity at a lower price in one market and selling it at a higher price in another.

The clearance of the balancing markets in Greece is handled by optimization algorithms aimed at minimizing overall balancing cost while respecting system constraints. In the capacity market, the ISP algorithm co-optimizes energy and reserves insofar as the commitment of a unit provides both energy and reserve capacity. The outcome of each ISP run is a set of committed units and reserve assignments that meet forecasted imbalances and reserve requirements at minimum cost [32]. This is essentially a centralized unit commitment/economic dispatch with reserve and transmission constraints. In the real-time balancing energy market, the Real-Time Balancing Market (RTBM) algorithm dispatches the committed resources by selecting balancing energy offers, typically every 15 minutes for mFRR or continuously through the AGC process for aFRR, to resolve actual imbalances. It effectively creates a merit order stack of available upward and downward regulation offers and activates them as needed to maintain frequency as close to nominal as possible.

Selected reserve capacity is remunerated on a pay-as-bid basis. Each BSP whose reserve offer is accepted in the ISP receives the price it offered for that capacity, applied pro-rata for the duration of the market's MTU (e.g. per 30-minute interval) [32]. These capacity payments are made regardless of whether the reserve is actually activated for energy later or not. In return, the BSP must physically guarantee that capacity: the plant must be online (or readily able to start) and capable of delivering the reserved upward or downward change when instructed. Failing to deliver when called (without justification) can lead to penalties or non-payment, as the reserve payment derives from the availability obligation.

Market	Clearing mechanism
DAM	Pay as clear
IDAs	Pay as clear
XBID	Continuous pay as bid
Balancing Capacity	Pay as bid
Balancing Energy (mFRR)	Pay as clear
Balancing energy (aFRR)	Hybrid

Table 2 Markets' clearance mechanism.

Greece's balancing energy market uses a mix of pricing schemes for different products, aligning with European Balancing Guideline principles. MFRR activations are settled on a marginal pricing basis (uniform price), whereas aFRR activations are settled at a pay-as-bid scheme for accepted offers. In practice, this means that when IPTO activates mFRR (e.g. calls on a generator to ramp up manually), all BSPs providing mFRR in that 15-min interval are paid the market marginal price, which is the price of the highest accepted bid for upward energy (or lowest accepted bid for downward energy) in that period [32] [40]. This market clearing practice is crucial for this dissertation, because identifying the peaks of this price is the purpose of the forecasting mechanism. By contrast, aFRR providers are paid their individual bid prices. IPTO does not publish separate prices for aFRR but it is obvious from various reports though that the afrr price is very close or sometimes the same to mFRR [42]. Figure 29 shows an average activated energy mFRR and aFRR up and down price for four weeks in early 2025.

This hybrid approach ensures that aFRR (often bid at lower prices to attain priority for activation) is not penalized for being cheaper, since they receive at least the same reward as the slower mFRR if the latter sets a higher price in the same interval [32]. In summary, mFRR uses pay-as-cleared pricing to incentivize competitive bidding, while aFRR uses pay-as-bid (with an adjustment) to reflect the continuous control nature, all while maintaining consistency between the two.

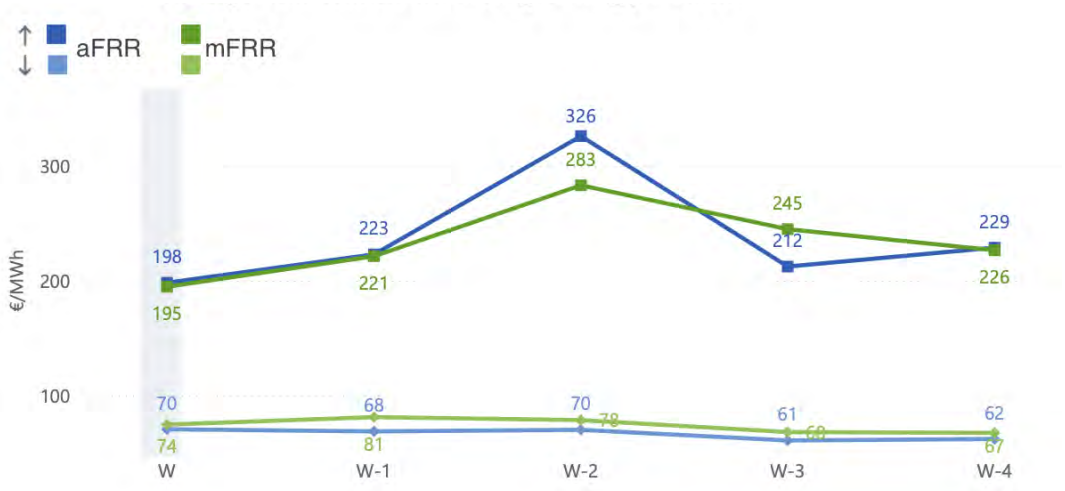


Figure 29 Average activated Balancing Energy Prices.

Balancing energy prices are fed into the imbalance price calculation. AFRR is actiavated continuously and cleared differently through AGC but it guaranteed at least the mFRR marginal price if their pay-as-bid price was lower. Greece has implemented a single imbalance price system: for each 15-minute imbalance settlement period, one price is determined and applied to all BRPs. This imbalance price is essentially the cost of the marginal balancing energy deployed. It reflects real-time balancing costs. If the system was short and expensive upward energy was activated, the imbalance price will be high; if the system had excess and costly downward regulation was needed, the imbalance price could be close to 0. In theory it could be even negative and regulatory reforms aim to make this possible within the next months in Greece. All imbalance charges to BRPs are calculated using this single price, in line with ACER's harmonization rules [38].

The balancing market originally inherited price caps similar to the day-ahead market, meaning initially, balancing energy offers were capped at around +/−€4,240 per MWh (upward/downward). This odd value came from automatic cap adjustments in the DAM) [32], and capacity offers were capped at €3,000/MWh with no negative prices for capacity. As the market evolved and became coupled with European platforms, these limits were revised. Following the introduction of continuous intraday trading and regional auctions, the maximum price caps have raised significantly. For example, the balancing capacity market price limit was increased to +€9,999/MWh for capacity payments and aligned with intraday trading caps [38]. Similarly, balancing energy price bounds have been adjusted to ±€9,999/MWh, in line with European balancing platforms [38]. These very high caps are largely theoretical safeguards – in practice, balancing energy prices in Greece have usually been much lower, though still quite volatile. As more renewables come online and the new market was learning, there are instances of high balancing prices. For example in 2024 some balancing intervals saw

prices well above €300-400/MWh. Recognised patterns have made activated energy in balancing market an area for potential profit for participants, earning more and more attention lately.

All participants in the balancing market abide to strict physical delivery obligations that aim to maintain system reliability. When a BSP's reserve offer is accepted in the balancing capacity market, that BSP has a commitment to be available and deliver balancing energy up to the reserved amount if called upon. In practice, this means that for an upward reserve, a generator might need to be synchronized at a minimum level so it can ramp up on instruction, while for a downward reserve, a plant needs to be generating so it can ramp down. Similarly, a flexible load must be online to drop consumption if needed. The Balancing Market Rulebook imposes technical requirements ensuring that reserves are not just promises on paper, but the provider must meet response times and ramp rates [38]. If a BSP fails to respond to an activation order (for example, a generator does not increase output when instructed), it faces financial penalties and possible sanctions, since such failure could endanger system stability [38] [39].

During real-time balancing, dispatch instructions from IPTO are mandatory. Unlike the energy markets, where transactions are voluntary, balancing commands (like an increase/decrease set-point) are imperative grid control actions. Generators must follow the set-point changes sent via the TSO's control center. Any significant deviation or non-compliance is penalized. The performance is monitored, and BSPs may be partially or fully removed from the reserve duty and lose capacity payment if they do not deliver the agreed response [32][38]. In imbalance settlement, any deviation by a market participant from its expected output is measured and imbalance charges apply, which also motivates compliance.

In summary, once reserves are procured and schedules finalized, balancing resources are under binding obligation to follow dispatch. The combination of pay-as-bid capacity remuneration and strict activation enforcement, gives BSPs both incentive and accountability to support the system [32]. This framework is critical in a real-time market. Unlike forward markets, there is no tolerance for parties "changing their mind". The power must flow as directed to maintain the grid's balance.

3.4 Balancing market reforms

The balancing market in Greece, since its launch with the Target Model in late 2020, has undergone continuous refinements. Regulators and the TSO have identified challenges, such as, high balancing costs in the initial phase, limited competition in reserves, and the need to integrate new resources. RAE intervened early on with emergency measures. Notably RAE Decision 54/2021 amended the Balancing Market Regulation to promote smoother operation and effective competition[32]. This included tightening offer price caps and rules to mitigate potential exercise of market power , since some generators were suspected of bidding very high prices for balancing energy. RAE measures indeed reduced extreme price spikes and encouraged more participants to enter the balancing markets.

Another area of reform is expanding the range of resources in the balancing market. Energy storage and demand response are poised to play a larger role. Batteries,

for instance, can respond very quickly and could provide FCR and aFRR services effectively. IPTO updated the regulatory framework to enable battery storage systems and other new technologies to provide balancing services (FCR, aFRR, mFRR) by the end of 2025 [46]. Pilot projects and updated rules are being considered though to let such resources participate on equal footing with conventional generators. Similarly, demand-side response aggregators are expected to join the balancing market to provide reserves (especially mFRR through interruptible loads), increasing liquidity and competition in reserve procurement.

Further improvements in market design are also being explored. One considered reform is moving from the current unit-based bidding to portfolio-based bidding in all markets, including balancing. Under unit-based bidding, each plant submits separate offers, whereas portfolio bidding allows an aggregator or company to offer a combined position from multiple units. This could provide more flexibility, simplify participation and potentially improve liquidity, by enabling smaller or distributed resources to participate via aggregation. Portfolio bidding is to be implemented by the end of 2025 in the BM.

3.5 Conclusion

The Greek balancing energy market has undergone a significant evolution, from a relatively immature mechanism with early-stage challenges to a more dynamic and structured mechanism, capable of supporting the country's broader energy transition. The increasing complexity of grid management, driven largely by the growth of intermittent renewables and expanding interconnections, has made accurate forecasting of balancing needs more critical than ever. Enhanced forecast accuracy helps participants choose their strategy and maximize their profits. It also minimizes reliance on costly real-time interventions supporting fairer market outcomes by penalizing systematic deviations. Simultaneously, infrastructure upgrades, such as the integration of non-interconnected islands into the mainland system, regional interconnection projects and integration of storage units in the grid, are expected to expand the balancing market's scope and improve operational efficiency. As the market matures, transparency, predictability, and the ability to manage volatility will play a key role. The ability to forecast key variables, such as the peak price of activated balancing energy, becomes not just a technical exercise but a strategic necessity. The following chapter presents the forecasting methodologies explored in this dissertation and details the implementation of the model developed to predict peak prices time and magnitude in the Greek energy market for activated energy. Such a forecasting mechanism is a significant contribution to both market participants' decision-making and the overall system efficiency.

4. Forecasting in the energy market

Forecasting plays a pivotal role in modern electricity markets, enabling participants to anticipate price movements and plan their operations. This section examines forecasting methodologies for electricity prices (with emphasis on balancing markets), the predictors used (particularly for the Greek balancing market), the specific forecasting model implemented for the Greek mFRR/aFRR balancing market, and the evaluation metrics typically used for assessing forecast performance. The focus is on short-term forecasting in the balancing context, where prices are highly volatile and driven by real-time supply-demand imbalances. Many different methods have been suggested in the literature for addressing the issue of capturing those sudden price movements [44]. Here, we will focus on forecasting approaches tailored specifically to short-term price volatility in the balancing energy market. In particular, we apply a regression-based model designed to predict both the timing and magnitude of peak activated energy prices, using a targeted set of physically relevant predictors derived from system imbalances and renewable output dynamics.

4.1 Forecasting Methodologies

Electricity price forecasting is a branch of energy forecasting, which employs mathematical, statistical, and machine learning models to predict future electricity prices [47]. Over the last few decades, a wide array of forecasting approaches has been developed. Broadly, these can be categorized into (a) traditional statistical/time-series methods, (b) machine learning methods, and (c) hybrid approaches (which combine elements of multiple methods). Each category offers unique advantages and challenges in capturing the complex dynamics of electricity markets.

Traditional Statistical Methods include classical time-series models like ARIMA (Auto-Regressive Integrated Moving Average), GARCH (Generalized Autoregressive Conditional Heteroskedasticity), and their variants. Such models rely on historical price patterns and often assume linear relationships and stationarity. They can capture daily or seasonal cycles to an extent, but struggle with the abrupt price spikes and regime changes common in electricity prices. Extended forms (e.g. ARIMA with exogenous inputs, or regime-switching models) improve performance by accounting for multiple price regimes or by incorporating other variables. For instance, mean-reverting jump-diffusion and Markov regime-switching models, classified as reduced-form models, explicitly model sudden jumps or different market states [48]. These statistical models are relatively transparent and fast to compute, but alone they often have limited ability to capture nonlinear effects and rare extreme events. In short-term forecasting (hourly or sub-hourly), pure time-series models tend to perform poorly in capturing high volatility and outlier prices, especially when they are not augmented with exogenous inputs such as load variations, renewable generation forecasts, or other physical system indicators [48].

Machine Learning approaches, including neural networks (ANN, CNN, LSTM), tree-based ensemble methods (Random Forests, Gradient Boosting, XGBoost), support

vector machines, etc., have become popular for electricity price forecasting. These methods can learn complex nonlinear relationships from data and handle numerous input features. For example, deep learning models (e.g. LSTM networks) can capture long-term dependencies and have shown success in day-ahead price prediction [48]. Similarly, gradient boosting and random forests have been used to model price as a function of many fundamental variables. Random forests build multiple decision trees on bootstrapped samples and average their predictions to reduce variance and avoid overfitting, making them effective for datasets with many noisy or correlated features. Gradient boosting, on the other hand, constructs trees sequentially, where each new tree is trained to correct the residuals of the previous ones, allowing the model to focus on difficult-to-predict instances and often yielding higher accuracy in practice [51]. The flexibility of Machine Learning models allows them to fit intricate patterns, including correlations between demand, weather, and other factors. However, they require large amounts of data and careful tuning to avoid overfitting [48]. Overfitting refers to a model's tendency to learn noise or random fluctuations in the training data rather than the underlying patterns, resulting in poor generalization to unseen data. Moreover, pure Machine Learning models may lack transparency, and their improvement over simpler models is not guaranteed in all cases [48]. In volatile balancing markets with limited historical data (relative to day-ahead markets), purely data-driven Machine Learning can face challenges. Nonetheless, studies have demonstrated that neural network and tree-based models can outperform linear models for imbalance price forecasting, especially when supplemented with relevant features, such as load variations, renewable generation forecasts, and market prices from earlier trading sessions [49]. Recent work also emphasizes explainability of Machine Learning forecasts in this domain, for example by using methods to interpret how input factors like demand or wind errors influence predicted imbalance prices [50].

Hybrid models combine multiple techniques to leverage their complementary strengths. For example, a model might use a statistical component to handle seasonal patterns and Machine Learning component to model residual nonlinearities. Researchers have combined ARIMA with neural networks or wavelet transforms to capture both linear trends and sudden changes [49]. Markov regime-switching has been paired with vector autoregression (VAR) in a hybrid model to improve short-term forecast accuracy under different market regimes. Agent-based simulation and fundamental models also fall into the broader mix of such forecasting approaches. Agent-based models simulate the actions of market participants to project prices [47]. They can incorporate strategic behavior and complex market rules, but often at the cost of high complexity and only qualitative accuracy [47]. Fundamental models rely on physical system data (like generator fuel costs, outages, and constraints) to forecast prices by simulating the merit order; these are more suited to medium-term horizons and can miss intra-day fluctuations. Overall, hybrid models have shown promise, especially for handling the extreme volatility in real-time markets. For instance, integrating a regime-switching mechanism to detect when the market is entering an extreme state (spike) and applying different predictive models in different regimes can substantially improve accuracy [50]. Similarly, filtering or preprocessing price data to remove or lessen outliers before applying statistical models is a practiced hybrid strategy [47]. The literature indicates that currently there is no model universally best for all markets or conditions. Instead, the most effective approach depends on data availability and the specific characteristics of the market in question. Consequently, recent research often tests multiple models or combinations to receive robust forecasts.

In summary, electricity price forecasting approaches range from classical statistical models to advanced Machine Learning, and increasingly hybrid methods that incorporate domain knowledge. In the context of the balancing market (real-time imbalance prices), forecasting is particularly challenging due to the cost of large scale storage whixh limits its widespread deployment nature of electricity and creates the need to balance supply and demand continuously. Prices in balancing markets exhibit unique behaviors such as abrupt spikes and regime shifts that are less prevalent in day-ahead market [47].

4.2 Predictors used

RES like wind and solar have variable outputs which are depending on weather conditions. As a result, their real-time output differs from what was scheduled beforehand. This can have a significant impact on the electricity market. In the real-time balancing markets, producers are expected to deliver the scheduled energy on the day-ahead power market. [43]. Therefore, specialized models (e.g. regime-switching, or ML models trained on imbalance drivers) are often employed. It is noteworthy that recent studies in some countries have found imbalance prices to be at least partially predictable despite their volatility [49]. For example, Bunn *et al.* (2021) showed that using a nonlinear model that accounts for weather and demand forecast errors (key drivers of imbalances) yielded better predictive accuracy for the British system imbalance price than a linear benchmark [49]. This underscores a recurring theme: combining solid data-driven methods with domain-specific is essential for successful forecasting in the energy market [48]. For example, higher electricity demand or lower available generation tends to increase prices, while high renewable output (wind, solar) can depress prices, unless those renewables deviate from forecast, causing imbalances. In short-term imbalance price forecasting, the changes or forecast errors in these variables often matter even more than their absolute values. This section describes typical predictors and why metrics capturing changes (known as ‘deltas’) are especially useful for imbalance forecasts.

Standard inputs for price models include total load (system demand), net load (demand minus renewable generation), generator outputs by fuel type (e.g. coal, gas, hydro output), and interconnection flows (imports/exports). Weather variables (temperature, wind speed, solar irradiance) are used indirectly, often via their impact on load and renewables. In balancing markets, an important direct predictor is the Net Imbalance Volume (NIV) – the total energy shortfall or surplus in the system at a given time. NIV reflects the real-time imbalance between generation and consumption; a large positive NIV (system short) usually leads to high up-regulation prices, while a large negative NIV (system long) leads to low or negative down-regulation prices [49]. However this metric can only be used very close to the physical delivery time and forecasts that are based on D-1 data cannot take advantage of it. More generally, forecast error variables are crucial: these represent the difference between expected and actual values of demand or generation. For instance, demand forecast error (actual load minus day-ahead forecasted load) and wind forecast error (actual wind output minus forecast) are strong predictors of balancing prices. A large forecast error means the system is out of balance with respect to planned operation, requiring the TSO to activate balancing resources, often at high cost. Bunn *et al.* note that the British imbalance price is driven significantly by demand and renewable forecast errors, exhibiting a regime-switching

behavior when these errors are large [49]. These findings justify the inclusion of variables that capture sudden changes or deviations in load and generation.

In our forecasting approach for the Greek balancing market, we place special emphasis on change metrics i.e. the rate of change or first derivative of time series for key data. The rationale is that imbalance prices are extremely sensitive to rapid fluctuations of the the demand or the supply of generation. For example, a steep rise in net load over a short period can indicate that generation is struggling to keep up, often triggering expensive reserve activation. Similarly, an abrupt drop in wind generation (perhaps due to forecast error or weather change) can cause a supply deficit and price spike in the balancing market. Of course we use the most updated forecast available near real time. By including the deltas of load and RES outputs as predictors (e.g. ΔLoad, ΔWind, ΔSolar), the model becomes sensitive to these rapid shifts. This is effectively a proxy for real-time forecast error: if day-ahead schedules anticipate a certain generation or load level, but the actual system ramps up or down rapidly which means to undergo a steep change in power demand or supply, an imbalance occurs. Empirical evidence supports that changes in wind output correlate with imbalance volume spikes and system operators report that large ramp events often coincide with balancing price extremes [49]. In summary in the balancing context, absolute values (like current total MW of load or wind generation) do not seem that important when compared with the trajectory (increasing or decreasing) of those values. A rising net load with insufficient ramping resources will drive prices up sharply; a sudden surplus of solar may drive balancing prices down (or even negative if curtailment bids are needed).

4.3 Impementation

The suggested forecasting model allows a flexible selection of predictors from a predefined list, including both level variables and their derivatives. The interface (a simple input dialog in MATLAB) lets the user specify which variables should consider and their corresponding weights. The available predictors encompass:

Predictor symbol	Explanation
y1	Net Load
l	Lignite generation
g	Gas generation
h	Hydro generation
pv	Photovoltaic generation
wind	Wind generation
im	Imports
ex	Exports
Dy1	Change in net load
Dpv	Change in pv generation
Dwind	Change in wind generation

Table 3 Predictors used in the model.

All predictors in table 3 are forecasted data that are announced by the IPTO on D-1 and updated regularly in the 3 ISPs, as explained in section 3. More details on the data and how they are retrieved are mentioned in section 5. These choices reflect the Greek power system's physics characteristics – e.g., lignite, gas, and hydro are key conventional sources, while PV and wind are the major RES. As mentioned earlier, Net Load (y1) is essentially system demand minus RES, indicating the load that must be met by conventional resources; it is a strong indicator of stress on the system as a high net load often precedes high balancing prices. The import (im) and export (ex) variables capture cross-border energy flows, which can buffer or exacerbate imbalances. For instance, high imports might alleviate a supply shortage, domestically, whereas high exports during a scarcity period could worsen the local imbalance. By offering these as selectable inputs, the model can be configured to test various hypotheses – for example, one can include dy1, dpv, dwind to focus on the impact of rapid changes on prices in the balanving market, or include y1, pv, wind to focus on absolute levels, or any combination thereof. In practice, we found that including at least one form of load metric and one form of renewable output metric was necessary for good predictions. Notably, using the deltas (dy1, etc.) improved the model's responsiveness to imbalance events: when a day experienced a sharp ramp in net load (morning or evening ramp) or a swift drop in wind, the model with delta predictors was more likely to foresee an upcoming price spike. This aligns with the principle that imbalance prices "spike" when

the system is caught off-guard, which is precisely when derivatives of fundamental variables are large.

To illustrate the aforementioned discussion, suppose the wind generation on a particular day unexpectedly drops by 500 MW within an hour; the day-ahead market would not have accounted for this, so the balancing market must call on reserves – likely pushing mFRR price to a peak. A model that included current wind power alone might not fully capture the urgency of this event, whereas a model including ΔWind would register a large magnitude for that predictor, leading to a more accurate prediction of price for that interval. This is exactly the behavior observed in the UK study by Goodarzi *et al.*, where the wind forecast error had a greater impact on imbalance outcomes than the level of wind generation itself [49]. In our model, the predictor selection interface ultimately serves as a tool for feature engineering – it allowed us to experiment and identify that certain combinations yielded better alignment with actual price movements. These findings underscore why change metrics are indispensable for imbalance price forecasting: they capture the magnitude of unpreparedness of the system. As a result, the final configuration of our Greek balancing market forecast model attaches weights on these predictors variables like dy1 (change in net load), dwind (change in Wind generation) and dpv (change in PV generation). The way weights are allocated between these predictors and which combinations give better results are examined in section 5, in detail.

4.4 Forecasting Model for the Greek Balancing Market

This subsection describes the forecasting model developed for the Greek balancing market, specifically targeting the mFRR and aFRR balancing services. The model was implemented in MATLAB and designed to predict the peak price, in terms of time and magnitude, in balancing energy price outcomes in real-time (15-minute) balancing market settlement periods. Here we will outline the structure of the MATLAB code and data pipeline, discuss how the model treats the mFRR and aFRR price data, and then delve into the two key aspects of the forecast mechanism: predicting the time of peak price (when the highest imbalance price occurs) and the value of that peak price. The code of the algorithm developed is included in Appendix 1. The specifics are described below.

The forecasting process involves several steps of data retrieval, preprocessing, and prediction. Figure 30 provides a schematic overview of the data pipeline from raw inputs to final outputs.

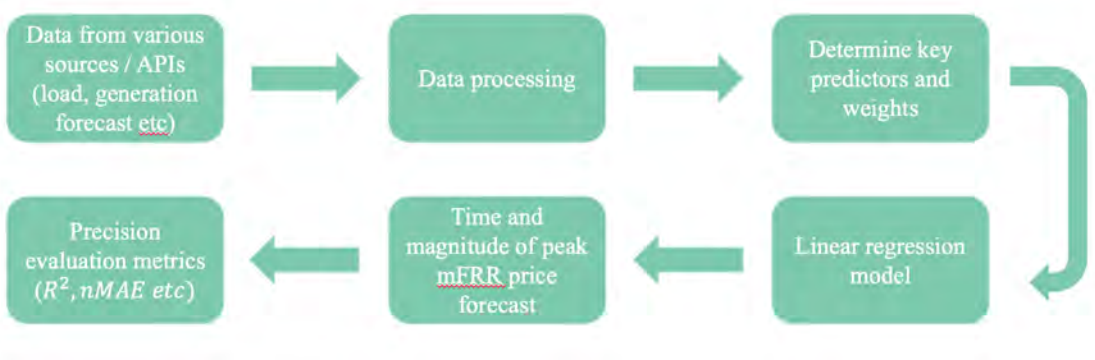


Figure 30 Matlab Model Pipeline.

The model uses multiple data sources from the Greek power system. First, it accesses system SCADA data (supervisory control and data acquisition) or similar system realization data, which contains the forecast load and generation values for each 15-minute interval. This provides the real-time forecasted values of demand and production by type (including renewables). Second, it retrieves DAM results, particularly the day-ahead clearing price, known as Market Clearing Price (MCP) for each hour, which is useful as a baseline and for comparison. Third, it obtains the balancing market data. Specifically, the accepted offers for balancing energy (mFRR up-regulation and down-regulation) and their prices are retrieved. In practice, the Greek TSO (IPTO) publishes balancing energy prices and volumes, often in the form of weekly data files. Our model reads a file that contains the mFRR balancing energy prices for a given week, segregating them in separate columns for upward and downward activation prices. Data collection is automated via file reading; the code is structured to loop through each day in the target range of dates, loading the relevant files for that day.

Once raw data for a day are loaded, the model performs filtering and computes the needed variables. Specifically, from the SCADA daily file (an Excel sheet of system forecasts for the next day), it extracts: total load, total renewables (RES) generation, and specific RES components (PV and wind generation). It then calculates Net Load, it also breaks down the RES total to PV and wind generation (by subtracting the summed PV from total RES to get wind). Conventional generation like lignite, gas, and hydro could be used for the creation of indicators which are countributing most to the energy mix though in the current model they serve more for context plotting than as inputs. Importantly, the code computes the rate of change for selected variables: for instance, dy1 = 15' difference in net load, dpv = 15' difference in PV output, and dwind = 15' difference in wind output. This is because the SCADA data is provided at 15' resolution, these differences capture quarter-hourly ramps. Any missing data or file issues are handled by skipping those days and the code logs a warning if a file is not found or cannot be read, then continues to the next day. The day-ahead MCP for that day is extracted to serve as a reference.

All these variables are assembled to become the inputs. The user specifies which predictors are actually used via the interface described in section 4.2. The code then constructs a matrix of selected features for that day. For example, if the chosen predictors are ["y1","dwind","dpv"], the feature matrix will have three columns: net load, change in wind, change in PV (each as a 96-length vector corresponding to the 96

intervals of the day). Delta variables have one fewer data point due to being a difference of a 96-length series, resulting in 95 values, the code aligns them with the rest by padding i.e. adding a zero at the beginning of a difference series so that all predictors have the same length.

The forecasting engine itself is a straightforward linear regression model, implemented as a weighted sum of the selected features. In the MATLAB code, this is encapsulated in a function (see Appendix A), which multiplies the input matrix by the weight vector to produce a predicted price series. The weights can be specified manually (based on prior calibration) or through an iteration step between 0.1 and 0.9 and returns all the possible combinations. Essentially, the model equation is:

$$\widehat{Price}(t) = w_1 X_1(t) + w_2 X_2(t) + \cdots + w_n X_n(t) \quad (1)$$

Where *Xi(t)* is predictor i and wi is its chosen weight. This linear form was chosen for simplicity and transparency, and it allows easy interpretation of how each predictor contributes. For instance, a positive weight on net load means that higher net load leads to higher predicted balancing price. A positive weight on delta of wind generation (dwind) means that when wind output is dropping (dwind is negative large), the price forecast will rise thus aligning with the expectation that losing wind generation drives the need for expensive balancing energy. Despite its simplicity, a weighted linear combination can capture first-order effects and was found adequate for predicting general trends and even peaks, especially when the appropriate change indicators are included. The model produces a forecasted price profile for the day: typically 96 values (one per 15-minute interval). Because our predictors include high-frequency information, the forecast can reflect intraday variations rather than just a flat or hourly value. We note that this approach can be viewed as a form of multiple linear regression, where the coefficients were determined by domain knowledge, and trial-and-error on available past data where we can test which combination worked better. In a more automated setting, one would calibrate these weights using a training dataset, via least squares regression for example to minimize error [48]. Given the limited data and the high volatility, which can make purely data-driven coefficient estimation unstable, the approach here balanced intuition with empirical adjustment.

The results and how these were decided to be presented are outlined in section 5. However there is an explanation in this section about why this model covers both mFRR and aFRR. The aFRR is activated continuously and autonomously in real-time to fine-tune frequency, whereas mFRR activation is typically initiated by the operator through the RTBM process in set intervals (after aFRR) to correct larger net imbalances or to replace exhausted aFRR (see Chapter 3). Despite being distinct processes during bidding, their prices are interrelated because they both reflect the cost of balancing energy. In the current Greek market design (aligning with European guidelines) aFRR price is given by equation 2.

$$aFRR_BE_UP_PRICE^{GBSE9}_{t,D,W,M} = max\left(BEP^{up}_{t,D,W,M}, BidStepaFRR^{up}_{t,D,W,M}\right) \quad (2)$$

Where BEPup is the mFRR upward balancing energy price for the same interval and BidStepaFRRup is the activated aFRR upward bid price that corresponds to the balancing energy volume actually used from aFRR. So the price of aFRR upward energy can never lower than that of mFRR upward energy. Given that IPTO does not announce a different price for aFRR and reports indicate that their prices match (see section 3 and figure 30) this forecast model, although run for mFRR could be used by a user for aFRR in order to predict its peaks.

4.4.1 Forecasting the point in time for Peak Price of activated energy

Accurately predicting when the peak balancing price will occur is of great importance. In the context of the Greek balancing market, the peak price usually signifies the interval of great system stress. For example, the moment of highest net load or a sudden drop in supply that could not be managed by earlier markets. Knowing this in advance has two main benefits: operational optimization (arbitrage) and insights into price dynamics**.**

From an arbitrage perspective, correctly identifying the time of the peak price is essential for any market participant aiming to capitalize on price fluctuations. Energy storage operators and demand response aggregators, in particular, can significantly benefit. Price of arbitrage, the strategy of buying low and selling higher by charging or consuming electricity when prices are low (or negative) and discharging or curtailing when prices peak is of great importance for the Greek market. Storage units are expected to be functioning in the Greek grid in October 2025 (see section 3). If a battery storage operator can forecast the time that the highest price of the day will occur it could be planned so that it is fully charged by that time, so that it discharges during that 15-minute window to sell at the peak price. Missing the timing, even by one interval, could drastically reduce revenues, since balancing prices can jump sharply to a spike and then drop back down in the next interval (see figure in chapter 5). In practical terms, capturing the correct hour or quarter-hour of the peak can be the difference between profiting from €300/MWh versus €100/MWh pricing. Thus, forecasting peak timing is critical. A study on aggregation and flexible assets noted that in order to maximize revenues, assets must be assigned to the most advantageous settlement period in the market [48]. It essentially highlighted that the settlement period with the highest price, can be identified as appropriate strategy vould be vreated for arbitrage. Our model's ability to predict the time of peak price therefore directly supports such decision-making. It is also useful for risk management: utilities exposed to imbalance charges want to know when (during the day) they are at risk of facing extreme imbalance prices, so they can adjust their operations or hedges accordingly. Knowing when the peak price in mFRR price will occur is also somewhat analogous to predicting when the sytem will flip into a stressed state and understanding system patterns.

4.4.2 Forecasting the magnitude of the peak price of activated energy

Forecasting the magnitude of the peak balancing price is a basic factor in risk management (preparing for worst-case prices), forming a bidding strategy (deciding

how much to offer or bid into the balancing market), and portfolio optimization (e.g., knowing the potential revenue from discharging at that time). Our model addresses this by trying to predict the full price profile and identifying the maximum predicted price as the peak value forecast.

The regression model described earlier produces a numerical price forecast for each time interval. The peak price value forecast is the largest of these numbers. For example, if the model predicts the following quarterly mFRR prices over a certain hour: [80, 120, 250, 180] €/MWh for four intervals, the peak value forecast for that hour is €250/MWh at the third interval. The code records this as maxForecastedPrice and time this max occurs as maxForecastedHour. In parallel, it also finds the actual peak price (maxMfrr_up_day) from the actual data. By comparing these, the error in peak value (forecasted vs actual), is calculated.

Forecasting the peak price magnitude is challenging because of the high volatility and occasional extremes in balancing markets. Balancing prices can have heavy-tailed distributions . Most of the time they can be moderate (e.g., €50–100/MWh), but a few intervals may shoot up to several hundred €/MWh. In chapter 5 there are examples of some days with very high prices, indicating this volatility (see figure 34). A linear model, especially one not explicitly trained on many spike examples, may over- or under-predict those extremes. In our approach, the hope is that by including the right predictors (net load surge, loss of renewables, etc.), the model will output a correspondingly high price when these extreme conditions occur. A very high accuracy when it comes to the prediction of magnitude is not expected. An attempt to calibrate the weights such that the model's peak value outputs line up with historical peak prices has been made. This calibration was done empirically by observing a set of days with known spikes and adjusting weights to approximate those outcomes and then by integrating the option to iterate through different weights for the chosen predictors in order to see which combination gives the best result. In a more rigorous setup, one would use regression fitting: minimizing the evaluation metrics of the price predictions (or even focusing a loss function on peak intervals specifically) to derive optimal weights (see section 4.4).

Another feature included in the forecasting model is a 10% and 15% threshold in the actual peak price. The logic behind that is that the model should get the correct order of magnitude, even if it does not hit the exact value. For example, if an actual peak is 300 €/MWh, the model might predict 250 €/MWh or 350 €/MWh in that interval – capturing that it's a very high price, though with some error. The reason this feature is that a very typical pattern in the mFRR market hsaa been noticed,where a maximum price was reached multiple times within the same day in the exact magnitude or with small differences. This typical behavior of the market is seen in figure 31 and figure 32, whete actual peak reach 450 eur multiple times through the day.

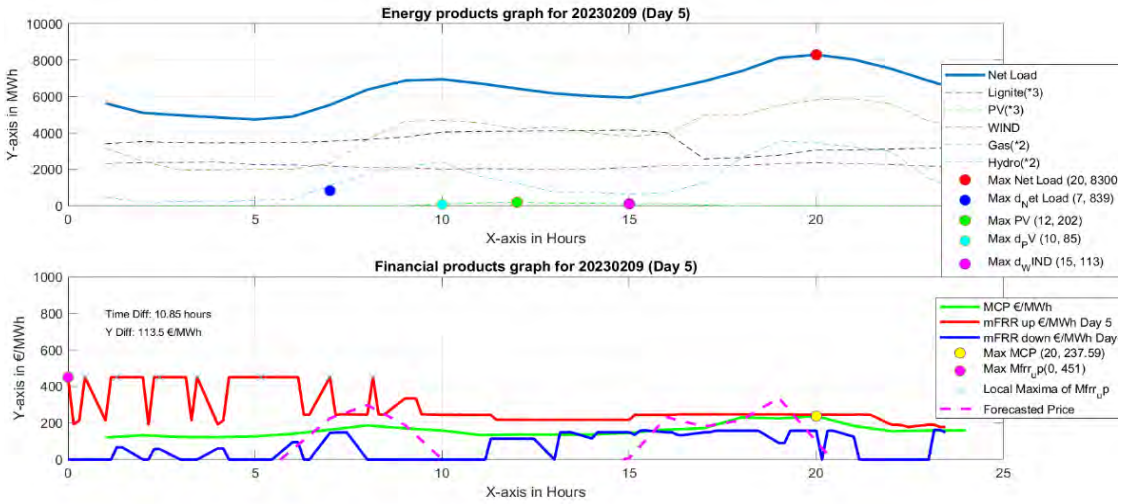


Figure 31 Pattern in actual mFRR price (red) for the 09/02/2023 over forecasted price (pink).

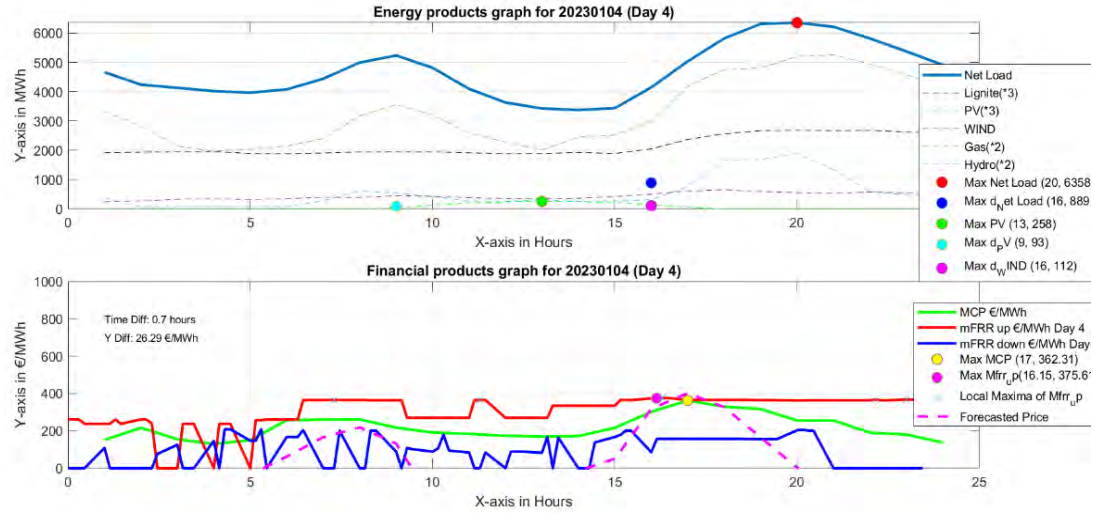


Figure 32 Pattern in actual mFRR price (red) for the 04/01/2023 over forecasted price (pink).

In conclusion, forecasting the magnitude of the peak balancing price is crucial for quantifying the expected severity of imbalance events. Our linear regression model yields a peak value prediction as the maximum of the predicted price curve for the day. While simple, it provides an estimate of how high prices could go given the current system conditions and it gives the opportunity to observe fundamental behaviors and patterns in the Greek grid. Of course, in order to able to evaluate the results of the model in chapter 5, it is important to understand and choose appropriately the right evaluation metrics.

4.5 Evaluation metrics

To assess the performance of the forecasting model, especially in a research or dissertation context, it is important to use a set of evaluation metrics that capture different aspects of accuracy. In energy market forecasting literature, common metrics include Root Mean Square Error (RMSE), Mean Absolute Error (MAE) or its

normalized variant (nMAE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination R^2 [48]. Additionally, reporting mean and median of error distributins can provide insight into bias and the impact of outliers. Below, we define and explain the key metrics used to evaluate our balancing price forecasts, and discuss their interpretation in this context. All equations assume a set of forecasted values $\widehat{Pt}$ and the actual values *Pt.*

Root Mean Square Error(RMSE):

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(\hat{P}_t - P_t)^2} \tag{3}$$

RMSE is the square root of the average of squared errors. It penalizes larger errors more heavily than smaller ones (due to squaring), making it sensitive to outliers. In energy price forecasting, RMSE (or its square, MSE) is widely reported as an overall measure of model fit [48]. A lower RMSE indicates that on average the model's predictions are closer to actual values. In our balancing market application, an RMSE could be calculated on the 15-min price predictions or on daily peak price predictions. High volatility in actual prices tends to increase RMSE. For example, if the model occasionally misses a price spike by a large margin in time and magnitude, the RMSE will be notably inflated, reflecting that volatility. This is a double-edged sword: RMSE is good for emphasizing the scenarios our model performs poorly on (which we want to identify), but a single extreme miss can dominate the metric. In our results, we found that removing a few extreme outlier days (massive misses) greatly reduced RMSE [48], highlighting that RMSE is very much influenced by those tail errors, which in balancing markets correspond to rare and extreme events.

Mean Absolute Error (MAE) and Normalized MAE (nMAE)**:**

$$\mathrm{MAE} = \frac{1}{N}\sum_{t=1}^{N}|\hat{P}_t - P_t| \tag{4}$$

MAE is the average of the absolute errors. Unlike RMSE, it weights all errors linearly, so it is more robust to outliers (a very large error does not dominate the sum as much, since it's not squared). MAE has a clear interpretation: it is the average absolute deviation of the forecast from reality, in the same units as the variable (€/MWh in our case). For instance, an MAE of 10 €/MWh on price predictions means that, on average, the forecast was off by 10 euros up or down. Normalized MAE (nMAE) is MAE expressed as a fraction of some reference value, often the mean of the actual values or perhaps the range of values. A common normalization is

$$\mathrm{nMAE} = \frac{\mathrm{MAE}}{\bar{P}} \times 100\% \tag{5}$$

Where $\bar{P}$ is the mean of the observed values.This yields a percentage error. In contexts like load forecasting, normalizing by peak load or average load is common; for prices, normalizing by the average price or an historical benchmark makes the MAE more

interpretable across different price levels. For example, if our MAE is 8 €/MWh and the average price was 50 €/MWh, the nMAE is 16%. In balancing markets, nMAE tends to be relatively high (compared to day-ahead price forecasts) because of the volatility so a 10%–20% error is not unusual [48]. MAE is often complemented by RMSE: if RMSE is much greater than MAE, it implies that a few large errors skew performance, whereas if RMSE is close to MAE, errors are more uniformly distributed. In our case, we did observe RMSE larger than MAE, confirming that some days were outliers (see chapter 5).

Mean and Median of errors: While not a formal "metric" on its own, we examine the mean and median of the forecast error distribution to understand bias and skewness. The mean error (sometimes called Mean Bias Error if signed, or mean of absolute errors if unsigned) indicates if the model has a systematic bias (e.g., consistently underestimating prices would show a negative mean error). The median absolute error provides a robust measure of typical error, less affected by outliers than the mean. In a highly skewed error distribution (common in price spikes), the median error may be much lower than the mean error. For instance, suppose on 9 out of 10 days the peak price error is about 5 €, but on 1 day the error is 100 €; the mean error is skewed upward (≈15 € in absolute terms) while the median error is 5 €. Reporting both can be informative: the median tells us what a "typical" day's error looks like, whereas the mean depicts the impact of the extreme cases where forecast can be weak [48]. This gap highlights the impact of extreme events. By monitoring the median, we ensure the model is performing well most of the time, and by monitoring the mean, we keep track of those few scenarios where it doesn't.

Coefficient of Determination R^2 is a standardized measure of how well the predictions explain the variance of the actual data. It is defined as:

$$R^2 = 1 - \frac{\sum_t (\hat{P}_t - P_t)^2}{\sum_t (P_t - \bar{P})^2} \tag{6}$$

where the numerator is the residual sum of squares and the denominator is the total variance of the actual data. An R^2 of 1 (100%) means a perfect fit – the forecast replicates all actual values exactly. An R^2 of 0 means the model is no better than using a constant mean prediction. In forecasting literature, R^2 is sometimes viewed with caution for time series (due to autocorrelation issues), but it is still a handy summary of fit. In our context, we compute R^2 on the sequence of daily peak prices to see how much of the variation in peak prices is captured by the model. If many peak prices are driven by certain factors that the model knows about, we'd get a moderately high R^2. A model achieving an R^2 of about 77% is considered very good for prive forecasting in the balancing market . Generally, price forecasts in the balancing market will have lower R^2 than day-ahead price forecasts, because there is more random volatility (noise). Values of R^2 in the range of 50–70% can be considered quite acceptable for imbalance models, for instance, Bunn *et al.* (2021) indicated that out-of-sample R^2above 65% is very good, whereas below 50% would be poor [48].

In interpreting these metrics for the balancing market forecast, one must keep in mind the nature of the task: predicting rare spikes is inherently difficult, so traditional error metrics (which average over all periods) may appear large when compared to other

forecasting problems. The importance of these metrics has to be understood if the model is to be developed further in the future.

4.6 AFRR reserve markets forecasting

While the primary focus of this study lies in forecasting price peaks in the balancing energy market, a parallel line of investigation emerged during the exploratory data analysis phase. Specifically, repeated observations of sudden and extreme price increases in the automatic Frequency Restoration Reserve (aFRR) capacity market prompted the consideration of a complementary forecast. These spikes in the aFRR upward reserve price, which at times exceeded 500 €/MW, appeared to occur predominantly under specific market conditions. A closer examination revealed a consistent pattern: these reserve price peaks often coincided with days when the DAM was abnormally low.

This recurring correlation suggested a potential causality rooted in system fundamentals. On days when the DAM price dropped significantly, it was typically due to the dominance of large, inflexible baseload units or high levels of renewable generation. These conditions limit the availability of fast-ramping, flexible units that are capable of providing aFRR upward reserves. As a result, scarcity in eligible providers drives the aFRR capacity price to unusually high levels. Conversely, when the DAM price is already high, implying that fast-start gas turbines or flexible resources are already online and setting marginal prices, the competition among available aFRR providers appears to restrain reserve price escalation. These observations prompted the development of a forecasting tool designed to anticipate days when the aFRR upward reserve price is likely to reach extreme values, using the DAM price as a key input. This model constitutes a form of event forecasting, aiming to predict the occurrence of high-price reserve capacity days based on observable patterns in day-ahead market prices.

The forecasting model is structured around a threshold-based classification mechanism. We define a high-price event as any instance where the aFRR reserve price falls within the top 10% of all daily prices recorded during the year. And then does something similar for DAM price. It classifies each operating day as either a low-price DAM or a normal-price day, based on the level of the DAM price relative to recent historical averages. The underlying assumption is that a sudden drop in the DAM price below a certain fraction of its recent trend value serves as an early signal of conditions conducive to an aFRR reserve price spike. This approach translates system-level heuristics into a tractable model, bypassing the need for real-time dispatch data or detailed generator availability information, which are typically inaccessible.

The implementation of the model was carried out in MATLAB, with a structure that iteratively tests various threshold levels of the MCP against the observed aFRR reserve prices. The code begins by computing a moving average of the MCP i.e over a 100-day rolling window to establish a dynamic baseline for normal pricing. It then evaluates for each day whether the current DAM price falls below a given percentage of this baseline. Thresholds are incrementally tested, starting at 10% and increasing in 10% steps, to determine the optimal level that best separates high-price aFRR days from others.

Each threshold setting is evaluated using a classification scheme consisting of four outcomes:

- **True Positive (TP):** a high-price day correctly identified,
- **False Positive (FP):** a normal-price day incorrectly flagged as high,
- **True Negative (TN):** a normal-price day correctly ignored,
- **False Negative (FN):** a high-price day missed by the model.

This classification is then used to evaluate performance and select the threshold that yields the most desirable trade-off, minimizing false positives while keeping false negatives acceptably low. Notably, in this application, false positives are particularly costly from a strategic or bidding perspective, as they may prompt unnecessary market actions. In detail, bidding in a high price when no peak price happens, in case of a false negative, will leave the participant out of the market. But also, in case of a false negative, bidding in a normal or low price while a peak price happens, means loss of profit because of the reserves' market pay as bid (see table 2) mechanism.

From a design perspective, the forecasting tool is simple yet intuitive. The MATLAB code can be found in appendix B. It leverages publicly available DAM data, requires minimal computational resources, and produces outputs that are directly interpretable. The rationale aligns with the broader forecasting philosophy adopted in this dissertation which is the use of interpretable models based on operationally meaningful predictors to anticipate extreme events in a volatile and complex market environment. In this case, the DAM price serves as a transparent and timely proxy for system conditions, enabling a forecast of aFRR reserve price surges well before balancing market gate closures (see figure 18).

This model will be further evaluated in Chapter 5, where we present its performance across a full year of historical data (2023). By integrating the aFRR reserve market dimension into our forecasting framework, the dissertation broadens its scope beyond activated energy markets to encompass reserve procurement dynamics. This holistic approach not only strengthens the relevance of the forecasting tool for market participants and system operators but also aligns with the evolving structure of the Greek balancing market, where both energy and capacity markets play critical roles in ensuring operational security.

4.7 Conclusion

This chapter outlined the methodological framework and practical implementation of a forecasting model tailored to the Greek balancing energy market, with a focus on predicting both the timing and magnitude of mFRR prices. As previously discussed, since the aFRR price is determined as the maximum between its own bid and the corresponding mFRR price, accurately forecasting mFRR peaks also provides effective coverage for aFRR price estimation. Through a systematic approach involving relevant predictors—particularly net load forecast dynamics and renewable forecasted output shifts—the model leverages a weighted linear regression to generate high-resolution price forecasts. Emphasis was placed on selecting predictors with physical relevance to

imbalance events and on quantifying forecast performance using robust evaluation metrics. While the model is intentionally simple to maintain interpretability, it captures key market behaviors and offers actionable insights for market participants aiming to anticipate balancing costs. The ability to forecast peak price events, especially in a volatile market like the balancing segment, is critical for operational flexibility, risk mitigation, and strategic bidding. In the following chapter, the framework is testes with actual data. The parameterization of the model, and the results obtained across a series of representative days enable a concrete evaluation of the model's effectiveness and reveal patterns and limitations observed in real-world performance.

5.Results

Chapter 5 presents the results and discussion of the developed forecasting models, focusing on the prediction of peak prices in the Greek balancing market. A primary aim is to identify which predictors have the greatest impact on forecasting of the timing and magnitude of price spikes. In our analysis, predictors capturing rapid system changes proved most influential. In particular, sudden shifts in net load and large forecast errors in renewable generation emerged as key drivers for price surges. Variables such as the change in net load (ΔLoad) and changes in wind/PV output (ΔWind, ΔPV) consistently led to better peak predictions when included in the model. These "delta" predictors effectively act as early warning signals of stress: for example, a sharp rise in net load or a steep drop in wind generation creates a supply-demand imbalance that often precipitates a price spike. By incorporating these high-frequency indicators, the model aligns with findings in literature that prices in balancing market spike when the system is caught off-guard, i.e. when real-time conditions deviate strongly from forecasts. Thus, the feature selection process highlighted that system imbalance metrics (and proxies for them) are the strongest predictors for both the time and the magnitude of price peak.

It turned out that the tool forecasted the timing of price peaks (time forecast) turned out to be a relative strength of the tool. The model is structured to produce a high-resolution price forecast (in 15-min interval predictions), which means it can pinpoint the quarter-hour of maximal price with fine granularity. Because it explicitly uses the aforementioned rapid-change predictors, the model often successfully triggers a price spike prediction in the correct period when an extreme system condition arises. This led to high accuracy in predicting when the peak would happen. In practice, capturing the timing of the peak is critical because missing the peak by even one interval can drastically reduce the arbitrage value for a storage or demand-response operator. The results demonstrated that the tool reliably identifies these peak intervals. For instance, in many test days the model's max predicted price occurred in the same hour (or 15-min block) as the actual peak, indicating that the timing error is often zero or only one interval off (a very good outcome for this application).

We underscore this performance by specific metrics applied to the results. From a statistical standpoint the model captures a significant portion of the price variability over time – the coefficient of determination (R^2) of the hourly price prediction is in a range considered acceptable for the volatility noticed in balancing market. Notably, price forecasts in the balancing market tend to have lower R^2 than day-ahead forecasts due to noise; values of 50–70% can be deemed acceptable. So, the model's fit falling in this range confirms its suitability. The evaluation metrics further highlight the model's timing aptitude: for example, a normalized mean absolute error in the 15-minute price position of around 10% was achieved, meaning the model's predicted peak time is usually very close to the actual. In sum, the forecasting tool is well-suited for peak timing prediction, providing system operators and market participants with confidence on when prices will spike – a capability that directly supports operational decisions and arbitrage strategies.

Forecasting the magnitude of price peaks (magnitude forecast) is a more challenging task, and the results reflect the inherent volatility of the balancing market. Unlike timing (which is often driven by identifiable events), the exact height of a price spike

can be highly erratic because it strongly depends in the operating status and balancing service offers of market participants. The Greek balancing prices exhibit a heavy-tailed distribution, typically around €50–100/MWh most of the time, but with occasional surges to several hundred €/MWh on days with extreme conditions. Our simple linear regression approach, while transparent, does not always capture these extreme nonlinear jumps precoselly. In fact, achieving very high accuracy in peak magnitude was not expected a priori, given that such peaks are not consistent events and difficult to correlate purely with system conditions. We introduced a pragmatic evaluation criterion: rather than requiring the exact spike value, we check whether the model at least predicts the correct order of magnitude of the peak. For instance, if the actual peak was 300 €/MWh and the model predicted from 270 €/MWh to 330€/MWh, we consider that a success in capturing a "high-price event," even if there is a deviation. This tolerance is important in such a volatile domain. Using standard error metrics, the peak magnitude forecasts had higher errors relative to the mean price level. In more mature/stable markets this is not expected to be the case. For example, the model's nMAE for price magnitude was on the order of 25% at the best scenario. An error of this level is a bit higher, but close to other balancing market studies (10–20% nMAE would be considered acceptable), underlining that even advanced models face difficulty with spike magnitudes [52]. The upside is that our model usually recognizes a spike as a spike but may slightly underestimate or slightly overestimate the peak value. Metrics suggest that it rarely misses the fact that a peak is occurring. We note that more complex models or additional data (e.g. incorporating behavior of bidders or probabilistic approaches) could further improve magnitude accuracy. Nonetheless, the current model provides a reasonable magnitude estimate relevant to the scale of imbalance events, which is useful for risk management i.e. preparing for worst-case imbalance costs even if it cannot predict the exact euro value every time. All simulator and analyses were performed using an Apple M3 with 8GB of RAM memory.

Finally, this chapter extends the analysis beyond the balancing energy market by including results for the aFRR reserve capacity. While the main focus is on mFRR activation prices, we also examined the capability to predict the event of a peak in reserved power price (capacity payment) in the aFRR market. This addition broadens the scope to a more holistic representation of the balancing market. The tool we developed for the capacity market (see chapter 4.6) predictions carry over to this domain as well, by using the day-ahead price information and a threshold mechanism, the model can successfully anticipate days with abnormally high aFRR reserve prices. AFRR is important in the capacity market is because it accounts for most of the volume and revenues in the reserves' markets [42]. In essence, if the day-ahead MCP is extremely low, signaling conditions that tend to lead to expensive reserve procurement, the model forecasts a high aFRR price for that period. The balancing market in Greece comprises both the activation prices and the reserve procurement costs, where market participants are exposed to both. Chapter 5 provides a more comprehensive discussion about this. It links the timing of price spikes in balancing market with the conditions leading to reserve scarcity (and high reserve prices), painting a fuller picture of how stress propagates through the system. The discussion emphasizes that forecasting aFRR reserve prices leverages system stress reflected in MCP and thus complements the mFRR price forecast. In summary, the introduction of aFRR forecasting results in Chapter 5 underscores how the developed tool can enhance decision-making across the entire balancing domain. This comprehensive outlook reinforces the dissertation's contribution to balancing market optimization and risk mitigation.

It is important to note that the primary goal of this dissertation is to uncover and interpret the underlying physical and operational mechanisms that influence price formation in the balancing market, rather than to pursue opaque complex models that may yield marginally better numerical accuracy at the expense of interpretability and system insight. This approach represents a deliberate trade-off between model transparency and forecasting performance. The following sections of chapter 5 present and evaluate the forecasting results in detail, highlighting the model's behavior across different predictor combinations and assessing its performance.

5.1 Data retrieval and preprocessing

Data for this study was obtained from publicly available sources via structured APIs and data portals. In particular, historical records of balancing market outcomes were fetched through energy market transparency platform and system operator databases (see appendix C). The raw dataset included time-stamped values such as balancing energy prices (for mFRR activations) and reserve deployment levels at high resolution i.e 15-minute intervals. To derive the target variables for our forecasts, daily peak prices of activated balancing energy were identified along with the timing (hour) of each daily peak. Similarly, for reserve analysis, time series of aFRR capacity reserve prices were collected from ENTSO-e. Basic preprocessing steps were applied: data was cleaned for missing entries or obvious outliers, and time indices were aligned to ensure consistency between features (e.g. demand, renewable generation) and the corresponding balancing period. Where necessary, data was resampled or aggregated (for example, computing daily maxima) to match the forecasting objectives (see tables 4,5,6). All feature engineering and preprocessing routines (such as normalization of inputs, handling of holidays/weekends, and creation of lagged features) were implemented in MATLAB code (see Appendix A). This ensured that the dataset used for model training and evaluation was reliable and representative of the underlying system dynamics.

Date	DayofYear	MaxNetLoadX	MaxNetLoadY	MaxDpvX	MaxDpvY	MaxpvX
1/2/23 0:00	2	20	6076	9	94	13
1/3/23 0:00	3	20	6642	9	97	13
1/4/23 0:00	4	20	6358	9	93	13
1/5/23 0:00	5	19	6514	9	89	13
1/6/23 0:00	6	20	5601	9	96	13
1/7/23 0:00	7	20	6104	9	97	13
1/8/23 0:00	8	20	5999	9	98	13
1/9/23 0:00	9	20	6388	9	98	13
1/10/23 0:00	10	20	6712	11	120	12

Table 4 Dataset of results from 1st of January.

MaxpvY	MaxWindX	MaxWindY	MaxDWindX	MaxDWindY	MaxMCPX	MaxMCPY	MaxMfrrUpX	MaxMfrrUpY
257	1	796	17	9	16	363,77	21,3	701,1
257	23	256	21	42	18	369,17	10	451
258	18	654	16	112	17	362,31	16,15	375,61
230	24	806	13	129	8	361,04	7,15	372,24
263	4	783	21	106	20	295,81	16	451
261	1	521	6	49	8	344,1	9	379
261	15	213	13	35	20	341,35	13	500,02
255	24	2357	17	235	8	351,25	1	385
162	4	2762	3	152	21	228,74	8,3	379

Table 5 Dataset of results from 1st of January.

MaxForecastedPrice	MaxForecastedPrice_hour	diffMaxForcastedMaxMfrrup	diffMaxForecastedMfrrUpY
386,2	17	4,3	314,9
336,9	17	6	114,1
401,9	17	0,7	26,29
331,6	17	1	40,64
409,6	17	1	41,4
399,4	17	0,55	20,4
425,1	17	4	74,92
336,4	8	1,7	48,6
328,7	8	0,45	50,3

Table 6 Dataset of results from 1st of January.

5.2 Forecasting Peak Price Timing (mFRR Balancing Energy)

One key task was to predict when the daily peak price of activated mFRR balancing energy would occur. This is essentially a daily forecast of timing for the maximum balancing price each day. Accurately anticipating the timing of price spikes is valuable for operators and market participants, as it allows proactive measures (such as rescheduling generation or reserving capacity) ahead of stress periods. In our analysis, we evaluated multiple models and predictor combinations for this timing prediction. Only the best-performing configurations are discussed here, focusing on their error metrics and insights.

We assessed timing prediction accuracy using related metrics such as RMSE in hours, nMAE, and R^2 (see chapter 4). For interpretability, we also computed the mean and median absolute time difference between predicted and actual peak times. An R^2 score indicates the fraction of variance in peak timing explained by the model, with 1.0 being a perfect fit. RMSE emphasizes larger errors by squaring the time differences, while nMAE provides a scale-free error measure. In general, lower RMSE and nMAE and higher R^2 signify better performance.

Table 7 summarizes the performance of various feature combinations. Notably, the best-performing configuration for timing utilized a weighted blend of explanatory variables capturing system conditions: it placed relatively high weight (0.4) on load

deviation and wind generation forecast deviation (0.5), and lower weight on PV generation forecast deviation (0.1) (see equation1). In this optimal model, the predictor corresponding to wind forecast error had a strong influence – aligning with intuitive expectations that unexpected wind shortfalls can trigger earlier activation of expensive balancing energy. The significant weight on the imbalance volume further underlines that the timing of price spikes is closely linked to when the system's reserve capacity starts getting exhausted. The solar PV forecast error received smaller weight in the timing model, suggesting it is less critical for pinpointing when the peak occurs, though it still carries useful information and metrics deteriorate if completely neglected. This outcome is consistent with findings in the literature that wind forecast errors and system imbalance indicators are primary drivers of real-time balancing needs [54]. In other studies, wind generation variability has been shown to strongly impact the timing and magnitude of balancing actions required [54], which reinforces that the suggested model benefits from giving wind-related features a prominent role.

Variables and weights				X forecast (time)				
dy1	dres	dpv	dwind	mean_timediff	median_timediff	R^2	RMSE	nMAE
0,1	0,9	0,8	0,1	4,42	3	0,31	5,98	0,35
0,1	0,9	0,7	0,2	2,77	0,85	0,52	5,02	0,22
0,1	0,9	0,6	0,3	4,49	2,85	0,31	6,21	0,34
0,1	0,9	0,5	0,4	4,32	2,77	0,2	6,07	0,32
0,1	0,9	0,4	0,5	4,61	2,7	0,2	6,6	0,35
0,1	0,9	0,3	0,6	4,45	2,55	0,2	6,55	0,35
0,1	0,9	0,2	0,7	4,41	2,25	0,2	6,66	0,36
0,1	0,9	0,1	0,8	4,44	2,4	0,2	6,6	0,35
0,2	0,8	0,7	0,1	3,39	1,25	0,43	5,47	0,26
0,2	0,8	0,6	0,2	3,21	1,25	0,49	5,2	0,25
0,2	0,8	0,5	0,3	3,19	1,25	0,49	5,2	0,25
0,2	0,8	0,4	0,4	3,16	1,25	0,47	5,2	0,25
0,2	0,8	0,3	0,5	3,19	1,15	0,47	5,2	0,25
0,2	0,8	0,2	0,6	3,23	1,25	0,46	5,3	0,25
0,2	0,8	0,1	0,7	3,37	1,25	0,42	5,48	0,26
0,3	0,7	0,6	0,1	2,84	0,85	0,36	5,09	0,37
0,3	0,7	0,5	0,2	2,9	0,85	0,37	5,17	0,35
0,3	0,7	0,4	0,3	2,87	0,85	0,37	5,04	0,38
0,3	0,7	0,3	0,4	2,86	0,85	0,37	4,99	0,39
0,3	0,7	0,2	0,5	2,88	0,85	0,37	5	0,39
0,3	0,7	0,1	0,6	2,91	1	0,53	4,97	0,23
0,4	0,6	0,5	0,1	2,75	0,85	0,53	5	0,22
0,4	0,6	0,4	0,2	2,74	0,85	0,53	5	0,22
0,4	0,6	0,3	0,3	2,78	0,85	0,53	5,02	0,22
0,4	0,6	0,2	0,4	2,89	0,85	0,53	5,1	0,21
0,4	0,6	0,1	0,5	2,62	0,7	0,58	4,9	0,2
0,5	0,5	0,4	0,1	2,76	0,85	0,52	5	0,21
0,5	0,5	0,3	0,2	2,77	0,85	0,53	5	0,21
0,5	0,5	0,2	0,3	2,787	0,85	0,52	5	0,22
0,5	0,5	0,1	0,4	2,83	0,85	0,52	5	0,22
0,6	0,4	0,3	0,1	2,78	0,85	0,51	5	0,22
0,6	0,4	0,2	0,2	2,77	0,7	0,52	5	0,21
0,6	0,4	0,1	0,3	2,77	0,7	0,53	5,02	0,22
0,7	0,3	0,2	0,1	2,77	0,85	0,52	5,03	0,22
0,7	0,3	0,1	0,2	2,79	0,7	0,51	5,06	0,22
0,8	0,2	0,1	0,1	2,78	0,7	0,52	5,05	0,22
0,8	0,2	0	0,2	2,77	0,85	0,51	5,05	0,22
0,9	0,1	0	0,1	2,78	0,85	0,52	5,05	0,22
0,9	0,1	0,1	0	2,82	0,85	0,51	5,08	0,22

Table 7 Peak price timing forecast metrics. The best combination of predictors' weights and results' metric is highlighted.

The model achieved an R^2 of about 0.58, meaning it could explain roughly 58% of the variability in daily peak timing. This level of accuracy, while not perfect, is significant given the volatile nature of balancing events. The top model's RMSE was approximately 4.9 hours, and its mean absolute timing error was about 2.6 hours. However, the median absolute error was 0.7 hours, indicating that on most days the peak price time was predicted within an hour of the true value. The disparity between mean and median errors suggests a distribution with occasional large outliers. In other words, the model was usually accurate but occasionally missed the timing by a larger margin (several hours). Such outliers typically correspond to days with unusual system events or abrupt shifts that were hard to foresee. Still, an nMAE around 20% (with time normalized to a 24-hour day) demonstrates reasonably good predictive performance for this type of problem.

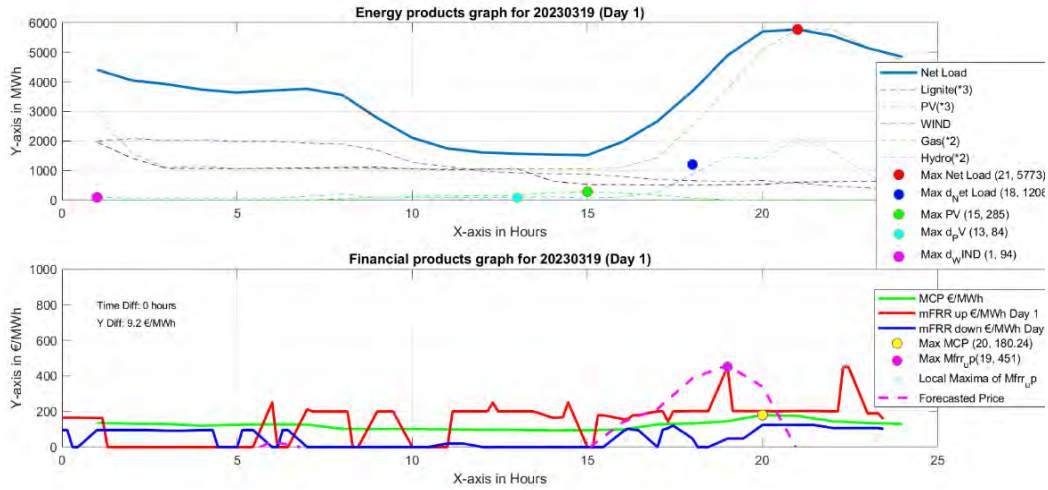


Figure 33 Pattern in actual mFRR price (red) for the 19/03/2023 over forecasted price(pink).

Figure 35 and 36 illustrate the model's R^2 as a function of two key feature weight factrs in the time forecast. A clear ridge of high R^2 values is observed when moderate weight is given to the previous day's forecast for the load and high weight to the reserve/wind indicators. This indicates that an optimal balance involves leveraging both of them. When either of these aspects clearly outweighs the other (for instance, too much reliance on just day-ahead load information or solely on renewables), performance degrades. The physics-informed approach of using fundamental variables is thus validated – the model that emerged is not a purely statistical black box, but rather reflects the underlying grid stress factors. It is worth emphasizing the rationale for evaluating peak timing forecasts: unlike day-ahead markets where timing of price peaks is relatively predictable (often coinciding with demand peaks), in the balancing market the peak price timing can vary unpredictably based on contingencies (e.g. a sudden drop in renewable output in the afternoon could shift the balancing stress to a later hour). By forecasting timing, operators gain foresight into when during the day the system is most likely to experience imbalance-driven price surges, enabling better preparation, such as having more fast-start units on standby at the right hour or managing controllable loads accordingly.

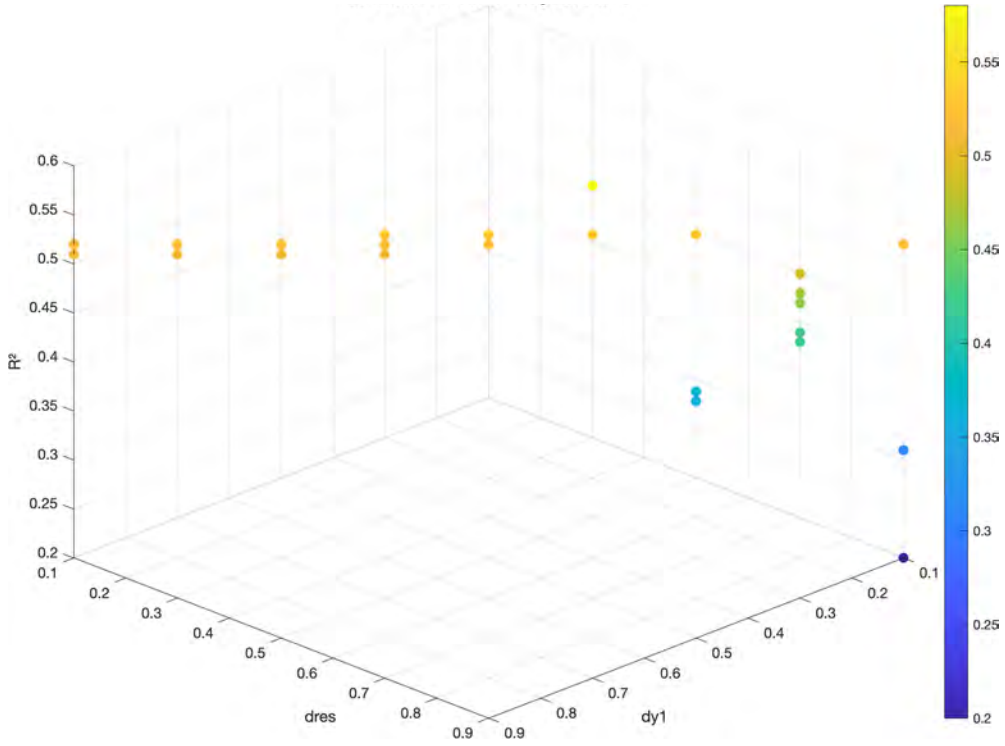


Figure 35 3D Scatter Plot of $\boldsymbol{R^2}$ vs dy1 and dres.

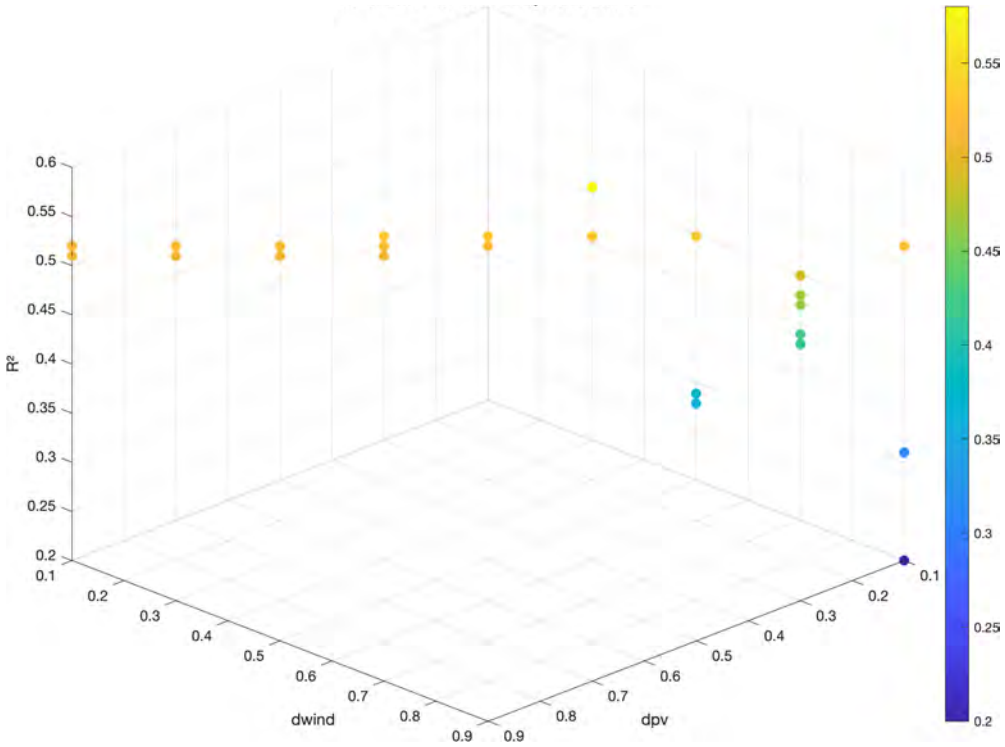


Figure 36 3D Scatter Plot of $\boldsymbol{R^2}$ vs dy1 and dres.

Our timing forecast results demonstrate moderate success in this challenging task. An R^2 around 0.5–0.6, though leaving nearly half the variance unexplained, is a notable improvement over purely statistical models (e.g. guessing peak occurs at the same time each day would yield far lower R^2). The median error, calculated under an hour, is especially encouraging. It means the model reliably pinpoints the peak period in most cases. The occasional larger errors highlight the limits of the model – these correspond to days with extraordinary events that the predictors could not capture. For example, an unexpected plant outage causing a late-evening price spike, which might not be fully explained by wind or load predictors. Such limitations are acknowledged, and they point to potential improvements like incorporating additional real-time information in future models.

5.3 Forecasting Peak Price Magnitude (mFRR Balancing Energy)

In addition to timing, forecasting the magnitude of the daily peak balancing price was investigated. Here, the target is to predict the highest price of activated mFRR energy each day (in €/MWh). Even if predicting this extreme value is inherently difficult due to the volatility and rarity of price spikes, it is of great practical importance. Greece balancing market spikes are common and quite extreme (see figure 34). System operators and market participants are interested in how high balancing prices can go, as extreme prices reflect stress events and have financial and reliability implications. Knowing that balancing activated energy is paid with a pay as clear mechanism, it is enough for market participants to predict when a peak will happen so that they are prepared offer the maximum possible quantity at that time, in order to maximize their reveue. Prior work has noted that power market participants try to forecast such extreme prices to manage risk and opportunity, optimally allocate their assets, and decide on market positions [54]. Indeed, the balancing market often exhibits occasional price extremes driven by physical supply-demand pressure rather than pure speculation [54], which suggests that a forecasting approach grounded in system physics could be effective.

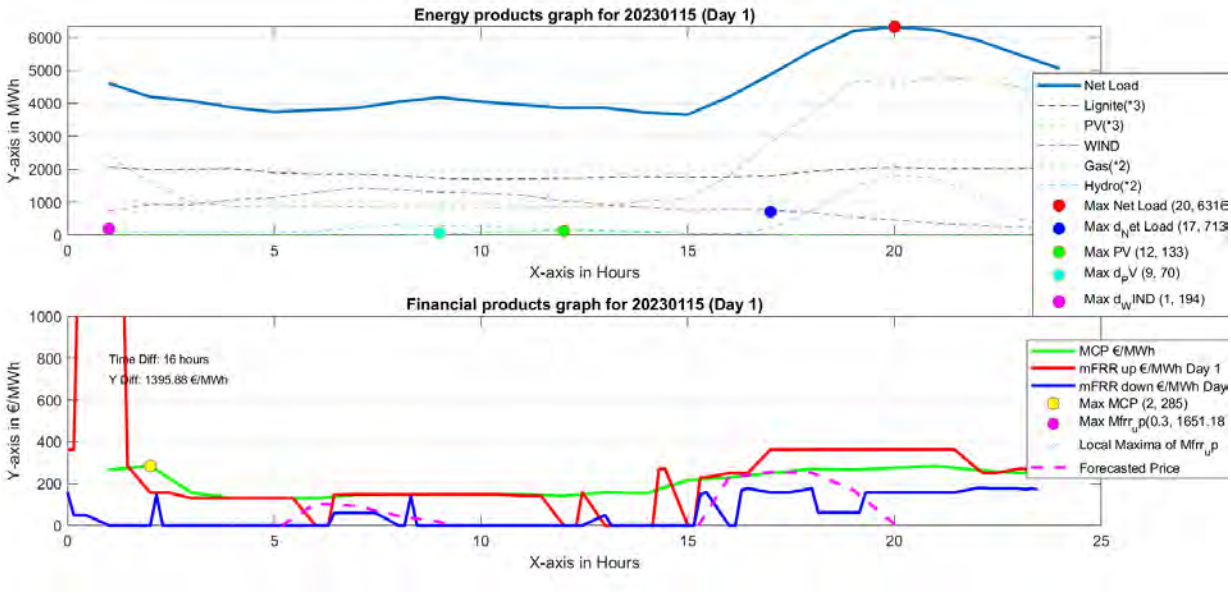


Figure 34 MFRR price (red) spike on the 15/01/2023 over forecasted price(pink)

Our models for peak price magnitude were evaluated with appropriate metrics (RMSE, nMAE), but focusing on price units (see table 8). The best-performing model for magnitude prediction achieved a normalized MAE of about 25%, meaning the average error was around one-quarter of the actual peak price value. For context, the mean price of daily maximum activated mFRR peak price was 401 €/MWh for 2023, while the model's average error would be on the order of 100 €/MWh. The median absolute error was €89 at best, indicating that on half the days the peak price was predicted within roughly €90 of the true peak, a reasonably tight range given that actual peaks can reach several hundred euros or more. The RMSE for this model was about €142, reflecting the impact of some days with larger error (again, heavy-tail behavior where a few extreme misses increase the quadratic error significantly). These metrics suggest the model has moderate reliability: it captures the general scale of peak prices and is often quite accurate, but it can under-predict or over-predict on days with exceptionally high spikes. This is not unexpected, as extreme price formation may involve unforeseen factors like sudden reserve depletion or market panic that are hard to quantify in advance.

The results, summarized in Table 8, show that there is one combination that yielded better accuracy across all metrics compared to other combinations (highlighted in green). That combination combined change in load forecast with the biggest weight (0.5), change in wind generation (0.4) and last the change in solar generation (0.1). Notably, it brought the nMAE down to 0.25, a substantial improvement over naive benchmarks. We also observe that models which overweighted a single type of predictor tended to perform worse. For example, a model that relied too much on just renewable forecast deviation but neglected load forecast context often under-forecasted the peak magnitude. Conversely, a model using only load information without accounting for daily physical conditions sometimes failed to predict spikes on days when a large forecast error (wind or solar) triggered a one-off price jump. Thus, the blend of predictors is crucial for capturing both recurrent patterns and event-driven anomalies.

Interestingly, the feature combination that worked best for peak magnitude was not identical to that for timing. The optimal magnitude model assigned significant weight to the previous day's load forecast and the system reserve indicator, as well as a notable weight to solar PV forecast deviation, while the wind error term had a smaller weight in this case. In other words, the magnitude of price spikes was more sensitive to conditions captured by load imbalance and solar generation shortfall. One possible interpretation is that solar PV shortfalls (e.g. due to forecasted clear weather turning cloudy) can create midday stress that drives prices sharply up, affecting the height of the price peak. Wind shortfalls, on the other hand, might more directly influence when the imbalance happens (as noted earlier) rather than how high the price goes. One explanation could be that when wind is low all day, other resources ramp up earlier and contain the price to some extent, whereas a sudden solar power drop during peak demand can cause a sharper price excursion. Meanwhile, it was proven that the load-related predictor must be given a significant weight (0.4 to 0.5) because the severity of price spikes corresponds to scarcity of balancing resources – a finding aligned with basic economic intuition (prices skyrocket when supply is scarce relative to demand).

Weight of predictor				Magnitude forecast (price)			
dy1	**dres**	**dpv**	**dwind**	**mean_Ydiff**	**median_Ydiff**	**RMSE**	**nMAE**
0,1	0,9	0,8	0,1	293	335	334	0,73
0,1	0,9	0,7	0,2	195	164	254	0,48
0,1	0,9	0,6	0,3	287	306	336	0,71
0,1	0,9	0,5	0,4	264	307	306	0,66
0,1	0,9	0,4	0,5	264	280	317	0,65
0,1	0,9	0,3	0,6	249	273	297	0,62
0,1	0,9	0,2	0,7	235	255	286	0,58
0,1	0,9	0,1	0,8	223	238	274	0,55
0,2	0,8	0,7	0,1	242	262	290	0,61
0,2	0,8	0,6	0,2	237	254	285	0,59
0,2	0,8	0,5	0,3	229	244	278	0,57
0,2	0,8	0,4	0,4	218	233	269	0,55
0,2	0,8	0,3	0,5	208	227	260	0,51
0,2	0,8	0,2	0,6	197	216	251	0,49
0,2	0,8	0,1	0,7	188	204	242	0,46
0,3	0,7	0,6	0,1	172	170	225	0,43
0,3	0,7	0,5	0,2	168	165	221	0,42
0,3	0,7	0,4	0,3	163	153	216	0,41
0,3	0,7	0,3	0,4	157	149	210	0,39
0,3	0,7	0,2	0,5	152	143	204	0,38
0,3	0,7	0,1	0,6	147	134	198	0,37
0,4	0,6	0,5	0,1	123	105	170	0,3
0,4	0,6	0,4	0,2	121	103	168	0,3
0,4	0,6	0,3	0,3	120	107	170	0,29
0,4	0,6	0,2	0,4	119	111	164	0,29
0,4	0,6	0,1	0,5	119	106	170	0,29
0,5	0,5	0,4	0,1	103	89	142	0,25
0,5	0,5	0,3	0,2	104	88	143	0,26
0,5	0,5	0,2	0,3	106	90	145	0,26
0,5	0,5	0,1	0,4	108	93	147	0,27
0,6	0,4	0,3	0,1	110	86	156	0,27
0,6	0,4	0,2	0,2	113	85	160	0,28
0,6	0,4	0,1	0,3	117	90	165	0,29
0,7	0,3	0,2	0,1	150	119	204	0,37
0,7	0,3	0,1	0,2	156	123	211	0,39
0,8	0,2	0,1	0,1	215	187	272	0,53
0,8	0,2	0	0,2	222	191	279	0,52
0,9	0,1	0	0,1	290	273	290	0,72
0,9	0,1	0,1	0	284	266	342	0,71

Table 8 Peak price magnitude forecast metrics. The best combination of predictors' weights and results' metrics is highlighted.

It should be noted that forecasting the exact magnitude of balancing price peaks remains a difficult endeavor, and literature on this specific topic is relatively scarce [52]. The

current deterministic model nonetheless provides a baseline level of insight and, importantly, it does so using a physics-based feature set rather than purely statistical lags. This means the model's behavior is interpretable in terms of grid conditions – an aspect that is valuable for engineers and operators who need trust in the forecast. Indeed, the approach of linking price spikes to underlying factors reflects the notion that electricity markets need to have deterministic drivers [54] , and our results confirm that incorporating those drivers (like load margins and renewable output deviations) yields practical predictive capability.

We acknowledge a few limitations in the suggested price magnitude forecast method. First, the extreme high-price events are by nature infrequent and sometimes driven by unforeseeable incidents (e.g. sudden plant outages, reserve activation failures). This makes it hard for any model to learn from a small sample of past extremes – a common challenge in tail-end forecasting. Second, the data span and feature set might not fully capture emergent behavior; for instance, if a new policy or market rule comes into effect (such as a change in price cap or imbalance settlement mechanism), past data may not be indicative of future peaks. Nonetheless, within the scope of historical testing, the model's performance is quite encouraging. It shows that even a relatively straightforward model can achieve adequate accuracy in predicting peak balancing prices. In summary, while there is room for improvement, the peak magnitude forecast model demonstrates the feasibility of anticipating not just when a balancing price spike will happen, but also how high that spike might be, information that is crucial for risk management in operations and trading.

5.6 AFRR (capacity) peak price forecast

During the analysis of 2023 Greek balancing market data fot the mFRR energy price, a clear relationship has been discovered between the day-ahead market MCP and the aFRR upward capacity. In simple terms, when day-ahead electricity prices are very low, the price for aFRR reserve price often spikes, as described in chapter 4. This behavior is rooted in the operational characteristics of the system: high MCP usually implies that expensive quick-response gas turbine units are already committed to generation (driving MCP up). Those same units are the primary providers of aFRR capacity due to their quick response, so if they are already online and competing to provide reserves, the aFRR capacity market is well-supplied and its price stays moderate. Conversely, when MCP is low (e.g. due to large baseload plants or renewables meeting demand), fast gas-fired units are likely offline due to their higher cost. If reserve capacity is needed in those low-MCP periods, some gas units must start up solely to provide aFRR, and with few competitors the aFRR capacity price can soar. This complementary market behavior means low MCP is a strong indicator of potential aFRR price spikes.

Building on this insight, we implemented a simple threshold-based classification model for forecasting aFRR reserve price events. Rather than a complex machine learning regression, this model uses a single heuristic rule: if the day-ahead MCP drops below a certain threshold, flag that day as likely to experience a high aFRR price (see chapter 4 and appendix B). Otherwise, predict a normal aFRR day. The threshold is defined as a fraction of recent MCP values. Effectively it is a mean-percentage (MAP) threshold. Initially, we set this threshold at 10% of the average MCP from the preceding 100 days, representing an exceptionally low price level. In other words, for each day

we compute the average MCP of the past 3 months and take 10% of that as the threshold (a dynamic benchmark that adapts to recent price level trends). If on the target day the MCP falls to or below that 0.1·mean value at any hour, the model predicts aFRR prices will reach high levels on that day and during the time the MCP is low. This straightforward rule is illustrated in figures 38 where a preak price is indeed reached between 12:00 and 15:00, that MCP is extremely low. In figure 35 and figure 36, the MCP (green line) dips under the threshold (black dashed line) and the aFRR capacity price (red line) correspondingly exhibits a significant spike. The model's positive prediction is confirmed. These typical success cases demonstrate the threshold model's ability to capture the required prediction sensitivity.

It is important to note that this approach performs classification, not numeric prediction. We do not forecast the exact aFRR price or reserve volume; we only predict the occurrence of a price spike event based on the MCP condition. This is a deliberate choice: given the volatility and limited data for aFRR capacity prices, formulating a robust regression model proved challenging. Instead, the threshold method leverages a transparent, explainable criterion grounded in market mechanics. The simplicity of this model is advantageous in avoiding overfitting and in offering an intuitive rationale. Furthermore, it aligns with operational timing – the day-ahead MCP is known by 14:00 on the day before delivery, and balancing service providers can still adjust their reserve offers until 16:00. Thus in practice, system operators can use the MCP information (available before balancing capacity market closure) to anticipate and exploit high reserve prices, which validates the practicality of our threshold-based predictor.

After defining the threshold model, we calibrated the threshold percentage to optimize performance. Starting from the initial 10% of mean MCP, we incrementally increased the threshold (e.g. to 20%, 30%, etc.) and evaluated the model's accuracy over the study. The evaluation focused on classification outcomes – each day's prediction was categorized as a true positive, true negative, false positive, or false negative(see chapter 4). In this context, we label a day as "positive" if the actual aFRR Up price reached unusually high levels (a pronounced peak or sustained high price), and "negative" if aFRR prices stayed low or ordinary. Because our heuristic is specifically keyed to the low-MCP mechanism, it cannot catch all aFRR price spikes. Since some spikes may be triggered by other conditions (these would be false negatives). However, the design priority is to minimize false alarms. In other words, we prefer a conservative predictor, which might miss a few spikes, rather than one that predicts a spike incorrectly. So, a "high aFRR" warning can be trusted.

Using this criterion, we found that a threshold around 30% of the mean MCP achieves the best balance of sensitivity and specificity. Empirically, raising the threshold from 10% up to 30% gradually improved detection of actual high-aFRR days with only a modest increase in false positives. At the 30% level, the model yielded only 4 false positive days over an entire year, while successfully capturing most of the true spike days. This was deemed a very acceptable trade-off. In comparison, a lower threshold (20%) was overly strict – it missed more actual spikes (higher False Negatice rate) for little gain in False Positive reduction – and a higher threshold (40%) became too lax, causing many more false positives as too many days qualified as "low MCP". Thus, 30% of recent average MCP was selected as the optimal threshold setting for the aFRR reserve forecasting model. With this tuning, the simple threshold classifier proved to

be a reliable forecasting tool for aFRR price surges, effectively translating a fundamental market relationship into a actionable predictive signal.

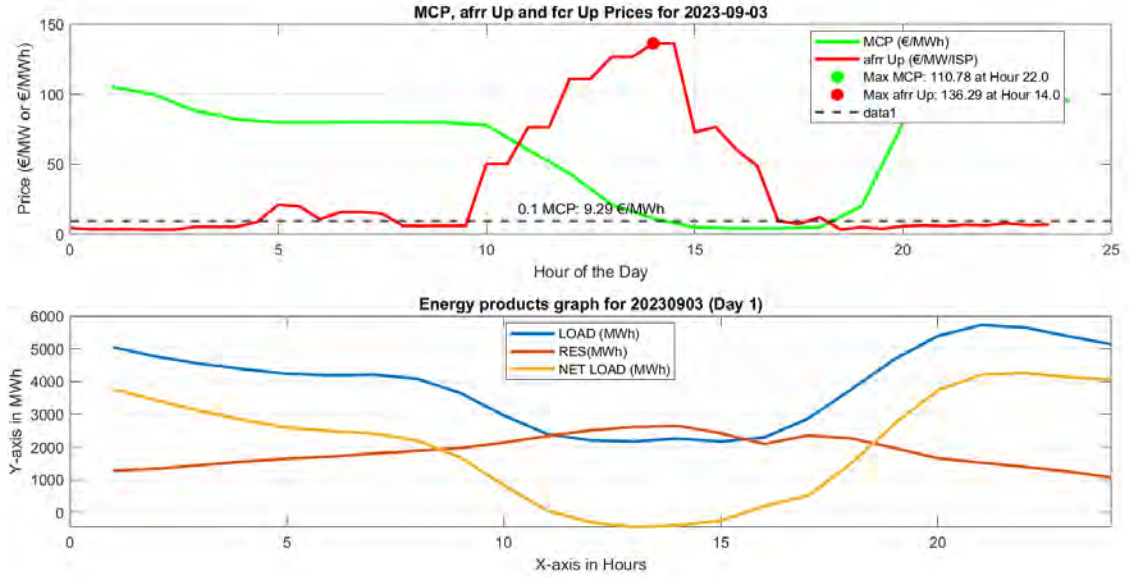


Figure 35 aFRR vs MCP price in 3th of September 2023. A peak in aFRR happends between 12:00 and 15:00 when MCP price is low.

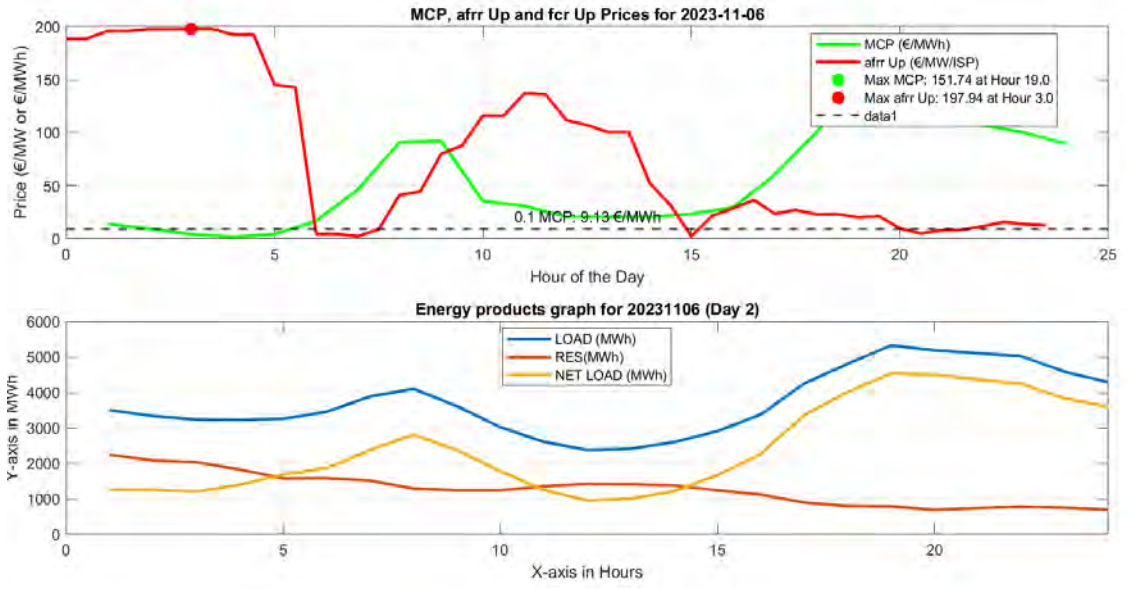


Figure 36 aFRR vs MCP price in 6th of November 2023. A peak in aFRR happens between 02:00 and 05:00 when MCP is low.

5.7 Conclusion

In this chapter, we developed and evaluated predictive models for balancing market forecasting, focusing on both mFRR energy and aFRR capacity products. A diverse set

of forecasting approaches was explored to capture the distinct behaviors of these two products. For mFRR, which exhibits more continuous patterns, we employed data-driven regression techniques (including various combinations of input features and model parameters) to predict timing and magnitude of peaks in activated mFRR price. In contrast, for aFRR, characterized by less frequent but important price spikes, we adopted a bespoke rule-based approach, using an MCP-threshold classifier. The methodologies were tailored to each product: the mFRR forecasts leveraged forecasts on physical parameters influencing the grid, while the aFRR method relied on a single powerful indicator (exceptionally low day-ahead price) to anticipate extreme reserve price events.

Key findings from the forecasting efforts were highlighted through rigorous evaluation and visualization. We tried numerous predictor combinations and configurations for the mFRR models. The best-performing combinations were retained as viable forecasting tools. The performance of each configuration was quantified using metrics such as the coefficient of determination and error measures, and these results were presented in 3D surface plots for clarity. Through these analyses, we identified clear optimal settings for the mFRR forecast. In summary, the chapter distilled a large design space down to a handful of robust forecasting models for reserve prediction.

For the aFRR reserve, the simple threshold-based model emerged as an effective tool to predict high-price days, as detailed above. Although not a conventional predictive model in the statistical sense, it demonstrated value in capturing price spikes when the MCP is extremely low with minimal false alarms. The success of this heuristic reinforces the importance of incorporating power system domain knowledge (market logic and operational timing) into forecasting techniques, rather than relying purely on black-box predictions.

Overall, Chapter 5 has presented a comprehensive assessment of suggested forecasting methods for balancing reserves, combining both advanced analytics and intuitive rule-based strategies. Each approach was rigorously validated, and the best models were identified based on quantitative performance. These validated forecasting tools can support system operators and market participants by providing foresight into reserve deployment and pricing. The findings here also serve as a foundation for the final discussions contained in the next chapter where we synthesize the insights from our forecasting study into overarching conclusions. In Chapter 6, we will present the overall conclusions of the project and offer engineering reflections, discussing the broader implications of the developed forecasting tools and the lessons learned throughout this research.

6. Conclusions

The core challenge addressed in this dissertation was the forecasting of daily peak prices in the Greek balancing energy market, specifically predicting both the timing (when the peak occurs each day) and the magnitude (how high that peak price reaches). This problem is of critical importance for the operation of the Greek electricity market and its balancing system. Balancing markets, by their nature, are highly volatile due to real-time supply-demand fluctuations and the growing penetration of intermittent renewable energy. Extreme price spikes can occur with little warning, posing risks to market participants and challenges to system stability. Accurately forecasting these peak price events is valuable because it enables better planning and risk management: producers, energy storage operators, and demand response providers can optimize their bidding and operational schedules to capture high prices or avoid penalties, while the transmission system operator (IPTO) can ensure sufficient reserves are in place to maintain grid stability. Given that the mFRR activated energy market operates under a pay-as-clear pricing mechanism, accurately forecasting the timing of the daily price peak is particularly critical. In such a setting, market participants benefit as long as their bids are accepted during the clearing process, making precise temporal alignment with peak periods a key factor in securing favorable revenues. Complementing this, the aFRR reserve peak price forecasting model, developed using a threshold-based classification approach, aims to anticipate costly events in the power reserves market based on the indicator of DAM price drops, thus offering a strategic advantage in reserve market positioning. Together, these forecasting tools contribute to a more proactive and informed participation in Greece's increasingly dynamic balancing markets. In the context of the Greek balancing market – introduced as part of the EU Target Model reforms – forecasting peak prices helps mitigate uncertainty in a crucial, last-resort energy market that supports real-time grid balance. The problem statement, therefore, centers on developing a tool to anticipate when the highest price of the day will occur and what that price is likely to be, addressing a gap in operational forecasting for Greece's balancing mechanism.

6.1 Contributions of this dissertation

This dissertation made several significant contributions toward the above challenge. First, it developed a regression-based forecasting model tailored to the Greek balancing market for predicting the daily peak activated balancing energy price in terms of both timing and magnitude. The model was implemented as a custom MATLAB tool, using a weighted linear regression framework using physically-informed predictors. Key predictors included indicators of system stress such as sudden changes in net load, forecast errors in wind and solar generation. By incorporating these fundamental drivers of imbalance events, the tool captures the conditions leading to price spikes. Second, the dissertation achieved noteworthy predictive performance. For the peak timing forecast, the model explained roughly 58% of the variance in daily peak timing ($R^2 \approx 0.58$) in the best working combination of predictors. The developed model demonstrated temporal precision typically identifying the peak within a narrow window of its actual occurrence, reflected in a median absolute error of approximately 1 hour while the RMSE is just below 5 hours because it penalizes outlier days of very high exetremes. The nMAE, which expresses the average absolute error as a fraction of the

daily time range, is 20% for the best combination of predictors and it further confirms the model's robustness across varying market conditions.

For the peak price magnitude forecast, the model reached a nMAE of about 25%, meaning the average prediction error was about one-quarter of the actual peak price. In practical terms, given an average daily peak around 400 €/MWh in 2023, the tool's average error was on the order of 100 €/MWh, with a median error of ~90 €. The Root RMSE was higher (~142 €) due to a few extreme misses, reflecting the challenge of predicting occasional extreme spikes. These metrics are in line with expectations for such a volatile market, where day-ahead price forecasts typically achieve higher accuracy than real-time balancing forecasts.

Third, the dissertation's scope extended beyond just the balancing energy price to also address the aFRR market, but with a clear distinction between aFRR energy and reserve components. Because the activated aFRR energy price in Greece is settled as the maximum of its own bid and the corresponding mFRR price, forecasting extreme mFRR price spikes inherently provides coverage for the aFRR activated energy price as well. However, the aFRR reserve capacity price (the capacity market for reserves) was tackled with a separate model. This model employed a simple threshold-based classifier using day-ahead market prices: if the day-ahead MCP fell below a certain fraction of its recent average (a dynamic low-price threshold), the day was flagged as likely to experience a high aFRR reserve price spike. In essence, extreme aFRR capacity price events were predicted through this heuristic rule rather than the regression used for energy prices. The results of the aFRR reserve capacity forecasting model demonstrated that the threshold-based approach successfully identified the majority of high-price days, offering a simple yet effective early-warning tool for extreme reserve market conditions with relatively low false positives.

This dual approach ensured the forecasting framework covered both imbalanced energy price peaks and reserve market stress events, enhancing its practical relevance for market participants and system operators. For the system operator, the combined energy-and-reserve forecasting perspective supports better operational scheduling and ensures that both energy and reserve sufficiency are accounted for when extreme events are expected. In summary, the dissertation delivered a forecasting solution for peak prices in balancing market Greece, demonstrated its efficacy with solid performance metricsand provided a richer market analysis by tying in the reserve market aspect, thereby offering a base comprehensive decision-support tool for the balancing market environment.

6.2 Future Work

While the developed forecasting models proved effective, there remains ample room for future work and enhancements. One direction is to explore more advanced modeling techniques beyond the linear regression approach. Machine learning and AI-based models, such as gradient boosting regression trees, random forests, or deep learning networks (e.g. LSTM neural networks), could potentially capture non-linear relationships and complex interactions in the data, potentially improving accuracy in predicting rare price spikes. These models could be tested against the regression baseline to see if they yield better performance, though care must be taken to avoid overfitting given the relatively limited size of historical balancing data as well as the

continuisly chaning regulatory framework. Another extension involves incorporating additional data sources and features to enrich the forecasting. Inclusion of real-time system information (for example, unexpected generator outages, transmission constraints, or cross-border flow data) could enhance the model's ability to foresee unusual price surges that are driven by events not fully captured in load/RES forecast errors. Integrating weather extremes or ramping capability constraints of the grid could similarly sharpen the predictions. Moreover, future research could consider a probabilistic forecasting approach: instead of single-point predictions, the model could output confidence intervals or probabilities of exceeding certain price thresholds, which would be highly useful for risk management by market participants. Another promising avenue is to develop a two-stage forecasting framework that first predicts the likelihood of a price spike (classification of whether an extreme event will occur on a given day), and then, conditional on that, forecasts the timing and magnitude – this could potentially handle the spike/no-spike decision explicitly and improve overall reliability. In terms of operational deployment, future work could focus on turning the model into an online tool that updates forecasts intra-day. For instance, the model could be recalibrated with the latest available data (updated load or RES forecasts, interim market prices) to refine predictions as real time approaches, thereby increasing usefulness for traders and operators in a live setting. Collaboration with the IPTO or market agencies could facilitate access to live data streams and pave the way for pilot testing the forecasting system in a real-world environment. Finally, extending the analysis to other products and markets would broaden its impact: for example, applying a similar forecasting strategy to predict upward vs. downward balancing prices separately, or to forecast reserve capacity prices for other products like FCR, could provide a more complete suite of tools for balancing market participants. In summary, the foundation laid by this thesis can be expanded with modern algorithms, richer data, probabilistic methods, and real-time adaptation, all aimed at further improving the anticipation of balancing market behavior in Greece.

6.3 Personal reflections

This dissertation journey has been transformative both technically and personally. From an academic and engineering standpoint**,** the author has deepened her expertise in energy market analysis, data-driven modeling, and the rigorous validation of forecasting tools. Through the process of tackling a real-world problem in the Greek electricity market, the author learned how crucial it is to combine engineering techniques with domain-specific knowledge. Developing the forecasting model required not only programming skill and statistical acumen, but also a thorough understanding of how the balancing market operates in detail, from market rules to physical grid constraints. This reinforced the lesson that effective solutions in the energy sector demand an integration of theory with practical system insight. The experience improved the author's ability to conduct independent research: formulating a clear problem statement, surveying relevant literature, designing a methodology, and iteratively refining the model based on evidence. The challenges encountered (such as handling data quality issues, high price volatility, and model selection) taught resilience and creative problem-solving, which are invaluable skills for any engineer.

Equally important, the author's development was fostered by close collaboration with her academic supervisor. Working under the guidance of an experienced professor instilled a sense of research rigor and discipline – from maintaining methodological

soundness to documenting results meticulously. Regular discussions and feedback sessions with the supervisor helped cultivate a more critical perspective, ensuring that findings were not taken at face value but examined in depth. This mentorship was instrumental in learning how to validate a model's performance properly, interpret results in the context of existing literature, and draw meaningful conclusions that stand up to scrutiny. The supervisor's emphasis on clarity and justification in each step of the project has undoubtedly made the author a more methodical and thorough researcher.

On a personal level, this project has opened new doors and confirmed the author's passion for the energy field. The skills and insights gained have directly led to professional opportunities. Notably, the author has begun her professional career at Rener Energy SA, where the knowledge from this dissertation about the Greek electricity market is being applied in an industry setting. Furthermore, the success of the thesis contributed to the author receiving an offer to pursue an MSc degree at Imperial College London, a development that underscores the academic growth achieved. These opportunities affirm that the effort invested in this research is both professionally rewarding and socially relevant. The ability to forecast balancing market outcomes is not merely an academic exercise but a sought-after expertise in the evolving landscape of renewable integration.

In closing, the journey of this dissertation has been a defining period of growth. It demonstrated the value of combining analytical skills with energy market understanding, highlighted the importance of mentorship in cultivating quality research, and solidified the author's dedication to the power systems field. The outcomes of this work, both the forecasting tool itself and the personal milestones reached, underscore the importance of rigorous, application-oriented research in driving innovation and career development in the energy sector.

References

[1] Decarbonization of Energy Systems in Europe. (2023). *IEEE Xplore*.

[2] ADMIE. (2023). *Yearly Press Release 2023*. ADMIE.

[3] Balkan Green Energy News. (2024). *New bill to support 2 GW of battery storage in Greece*.

[4] Dikaiakos, C. (2019). *Contribution to the analysis and design of modern electricity markets with applications to real systems* (PhD Thesis). University of Patras.

[5] Dong, Z., & Zhang, P. (2010). *Emerging techniques in power system analysis*. Springer.

[6] Ederer, N. (2015). *The European electricity market: Challenges and opportunities*. Springer.

[7] Forecasting Electricity Balancing Market Prices. (2023). *MDPI Energy, 18*(4), 911.

[8] Jomaux, J. (2023). *Thoughts on the energy transitions*. GEM Energy Analytics.

[9] Sustainability in Energy Markets. (2023). *MDPI Sustainability, 15*(4), 3767.

[10] Lexology. (2022). *Greece introduces legal framework for electricity storage*.

[11] M. Farrokhseresht and F. Nobel, *"The Impact of RES Integration on Balancing Markets,"* in *Proceedings of the 2022 18th International Conference on the European Energy Market (EEM)*

[12] Kirschen, D., & Strbac, G. (2004). *Fundamentals of Power System Economics*. Wiley.

[13] International Energy Agency. (2023). *Switzerland 2023 Energy Policy Review*. IEA.

[14] Offshore Energy. (2024). *Construction of €1B Greek electrical interconnection done, operations in spring*. Offshore Energy.

[15] ADMIE. (2024). *Inauguration of new electricity interconnection between Greece and Bulgaria*. ADMIE.

[16] Regulatory Authority for Waste, Energy, and Water (RAAEY). (2024). *Wholesale Electricity Market Reports 2023*.

[17] Independent Power Transmission Operator (IPTO), *Μελέτη Επάρκειας Ισχύος 2020-2030*, Athens, Greece: ADMIE S.A., 2020. [Online]. Available: https://www.admie.gr

[18] Regulatory Authority for Waste, Energy, and Water (RAAEY), *"November 2023 Monthly Report,"* Feb. 2024. [Online]. Available: https://www.raaey.gr/energeia/wp-content/uploads/2024/02/202311_Monthly_Report_Public_2.pdf.

[19] Regulatory Authority for Waste, Energy, and Water (RAAEY), *"Electricity Networks in Greece"*, 2024. [Online].
Available: https://www.raaey.gr/energeia/ilektrismos/diktya/

[20] Energy KnowledgeBase, *"Electric Grid,"* [Online].
Available: https://energyknowledgebase.com/topics/electric-grid.asp. [Accessed: Feb. 22, 2024].

[21] Ecopress, *"Renewable Energy Coverage in Greece Exceeds 50%"*, 2024. [Online]. Available: https://ecopress.gr/apo-ape-pano-apo-to-50-tis-zitisis-ilektr/

[22] Statista, *"Installed power capacity in Greece in 2022, by source,"* [Online].
Available: https://www.statista.com/statistics/1153672/installed-power-capacity-greece-by-source/.

[23] IPTO (ADMIE), *"2024 Energy Generation and Export Infographic"*, LinkedIn, Feb. 2024. [Online]. Available: https://www.linkedin.com/posts/ipto-admie_infographic-ipto-renewableenergy-activity-7297895736568901632-lD1p

[24] European Biomass Industry Association, "Biomass Power Generation Technologies," 2023.

[25] Regulatory Authority for Waste, Energy, and Water (RAAEY), *Διεθνείς Διασυνδέσεις και Ενεργειακή Αγορά της Ελλάδας*, 2024.

[26] "Biomass Gasification: A Comprehensive Guide," Pellet Making, 2024. [Online].
Available: https://www.pellet-making.com/blog/biomass-gasification.html.
[Accessed: 25-Dec-2024].

[27] Offshore Energy, "Construction of €1B Greek electrical interconnection done, operations in spring," 2024. [Online]. Available: https://www.offshore-energy.biz/construction-of-e1b-greek-electrical-interconnection-done-operations-in-spring/

[28] Reuters, "Cyprus says progress seen in talks with Greece on multi-billion electric cable link," 2024. [Online]. Available: https://www.reuters.com/technology/cyprus-says-progress-seen-talks-with-greece-multi-billion-electric-cable-link-2024-09-17/

[29] ΑΔΜΗΕ (ΙΡΤΟ), "Χάρτης Γραμμών Μεταφοράς," admie.gr, [Online].
Available: https://www.admie.gr/systima/perigrafi/hartis-grammon.

[30] Energypress, "Δημοσιεύτηκε σε ΦΕΚ η υπουργική για τις standalone μπαταρίες - Στα 4.700 MW η ισχύς," Energypress.gr, Mar. 2025. [Online].
Available: https://energypress.gr/news/dimosieytike-se-fek-i-ypoyrgiki-gia-tis-standalone-mpataries-sta-4700-mw-i-ishys

[31] The Green Tank, "ΑΔΜΗΕ: Δεκέμβριος 2024 – Ηλεκτροπαραγωγή και εξαγωγές," *The Green Tank*, Jan. 30, 2025. [Online]. Available: https://thegreentank.gr/2025/01/30/admie-dec24-el/

[32] J. J. Makrygiorgou, C.-S. Karavas, C. Dikaiakos, and I. P. Moraitis, "The Electricity Market in Greece: Current Status, Identified Challenges, and Arranged Reforms," *Sustainability*, vol. 15, no. 4, p. 3767, Feb. 2023. [Online]. Available: https://www.mdpi.com/2071-1050/15/4/3767

[33] Hellenic Energy Exchange (HEnEx), *Day-Ahead & Intra-Day Markets Trading Rulebook*, Version 2.1, Dec. 2024. [Online]. Available: https://www.enexgroup.gr/documents/20126/144557/20250417_Decision_10_en.pdf

[34] HEnEx, *Trading Calendar and Timeline Procedures*, Annex to Rulebook, Dec. 2024

[35] Hellenic Energy Exchange (HEnEx), "Homepage," [Online]. Available: https://www.enexgroup.gr/el/home

[36] EPEX SPOT, "Market Results," [Online]. Available: https://www.epexspot.com/en/market-results.

[37] ENTSO-E, ENTSO-E Market Report 2024, European Network of Transmission System Operators for Electricity, Jun. 2024. [Online]. Available: https://eepublicdownloads.entsoe.eu/clean-documents/nc-tasks/240628_ENTSO-E_Market_Report_2024.pdf

[38] IPTO (ΑΔΜΗΕ), *Κανονισμός Αγοράς Εξισορρόπησης*, Έκδοση 16.0, Ιούνιος 2024. [Online]. Available: https://www.admie.gr/sites/default/files/users/drthad/kae/ΚΑΝΟΝΙΣΜΟΣ_ΑΓΟΡΑΣ%20ΕΞΙΣΟΡΡΟΠΗΣΗΣ_v17.pdf

[39] IPTO (ΑΔΜΗΕ), *Τεχνική Απόφαση ΔΕΠ*, Έκδοση 4, Ιούνιος 2024. [Online]. Available: https://www.admie.gr/sites/default/files/users/dda/ΔΕΠ/Τεχνική%20Απόφαση%20ΔΕΠ_v2-v1.pdf

[40] Independent Power Transmission Operator (IPTO/ADMIE), *Μεθοδολογία Υπολογισμού Τιμών Αγοράς Εξισορρόπησης*, Version 1, Oct. 2020. [Online]. Available: https://www.admie.gr/sites/default/files/users/dda/BSPs/Μεθοδολογία%20Υπολογισμού%20Τιμών%20Αγοράς%20Εξισορρόπησης_v1.pdf

[41] IPTO (Independent Power Transmission Operator), *National Report for the Balancing Market 2024*, Jun. 2024. [Online]. Available: https://www.admie.gr/sites/default/files/attached-files/type-file/2024/06/IPTO_national_report_for_Balancing_2024_final_for_site_0.pdf

[42] Independent Power Transmission Operator (IPTO), "Εβδομαδιαίο Δελτίο Αγοράς Εξισορρόπησης: 27/01/2025 - 02/02/2025," Feb. 2025. [Online].

Available: https://www.admie.gr/sites/default/files/attached-files/type-file/2024/06/IPTO_national_report_for_Balancing_2024_final_for_site_0.pdf

[43] S. Kampouris, I. Roussakis, M. Zervos, and E. Dialynas, "Balancing market enhancement in the Greek power system: Introducing ancillary services by demand side and storage resources," in *2022 18th International Conference on the European Energy Market (EEM)*, Ljubljana, Slovenia, Sep. 2022, pp. 1–6. [Online]. Available: https://ieeexplore.ieee.org/document/9921068

[44] I. Roussakis, M. Zervos, and E. Dialynas, "Balancing Market Design Integration of Demand Side Resources and Storage: A Simulation Study for the Greek Power System," *Energies*, vol. 13, no. 20, p. 5420, Oct. 2020. [Online]. Available: https://www.mdpi.com/1996-1073/13/20/5420

[45] Hellenic Energy Exchange (HEnEX), Κανονισμός Συναλλαγών Ημερησίου και Ενδοημερησίου Ενεργειακού Προγραμματισμού – Κύριο Σώμα, Έκδοση 2.1, 17 Απρ. 2025 [Online]. Available:

[46] IPTO (ADMIE), *Δημόσια Διαβούλευση – Αρχικός Σχεδιασμός Συμμετοχής των Εγκαταστάσεων Αποθήκευσης Ηλεκτρικής Ενέργειας στην Αγορά*, May 2024. [Online]. Available: https://www.admie.gr/anakoinoseis/diaboyleyseis/dimosia-diaboyleysi-arhikos-shediasmos-symmetohis-ton-egkatastaseon

[47] "Electricity pricing," *Wikipedia*, https://en.wikipedia.org/wiki/Electricity_pricing

[48] Andreadis, I. et al. (2020). *Price forecasting for the balancing energy market using machine-learning regression*. *Energies, 13*(20), 5420. Available: https://www.mdpi.com/1996-1073/13/20/5420#:~:text=market%20data,in%20the%20power%20systems%20as

[49] Bunn, D. W., Inekwe, J., & Macgeehan, D. (2021). *Analysis of the fundamental predictability of prices in the British balancing market*. *IEEE Trans. Power Systems, 36*(2), 1309–1316. Available: https://scispace.com/pdf/analysis-of-the-fundamental-predictability-of-prices-in-the-1f0w27racc.pdf#:~:text=information%20on%20renewables'%20forecasts%2C%20as,less%20than%20wind%20forecast%20errors

[50] J. Bottieau, G. Audemard, S. Bellart, J.-M. Lagniez, P. Marquis, N. Szczepanski, and J.-F. Toubeau, "Logic-based explanations of imbalance price forecasts using boosted trees," *Electr. Power Syst. Res.*, vol. 235, p. 110699, Oct. 2024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0378779624005856

[51] J. Lago, F. De Ridder, and B. De Schutter, "Forecasting day-ahead electricity prices: A review of state-of-the-art algorithms, best practices and an open-access benchmark," *Appl. Energy*, vol. 293, p. 116983, Jul. 2021. [Online]. Available: https://doi.org/10.1016/j.apenergy.2021.116983

[52] K. Plakas, Nikos Andriopoulos, Dimitrios Papadaskalopoulos, Alexios Birbas, and I. Moraitis, "Prediction of Imbalance Prices Through Gradient Boosting Algorithms: An Application to the Greek Balancing Market," *IEEE Access*, vol. PP, no. 99, p. 1, Jan. 2025, doi: https://doi.org/10.1109/ACCESS.2025.3580274.

[53] Santos and H. Algarvio, “A Machine Learning Model for Procurement of Secondary Reserve Capacity in Power Systems with Significant vRES Penetrations,” *Energies*, vol. 18, no. 6, pp. 1467–1467, Mar. 2025, doi: https://doi.org/10.3390/en18061467.

[54] A. Lucas, K. Pegios, E. Kotsakis, and D. Clarke, “Price Forecasting for the Balancing Energy Market Using Machine-Learning Regression,” *Energies*, vol. 13, no. 20, p. 5420, Oct. 2020, doi: https://doi.org/10.3390/en13205420.

Appendices

Appendix A

```
clear all;
clc;
close all;

% Input: start and end dates
startDate = '2023-03-27'; % 'YYYY-MM-DD'
endDate = '2023-12-17';   % 'YYYY-MM-DD'

% Convert input dates to datetime
startDatetime = datetime(startDate, 'InputFormat', 'yyyy-MM-dd');
endDatetime = datetime(endDate, 'InputFormat', 'yyyy-MM-dd');

% Folder to save graphs
graphFolder =
'C:\Users\Dell\Documents\ΔΙΠΛΩΜΑΤΙΚΗ\graphs\diffY(incl_10%_and_time_diff)\
05dy102dpv03dwind';
% Excel to save important data for each day
excelFilePath = fullfile(graphFolder, 'data_table_05dy102dpv03dwind.xlsx');

% Check if the Excel file exists and read it
if isfile(excelFilePath)
    existingTable = readtable(excelFilePath);
    if istable(existingTable) && any(strcmp('Date',
existingTable.Properties.VariableNames))
        if height(existingTable) > 0 % Ensure the table has at least one row
            % Check the type of the first entry in the Date column
            if isnumeric(existingTable.Date(1))
                existingTable.Date = datetime(existingTable.Date, 'ConvertFrom', 'excel');
            elseif iscell(existingTable.Date)
                % Assuming the dates are in a recognizable string format, e.g., 'yyyy-MM-
dd'
                existingTable.Date = datetime(existingTable.Date, 'InputFormat', 'yyyy-
MM-dd'); % Adjust 'InputFormat' as necessary
            end
        else
            % Initialize the Date column correctly if planning to append data later
            existingTable.Date = datetime([], 'ConvertFrom', 'excel'); % This initializes
the column if you're going to append data
        end
    end
else
    existingTable = table();
end

% Initialize matrices for storing daily data
allMcp = []; % Matrix to store daily MCP data
```

```
allMfrr_up = []; % Matrix to store daily mFRR_up data
allforecasted = [];

% Find the most recent Monday
currentDate = startDatetime;

prompt = {'Enter variables separated by commas
(y1,im,ex,l,pv,wind,g,h,dy1,dpv,dwind):', 'Enter corresponding weights separated by
commas:'};
dlgtitle = 'Input for Forecasting Function';
dims = [1 50];
answer = inputdlg(prompt, dlgtitle, dims);
if isempty(answer)
    error('User cancelled the dialog or entered an empty input.');
end

selectedVars = strsplit(answer{1}, ',');
weights = str2double(strsplit(answer{2}, ','));
weights = weights(:)';
disp(size(weights));

% Loop through the interval
while currentDate <= endDatetime
    % Extract the date in the format 'yyyymmdd'
    currentDateStr = datestr(currentDate, 'yyyymmdd');

    % File names based on the extracted date
    tableDataFilename = [currentDateStr '_SystemRealizationSCADA_01.xls'];
    fullFilePath = fullfile('C:\Users\Dell\Documents\ΔΙΠΛΩΜΑΤΙΚΗ\SCADA',
tableDataFilename);
    disp(['Checking file: ', fullFilePath]); % Display the full file path to check it
    mfrrPath = 'C:\Users\Dell\Documents\ΔΙΠΛΩΜΑΤΙΚΗ\mfrr';

    % Calculating mfrrDataFilename based on whether the current date is a Monday
    if weekday(currentDate) == 2
        mfrrDataFilename = fullfile(mfrrPath, [currentDateStr '_IMBABE_01.csv']);
    else
        % Find the most recent Monday
        mostRecentMonday = currentDate;
        while weekday(mostRecentMonday) ~= 2
            mostRecentMonday = mostRecentMonday - days(1);
        end
        % Calculate mfrrDataFilename based on the most recent Monday
        mostRecentMondayStr = datestr(mostRecentMonday, 'yyyymmdd');
        mfrrDataFilename = fullfile(mfrrPath, [mostRecentMondayStr
'_IMBABE_01.csv']);
    end

    % Check if the file exists
    if exist(fullFilePath, 'file') ~= 2
```

```
        warning('File does not exist: %s', fullFilePath);
        currentDate = currentDate + days(1);
        continue;
    end

    try
        sheetIndex = 2;
        table_data = readtable(fullFilePath, 'Sheet', sheetIndex, 'PreserveVariableNames',
true);
    catch ME
        warning('Error reading file: %s\n%s', fullFilePath, ME.message);
        currentDate = currentDate + days(1);
        continue;
    end

    data_mfrr = readtable(mfrrDataFilename);

    % Extract data from data_mcp based on the current date
    day = weekday(currentDate);
    dayOfYear = floor(days(currentDate - datetime(year(currentDate), 1, 1))) + 1;
    startRow = (dayOfYear-1)*27 + 3;
    endRow = (dayOfYear-1)*27 + 26;
    rowsToExtract = startRow:endRow;
    mcpPath = 'C:\Users\Dell\Documents\ΔΙΠΛΩΜΑΤΙΚΗ\MCP';
    filename = fullfile(mcpPath, 'Day-ahead Prices_202301010000-
202401010000.xlsx');
    data_mcp = readtable(filename, 'PreserveVariableNames', true);
    mcpStr = data_mcp{rowsToExtract, 2};
    % Remove single quotes around the numbers
    mcpStr = strrep(mcpStr, "'", "");
    mcp = str2double(mcpStr);
    x1 = table_data{9, 2:25}; % Fifth row as x-axis
    y1 = table_data{6, 2:25}; % Eleventh row as y-axis

    x2_data = xlsread('20231022_EL-DAM_Results_EN_v01.xlsx', 'EL-
DAM_Results');
    x2 = x2_data(1:24, 2);

    hour = xlsread('24hour_15.xls'); % File that contains 24 hours in 15' segments
    x3 = hour(1:96, 1); % Extract data from the xls file

    % Additional data variables
    im = table_data{20, 2:25};
    ex = table_data{26, 2:25};
    l = table_data{48, 2:25};
    anasRowIndex = find(strcmp(table_data{:, 1}, 'ΑΝΑΝΕΩΣΙΜΑ'));
    % Find all rows under 'ΑΝΑΝΕΩΣΙΜΑ' where the first column contains 'PV'
    pvRows = contains(table_data{anasRowIndex+1:end, 1}, 'PV');
    % Get the actual row indices
    pvRowIndices = anasRowIndex + find(pvRows);
```

```
% Sum these rows
if ~isempty(pvRowIndices)
    pvData = sum(table_data{pvRowIndices, 2:25}, 1);
else
    error('No PV rows found under ΑΝΑΝΕΩΣΙΜΑ');
end
resRowIndex = find(strcmp(table_data{:, 1}, 'TOTAL RES'));
if isempty(resRowIndex)
    error('The row with TOTAL RES was not found.');
else
    resData = table_data{resRowIndex, 2:25};
    wind = resData - pvData; % Subtracting PV data from TOTAL RES data to get
Wind data
end
g = table_data{81, 2:25};
h = table_data{104, 2:25};
% Calculate the rate of change for y1 and res
dy1 = diff(y1);
dpv = diff(pvData);
dwind = diff(wind);
% Extract mfrr_up data for the current day
if day == 1  % Sunday
    rowsToExtract_mfrr = 577:672;
else  % Monday to Saturday
    rowsToExtract_mfrr = (day - 2) * 96 + 1 : (day - 1) * 96;
end
dayData_up = data_mfrr{rowsToExtract_mfrr, 9};
dayData_down = data_mfrr{rowsToExtract_mfrr, 10};
mfrr_up = dayData_up(:);
mfrr_down = dayData_down(:);

% selected variables into a matrix for the current day
varsMatrix = [];
for idx = 1:length(selectedVars)
    varName = selectedVars{idx};  % The name of the current variable being used

    if exist(varName, 'var')
        currentVarData = eval(varName);  % variable's data

        % Ensure it's a column vector
        if isrow(currentVarData)
            currentVarData = currentVarData';
        end

        % Adjust for 'dres' or 'dy1' which have one less data point
        if ismember(varName, {'dpv','dwind', 'dy1'})
            % Append a zero if necessary
            currentVarData = [0; currentVarData];  % Adjusting the data length
        end
```

```
            % Append the current variable's data to varsMatrix
            if isempty(varsMatrix)
                varsMatrix = currentVarData;
            else
                % Only append if dimensions match
                if size(currentVarData, 1) == size(varsMatrix, 1)
                    varsMatrix = [varsMatrix, currentVarData];
                else
                    % Handle dimension mismatch error or warning
                    disp(['Dimension mismatch for variable ', varName, '. Skipping.']);
                end
            end
        else
            disp(['Warning: Variable ', varName, ' does not exist and will be skipped.']);
        end
    end
    forecastedPrices = forecastPrice(varsMatrix, weights);

    % Find the max points for Net Load (y1) and RES (res)
    [max_y1, idx_max_y1] = max(y1);
    [max_dy1, idx_max_dy1] = max(dy1);
    [max_pv, idx_max_pv] = max(pvData);
    [max_dpv, idx_max_dpv] = max(dpv);
    [max_wind, idx_max_wind] = max(wind);
    [max_dwind, idx_max_dwind] = max(dwind);
    [maxMcp, idxMaxMcp] = max(mcp);
    [maxForecastedPrice, maxForecastedHour] = max(forecastedPrices);
    [maxMfrr_up_day, idxmaxMfrr_up_day] = max(mfrr_up);

    % Find local maxima within ±10% range of the maxMfrr_up_day
    range10 = maxMfrr_up_day * 0.1;
    lowerBound = maxMfrr_up_day - range10;
    upperBound = maxMfrr_up_day + range10;
    localMaximaIndices = find(islocalmax(mfrr_up) & mfrr_up >= lowerBound &
mfrr_up <= upperBound);

    if isempty(localMaximaIndices)
        % If no local maxima are found, use the overall maximum
        closestMaxIdx = idxmaxMfrr_up_day;
    else
        % Find the closest local maximum to the max forecasted price
        [~, closestLocalMaxIdx] = min(abs(x3(localMaximaIndices) -
maxForecastedHour));
        closestMaxIdx = localMaximaIndices(closestLocalMaxIdx);
    end

    timeDifference = abs(x3(closestMaxIdx) - maxForecastedHour);
    yDifference = abs(maxMfrr_up_day - maxForecastedPrice);

    % Plotting
```

```
    figure('Position', [100, 100, 1200, 550]);
    % First Graph (Top Subplot)
    subplot(2, 1, 1);
    plot(x1, y1, 'DisplayName', 'Net Load', 'Linewidth', 2);
    hold on;
    plot(x1, l * 3, 'DisplayName', 'Lignite(*3)', 'Color', 'k', 'LineStyle', '--');
    plot(x1, pvData, 'DisplayName', 'PV(*3)', 'Color', 'g', 'LineStyle', '--');
    plot(x1, wind, 'DisplayName', 'WIND', 'LineStyle', '--');
    plot(x1, g * 2, 'DisplayName', 'Gas(*2)', 'LineStyle', '--');
    plot(x1, h * 2, 'DisplayName', 'Hydro(*2)', 'LineStyle', '--');
    plot(x1(idx_max_y1), max_y1, 'o', 'MarkerSize', 8, 'MarkerFaceColor', 'red',
'DisplayName', ['Max Net Load (' num2str(x1(idx_max_y1)) ', ' num2str(max_y1)
')']);
    plot(x1(idx_max_dy1), max_dy1, 'o', 'MarkerSize', 8, 'MarkerFaceColor', 'blue',
'DisplayName', ['Max d_Net Load (' num2str(x1(idx_max_dy1)) ', '
num2str(max_dy1) ')']);
    plot(x1(idx_max_pv), max_pv, 'o', 'MarkerSize', 8, 'MarkerFaceColor', 'green',
'DisplayName', ['Max PV (' num2str(x1(idx_max_pv)) ', ' num2str(max_pv) ')']);
    plot(x1(idx_max_dpv), max_dpv, 'o', 'MarkerSize', 8, 'MarkerFaceColor', 'cyan',
'DisplayName', ['Max d_PV (' num2str(x1(idx_max_dpv)) ', ' num2str(max_dpv) ')']);
    plot(x1(idx_max_dwind), max_dwind, 'o', 'MarkerSize', 8, 'MarkerFaceColor',
'magenta', 'DisplayName', ['Max d_WIND (' num2str(x1(idx_max_dwind)) ', '
num2str(max_dwind) ')']);
    xlabel('X-axis in Hours');
    ylabel('Y-axis in MWh');
    title(['Energy products graph for ' currentDateStr ' (Day ' num2str(day) ')']);
    grid on;
    lgd_top = legend;
    lgd_top.Position = [0.88, 0.45, 0.1, 0.4];

    % Second Graph (Bottom Subplot)
    subplot(2, 1, 2);
    plot(x2, mcp,'g', 'DisplayName', 'MCP €/MWh', 'Linewidth', 2);
    hold on;
    plot(x3, mfrr_up,'r','DisplayName', ['mFRR up €/MWh Day ' num2str(day)],
'Linewidth', 2);
    plot(x3, mfrr_down,'b','DisplayName', ['mFRR down €/MWh Day ' num2str(day)],
'Linewidth', 2);
    plot(x2(idxMaxMcp), maxMcp, 'o', 'MarkerSize', 8, 'MarkerFaceColor', 'yellow',
'DisplayName', ['Max MCP (' num2str(x2(idxMaxMcp)) ', ' num2str(maxMcp) ')']);
    plot(x3(idxmaxMfrr_up_day), maxMfrr_up_day, 'o', 'MarkerSize', 8,
'MarkerFaceColor', 'magenta', 'DisplayName', ['Max Mfrr_up('
num2str(x3(idxmaxMfrr_up_day)) ', ' num2str(maxMfrr_up_day) ')']);
    % Plot local maxima
    plot(x3(localMaximaIndices), mfrr_up(localMaximaIndices), 'x', 'MarkerSize', 8,
'MarkerFaceColor', 'blue', 'DisplayName', 'Local Maxima of Mfrr_up');
    text(1, 800, ['Time Diff: ', num2str(timeDifference), ' hours'], 'FontSize', 8, 'Color',
'black');
    text(1, 700, ['Y Diff: ', num2str(yDifference), ' €/MWh'], 'FontSize', 8, 'Color',
'black');
```

```
    % Plot forecasted prices
    plot(x2, forecastedPrices, 'DisplayName', 'Forecasted Price', 'LineStyle', '--',
'LineWidth', 2, 'Color', 'magenta');
    legend('show');

    % Additional plot customization (if needed)
    xlabel('X-axis in Hours');
    ylabel('Y-axis in €/MWh');
    title(['Financial products graph for ' currentDateStr ' (Day ' num2str(day) ')']);
    ylim([0 1000]);
    grid on;
    lgd = legend('show');
    lgd.Position = [0.88, 0.2, 0.1, 0.2];

    % Save the plot
    graphFilename = fullfile(graphFolder, [currentDateStr '_graph.png']);
    saveas(gcf, graphFilename);

    clf;
    newRow = table();
    % Fill in the values
    newRow.Date = currentDate;
    newRow.DayofYear = dayOfYear;
    newRow.MaxNetLoadX = idx_max_y1;
    newRow.MaxNetLoadY = max_y1;
    newRow.MaxDpvX = idx_max_dpv;
    newRow.MaxDpvY = max_dpv;
    newRow.MaxpvX = idx_max_pv;
    newRow.MaxpvY = max_pv;
    newRow.MaxWindX = idx_max_wind;
    newRow.MaxWindY = max_wind;
    newRow.MaxDWindX = idx_max_dwind;
    newRow.MaxDWindY = max_dwind;
    newRow.MaxMCPX = idxMaxMcp;
    newRow.MaxMCPY = maxMcp;
    newRow.MaxMfrrUpX = x3(idxmaxMfrr_up_day);
    newRow.MaxMfrrUpY = maxMfrr_up_day;
    newRow.MaxForecastedPrice = maxForecastedPrice;
    newRow.MaxForecastedPrice_hour = maxForecastedHour;
    newRow.diffMaxForcastedMaxMfrrup = timeDifference;
    newRow.diffMaxForecastedMfrrUpY = yDifference;

    % Check if the date already exists in the existing table
    rowIndex = find(existingTable.Date == currentDate);

    if isempty(rowIndex)
        % If the date does not exist, append the new row
        existingTable = [existingTable; newRow];
    else
        % If the date exists, update the existing row
```

```
        existingTable(rowIndex, :) = newRow;
    end

    % Increment current date by one day
    currentDate = currentDate + days(1);
end

% Sort existingTable by date to ensure chronological order
existingTable = sortrows(existingTable, 'Date');

% Write the updated dataTable to the Excel file
writetable(existingTable, excelFilePath);

% Save the 3D plot as a MATLAB figure
graphFilename3D = fullfile(graphFolder, '3D_plot.fig');
savefig(gcf, graphFilename3D);

% Initialize arrays to store data for 3D plot
day_3D = existingTable.Date;
maxMCPX_3D = existingTable.MaxMCPX;
maxMCPY_3D = existingTable.MaxMCPY;
mfrr_upX_3D = existingTable.MaxMfrrUpX;
mfrr_upY_3D = existingTable.MaxMfrrUpY;

disp(existingTable); % Display the updated table

% Calculate and display mean and median differences
meanDiffTime = mean(existingTable.diffMaxForcastedMaxMfrrup, 'omitnan');
medianDiffTime = median(existingTable.diffMaxForcastedMaxMfrrup, 'omitnan');
meanDiffY = mean(existingTable.diffMaxForecastedMfrrUpY, 'omitnan');
medianDiffY = median(existingTable.diffMaxForecastedMfrrUpY, 'omitnan');

disp(['Mean of diffMaxForecastedMaxMfrrup (time): ' num2str(meanDiffTime)]);
disp(['Median of diffMaxForecastedMaxMfrrup (time): ' num2str(medianDiffTime)]);
disp(['Mean of diffMaxForecastedMfrrUpY: ' num2str(meanDiffY)]);
disp(['Median of diffMaxForecastedMfrrUpY: ' num2str(medianDiffY)]);

% Create 3D plot with connecting lines
[Days, Hours] = size(allMfrr_up); % Assuming this gives the correct dimensions
[DayGrid, HourGrid] = meshgrid(1:Days, linspace(0, 24, Hours));
figure;
surf(DayGrid, HourGrid, allMfrr_up', 'FaceColor', 'interp'); % Transpose allMcp
hold on;
[Days_f, Hours_f] = size(allforecasted);
[DayGrid_f, HourGrid_f] = meshgrid(1:Days_f, 1:Hours_f);
surf(DayGrid_f, HourGrid_f, allforecasted', 'FaceAlpha', 0.5, 'FaceColor', 'red'); %
Transpose allforecasted
xlabel('Day');
ylabel('Hour of Day');
zlabel('Mfrr_up (€/MWh)');
```

```
title('Mfrr_up Data real(blue) and forecasted(red) Over Days and Hours');
colorbar;
view(-45, 45);

% Save 3D plot as a MATLAB figure
graphFilename3D = fullfile(graphFolder, '3D_plot.fig');
savefig(gcf, graphFilename3D);

close all;

function forecastedPrice = forecastPrice(variables, weights)
    % weights are a row vector
    weights = weights(:)';
    % Calculating the weighted sum of the variables
    forecastedPrice = variables * weights'; % variables is [24 x N] and weights is [N x
1]
end
```

Appendix B

```
%function plot_mcp_afrr_each_day(startDate, endDate)
    % Input:
    startDate = '2023-12-11';
    endDate = '2023-12-13';
    % Convert input dates to datetime format
    startDatetime = datetime(startDate, 'InputFormat', 'yyyy-MM-dd');
    endDatetime = datetime(endDate, 'InputFormat', 'yyyy-MM-dd');

    % Paths to relevant Excel files
    mcpFilePath2023 = 'C:\Users\Dell\Documents\ΔΙΠΛΩΜΑΤΙΚΗ\MCP\Day-ahead
Prices_202301010000-202401010000.xlsx';
    mcpFilePath2022 = 'C:\Users\Dell\Documents\ΔΙΠΛΩΜΑΤΙΚΗ\MCP\Day-ahead
Prices_202201010000-202301010000.xlsx';
    afrrFilePath = 'C:\Users\Dell\Documents\ΔΙΠΛΩΜΑΤΙΚΗ\afrr\afrr_prices.xlsx';
% Previously generated afrr data
    fcrFilePath = 'C:\Users\Dell\Documents\ΔΙΠΛΩΜΑΤΙΚΗ\fcr\fcr_prices.xlsx';
    metricsFilePath =
'C:\Users\Dell\Documents\ΔΙΠΛΩΜΑΤΙΚΗ\afrr_mcp_plots\10%threshold\metrics_d
ata.xlsx';

    % Read the afrr data from the previously generated Excel file
    try
        afrr_up = readtable(afrrFilePath, 'Sheet', 'Afrr Up', 'PreserveVariableNames',
true);
        afrr_down = readtable(afrrFilePath, 'Sheet', 'Afrr Down',
'PreserveVariableNames', true);
    catch ME
        error('Error reading FCR (afrr) data from file: %s\n%s', afrrFilePath,
ME.message);
    end
```

```
    % Read the fcr data from the previously generated Excel file
    try
        fcr_up = readtable(fcrFilePath, 'Sheet', 'Fcr Up', 'PreserveVariableNames', true);
        fcr_down = readtable(fcrFilePath, 'Sheet', 'Fcr Down', 'PreserveVariableNames',
true);
    catch ME
        error('Error reading FCR (afrr) data from file: %s\n%s', afrrFilePath,
ME.message);
    end
    metrics = table();
    % Set up hours for the x-axis (24-hour format)
    hours = 0:0.5:23.5;  % Creates a 24-hour interval with 30-minute steps
    x2 = 1:1:24;
    disp(x2);

    currentDate = startDatetime;
    % Load initial MCP data for the first 100 days
    initialDays = currentDate - days(1:100);
    %initialDays = initialDays(initialDays >= datetime(year(currentDate), 1, 1));
    previousMCPs = [];

    for i = 1:length(initialDays)
        d = initialDays(i);
        if year(d) == 2022
            mcpFilePath = mcpFilePath2022;
        else
            mcpFilePath = mcpFilePath2023;
        end
        dayOfYear_loop = floor(days(d - datetime(year(d), 1, 1))) + 1;

        % Define row indices based on date
        if (d.Month == 10 && d.Day >= 30) || d.Month == 11 || d.Month == 12
            rows = (dayOfYear_loop-1)*27 + 4 : (dayOfYear_loop-1)*27 + 27;
        else
            rows = (dayOfYear_loop-1)*27 + 3 : (dayOfYear_loop-1)*27 + 26;
        end

        % Load MCP values for the day
        data_mcp = readtable(mcpFilePath, 'PreserveVariableNames', true);
        mcpStr = data_mcp{rows, 2};
        mcpStr = strrep(mcpStr, """, "");
        previousMCPs = [previousMCPs; str2double(mcpStr)];
    end

    % Loop through the interval from startDate to endDate

    while currentDate <= endDatetime
        % choose the correct MCP file based on the current date
        if year(currentDate) == 2022
            mcpFilePath = mcpFilePath2022;
```

```
        else
            mcpFilePath = mcpFilePath2023;
        end
        currentDateStr = datestr(currentDate, 'yyyymmdd');
        % Extract data from data_mcp based on the current date
        day = weekday(currentDate);
        dayOfYear = floor(days(currentDate - datetime(year(currentDate), 1, 1))) + 1;
        tableDataFilename = [currentDateStr '_SystemRealizationSCADA_01.xls'];
        fullFilePath = fullfile('C:\Users\Dell\Documents\ΔΙΠΛΩΜΑΤΙΚΗ\SCADA',
tableDataFilename);
        if currentDate.Month == 10 && currentDate.Day >= 30 || currentDate.Month ==
11 || currentDate.Month == 12
            rowsToExtract = (dayOfYear-1)*27 + 4 : (dayOfYear-1)*27 + 27;
        else
            rowsToExtract = (dayOfYear-1)*27 + 3 : (dayOfYear-1)*27 + 26;
        end
        mcpPath = 'C:\Users\Dell\Documents\ΔΙΠΛΩΜΑΤΙΚΗ\MCP';
        filename = fullfile(mcpPath, 'Day-ahead Prices_202301010000-
202401010000.xlsx');
        data_mcp = readtable(filename, 'PreserveVariableNames', true);
        mcpStr = data_mcp{rowsToExtract, 2};
        % Remove single quotes around the numbers
        mcpStr = strrep(mcpStr, """, "");
        mcp = str2double(mcpStr);
        disp(mcp);

        thresholdMCP = mean(previousMCPs) * 0.1;

        % Update the rolling MCP values
        previousMCPs = previousMCPs(1:end-24);  % Remove the last 24 rows
        previousMCPs = [mcp;previousMCPs];
        % Extract afrr data for the current date
        % Find the corresponding row in the afrr file by matching the date
        afrrRow = find(afrr_up.Date == currentDate);
        % Extract the FCR up and down prices for the current date
        afrr_up_prices = afrr_up{afrrRow, 2:end};  % Skip the 'Date' column
        %afrr_down_prices = afrr_down{afrrRow, 2:end};  % Skip the 'Date' column
        %disp(afrr_up_prices);
        % Find the maximum values and their indices
        [maxMCP, idxMaxMCP] = max(mcp);
        [maxAfrrUp, idxMaxAfrrUp] = max(afrr_up_prices);

        %Extract data from SCADA file for load, net load, res
        try
            sheetIndex = 2;
            table_data = readtable(fullFilePath, 'Sheet', sheetIndex,
'PreserveVariableNames', true);
        catch ME
            warning('Error reading file: %s\n%s', fullFilePath, ME.message);
            currentDate = currentDate + days(1);
```

```
            continue;
        end
        y1 = table_data{6, 2:25}; % load (named net load at admhe but it includes RES
        resRowIndex = find(strcmp(table_data{:, 1}, 'TOTAL RES'));
        if isempty(resRowIndex)
            error('The row with TOTAL RES was not found.');
        else
            resData = table_data{resRowIndex, 2:25};
            netload = y1 - resData;% Subtracting RES data from load to get net load
        end

        % Extract fcr data for the current date
        fcrRow = find(fcr_up.Date == currentDate);          %find the corresponding row
based on the date
        % Extract the FCR up and down prices for the current date
        fcr_up_prices = fcr_up{fcrRow, 2:end};  % Skip the 'Date' column
        %fcr_down_prices = fcr_down{fcrRow, 2:end};  % Skip the 'Date' column
        disp(fcr_up_prices);
        % Find the maximum values and their indices
        [maxMCP, idxMaxMCP] = max(mcp);
        [maxAfrrUp, idxMaxAfrrUp] = max(afrr_up_prices);
        [maxFcrUp, idxMaxFcrUp] = max(fcr_up_prices);


        % Find the intervals where MCP <= thresholdMCP
        belowThresholdIdx = find(mcp <= thresholdMCP);

        % Initialize integrals for total and above-threshold values
        integralAfrr = 0;
        integralAfrrBelowThreshold = 0;
        integralFcr = 0;
        integralFcrBelowThreshold = 0;
        integralMCP = 0;
        integralMCPBelowThreshold = 0;

      for i = 1:length(hours) % Loop over the 30-minute intervals

            % Add to total integrals
            integralAfrr = integralAfrr + afrr_up_prices(i);
            integralFcr = integralFcr + fcr_up_prices(i);

            % Add to above-threshold integrals if MCP is above threshold
            correspondingMCPIdx = floor(i / 2);
            if ismember(correspondingMCPIdx, belowThresholdIdx)
                integralAfrrBelowThreshold = integralAfrrBelowThreshold +
afrr_up_prices(i);
                integralFcrBelowThreshold = integralFcrBelowThreshold +
fcr_up_prices(i);
            end
        end
```

```
        for j = 1:length(x2) % Loop over the hourly intervals

            % Add to total MCP integral
            integralMCP = integralMCP + mcp(j);

            % Add to above-threshold MCP integral if MCP is above threshold
            if ismember(j, belowThresholdIdx)
                integralMCPBelowThreshold = integralMCPBelowThreshold + mcp(j);
            end
        end

        afrrMetric = integralAfrrBelowThreshold / integralAfrr;
        fcrMetric = integralFcrBelowThreshold / integralFcr;
        mcpMetric = integralMCPBelowThreshold / integralMCP;

        metrics = [metrics; table(currentDate, mcpMetric, afrrMetric, fcrMetric, ...
        'VariableNames', {'Date', 'MCP Metric', 'aFRR Metric', 'FCR Metric'})];
%append metrcs to the table

        % Plot MCP and afrr data on the same plot
        figure('Position', [100, 100, 1200, 550]);
        subplot(2,1,1);
        plot(x2, mcp, 'g', 'DisplayName', 'MCP (€/MWh)', 'LineWidth', 2);
        hold on;
        plot(hours, afrr_up_prices, 'r', 'DisplayName', 'afrr Up (€/MW/ISP)', 'LineWidth',
2);
        %plot(hours, fcr_up_prices, 'b', 'DisplayName', 'fcr Up (€/MW/ISP)',
'LineWidth', 2);
        % Mark maximum points on the plot
        plot(x2(idxMaxMCP), maxMCP, 'og', 'MarkerSize', 8, 'MarkerFaceColor', 'g',
'DisplayName', ...
            sprintf('Max MCP: %.2f at Hour %.1f', maxMCP, x2(idxMaxMCP)));
        plot(hours(idxMaxAfrrUp), maxAfrrUp, 'or', 'MarkerSize', 8, 'MarkerFaceColor',
'r', 'DisplayName', ...
            sprintf('Max afrr Up: %.2f at Hour %.1f', maxAfrrUp,
hours(idxMaxAfrrUp)));
        %plot(hours(idxMaxFcrUp), maxFcrUp, 'or', 'MarkerSize', 8, 'MarkerFaceColor',
'b', 'DisplayName', ...
            %sprintf('Max fcr Up: %.2f at Hour %.1f', maxFcrUp,
hours(idxMaxFcrUp)));

         % Plot a horizontal line at the average MCP
        yline(thresholdMCP, '--k', sprintf('0.1 MCP: %.2f €/MWh', thresholdMCP),
'LabelHorizontalAlignment', 'center', 'LineWidth', 1.5);
        % Add labels and title
        xlabel('Hour of the Day');
        ylabel('Price (€/MW or €/MWh)');
        title(['MCP, afrr Up and fcr Up Prices for ' datestr(currentDate, 'yyyy-mm-dd')]);
        legend('Location', 'best');
```

```
        grid on;

        subplot(2,1,2);
        plot(x2, y1, 'DisplayName', 'LOAD (MWh)', 'LineWidth',2);
        hold on;
        plot(x2, resData, 'DisplayName', 'RES(MWh)', 'LineWidth',2);
        plot(x2, netload, 'DisplayName', 'NET LOAD (MWh)', 'LineWidth',2);
        % Additional plot customization (if needed)
        xlabel('X-axis in Hours');
        ylabel('Y-axis in MWh');
        title(['Energy products graph for ' currentDateStr ' (Day ' num2str(day) ')']);
        %ylim([0 1000]);
        grid on;
        legend('Location', 'best');



        % Set x-axis limits to represent 24 hours
        xlim([0, 24]);

        % Save the plot as a PNG file
        saveas(gcf,
fullfile('C:\Users\Dell\Documents\ΔΙΠΛΩΜΑΤΙΚΗ\afrr_mcp_plots\10%threshold',
[datestr(currentDate, 'yyyymmdd'), '_MCP_afrr.png']));

        % Close the figure to avoid display overload
        close(gcf);

        % Increment to the next day
        currentDate = currentDate + days(1);
    end
if isfile(metricsFilePath)
        existingMetrics = readtable(metricsFilePath, 'PreserveVariableNames', true);
        % Check and align column names if they differ
        if ~isequal(existingMetrics.Properties.VariableNames,
metrics.Properties.VariableNames)
            existingMetrics.Properties.VariableNames =
metrics.Properties.VariableNames;
        end
        % Remove any duplicate dates in the existing file
        existingMetrics = existingMetrics(~ismember(existingMetrics.Date,
metrics.Date), :);
        % Combine with new metrics and sort by Date
        metrics = [existingMetrics; metrics];
        metrics = sortrows(metrics, 'Date');
 end

    % Write or update the metrics data in the file
    writetable(metrics, metricsFilePath);
    fprintf('Metrics have been successfully written to %s\n', metricsFilePath);
```

Appendix C

```
% Input: start and end dates
startDate = '2023-09-11'; % Format: 'YYYY-MM-DD'
endDate = '2023-11-10';   % Format: 'YYYY-MM-DD'

% Convert input dates to datetime
startDatetime = datetime(startDate, 'InputFormat', 'yyyy-MM-dd');
endDatetime = datetime(endDate, 'InputFormat', 'yyyy-MM-dd');

% URL
Url = 'https://www.admie.gr/sites/default/files/attached-files/type-file';

% Specify directory
Directory = 'C:\Users\Dell\Documents\ΔΙΠΛΩΜΑΤΙΚΗ\mfrr';

% Loop through dates and download files
currentDate = startDatetime;
while currentDate <= endDatetime
    % Check if the current day is Monday (weekday 2 in MATLAB)
    if weekday(currentDate) == 2

        % Find the corresponding Sunday of the current week
        sundayDate = currentDate + days(6);

        % Convert the date to a format suitable for the URL
        urlDate = datestr(currentDate, 'yyyymmdd');

        % Construct the URL
        modifiedUrl = sprintf('%s/%s/%s/%s_IMBABE_01.xlsx', Url,
datestr(currentDate, 'yyyy'),datestr(sundayDate, 'mm'),  urlDate);

        % Download the file using webread
        data = webread(modifiedUrl);

        % Construct the full file path
        filename = fullfile(Directory, sprintf('%s_IMBABE_01.csv', urlDate));

        % Write the table data to a CSV file
        writetable(data, filename);

        disp(['File downloaded for date: ', datestr(currentDate, 'yyyy-mm-dd')]);

    end
    % Increment current date by one
    currentDate = currentDate + caldays(1);
end

disp('All files downloaded successfully.');
```