ML6 & Nodis Consulting

AI in the Energy Sector: Advanced forecasting framework for BRPs

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1. Introduction

Forecasting is one of the most important capabilities for Balance Responsible Parties (BRPs) and several emerging trends make this activity increasingly challenging. New IT and AI techniques can significantly enhance this capability and contribute to the accuracy and automation of forecasting. To point out the relevance of advanced forecasting, some of the following trends deserve particular attention.

- **Rapid penetration of intermittent renewable production.**
  The exponential growth of renewables means BRPs are increasingly exposed to the variability of the weather.

- **The electrification of society.**
  Industry, heat and mobility drive electrification and renewables are increasingly backed by batteries. This means a fast deployment of flexible electric assets behind the meter with volatile power patterns, making net loads harder to predict.

- **Evolving residential metering regimes.**
  With large-scale smart meter rollouts underway, off-take and injection are measured separately and meter allocation regimes reflect real quarter-hour measurements as opposed to profiled production and consumption patterns.

- **Adoption of (home) energy management systems.**
  Customers increasingly deploy EMS systems to optimize their flexible assets. These systems, empowered by virtual power plants, bring new data feeds allowing for better estimation of load flows. As these assets are typically optimized locally and on the market, they become harder to predict, making the data coming directly from the EMS indispensable for accurate forecasting.

- **Short-term market evolutions.**

  The maturing of short-term markets allows for BRP position management closer to delivery. Intraday trading (ID) is increasing in popularity, intraday auctions were recently rolled out and it is planned to move the cross-border ID gate closure time to 30 minutes before real-time. These evolutions reiterate the system operators' ambition to facilitate markets closer to real-time, helping them reduce imbalances upfront.

- **Rising imbalance prices.**

  Recent years have seen a steady rise in imbalance prices and the evolutions described above are making forecast errors more likely. The combination of increasing imbalance prices and forecast errors is driving up the imbalance costs for BRPs as shown in Figure 1 for sun and wind forecasting error costs.

Nodis Consulting and ML6 present this whitepaper giving recommendations on how BRPs can implement an advanced forecasting framework powered by a well-managed IT and AI setup. The paper focuses on strategies for automated portfolio segmentation (chapter 2) and the best practices for IT setups for AI model management and near-real-time forecasting (chapter 3).

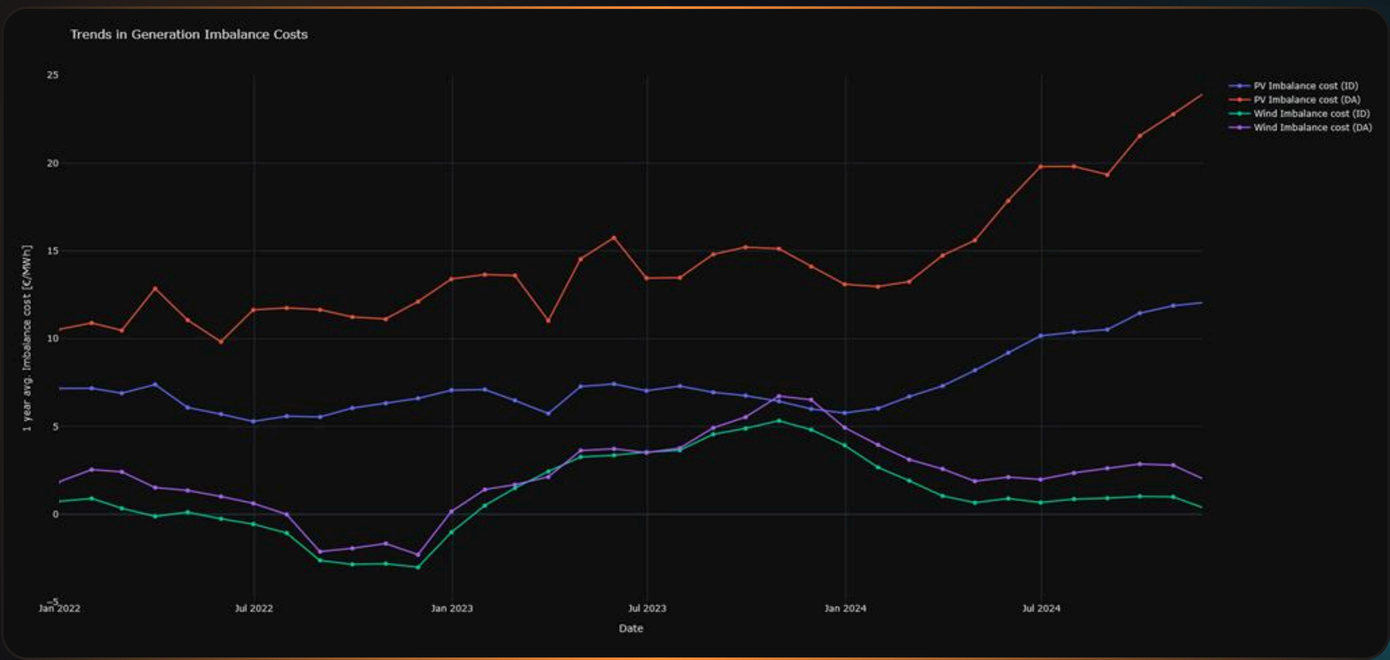

Figure 1: Illustrating imbalance costs caused by PV and wind forecasting errors for DA & ID vs measured values. Based on data from Elia's open data platform.

2. Portfolio segmentation

In this chapter, we elaborate on strategies for multilevel portfolio segmentation. We introduce how automatic ingestion of portfolio master data allows for the initial structuring of dynamic portfolios and how AI enables further refinement of the portfolio segments. With this deep segmentation, we achieve a higher accuracy by enabling the application of tailored forecasting models.

Automated hierarchical portfolio segmentation

BRPs are facing increasingly complex portfolio management. This complexity stems from a mix of diverse consumption patterns and metering regimes and the evolution of distributed energy resources. Portfolio segmentation provides a structured approach to addressing these challenges by grouping assets and customers based on shared characteristics. Figure 2 provides an example of such a hierarchical segmentation.

Asset and customer segmentation should not simply involve basic categorization of assets and grid users by energy production types and basic customer characteristics such as metering regimes and industrial groups. Deeper segmentation levels include differentiating between behind the meter setups such as PV, EV and heat pumps, types of commerce and industries, asset grouping, geolocalisation, etc.

Manual segmentation approaches are increasingly challenging to keep pace with the speed and complexity of a rapidly evolving portfolio. Automated segmentation, driven by clustering techniques, brings a transformative edge to portfolio management. Initial segmentation can often be based on readily available master data, such as customer type, consumption category, NACE code, and known asset ownership. For example, residential clients can be grouped by known attributes like having solar panels or electric vehicles. This first level of segmentation sets the foundation for further refinement.

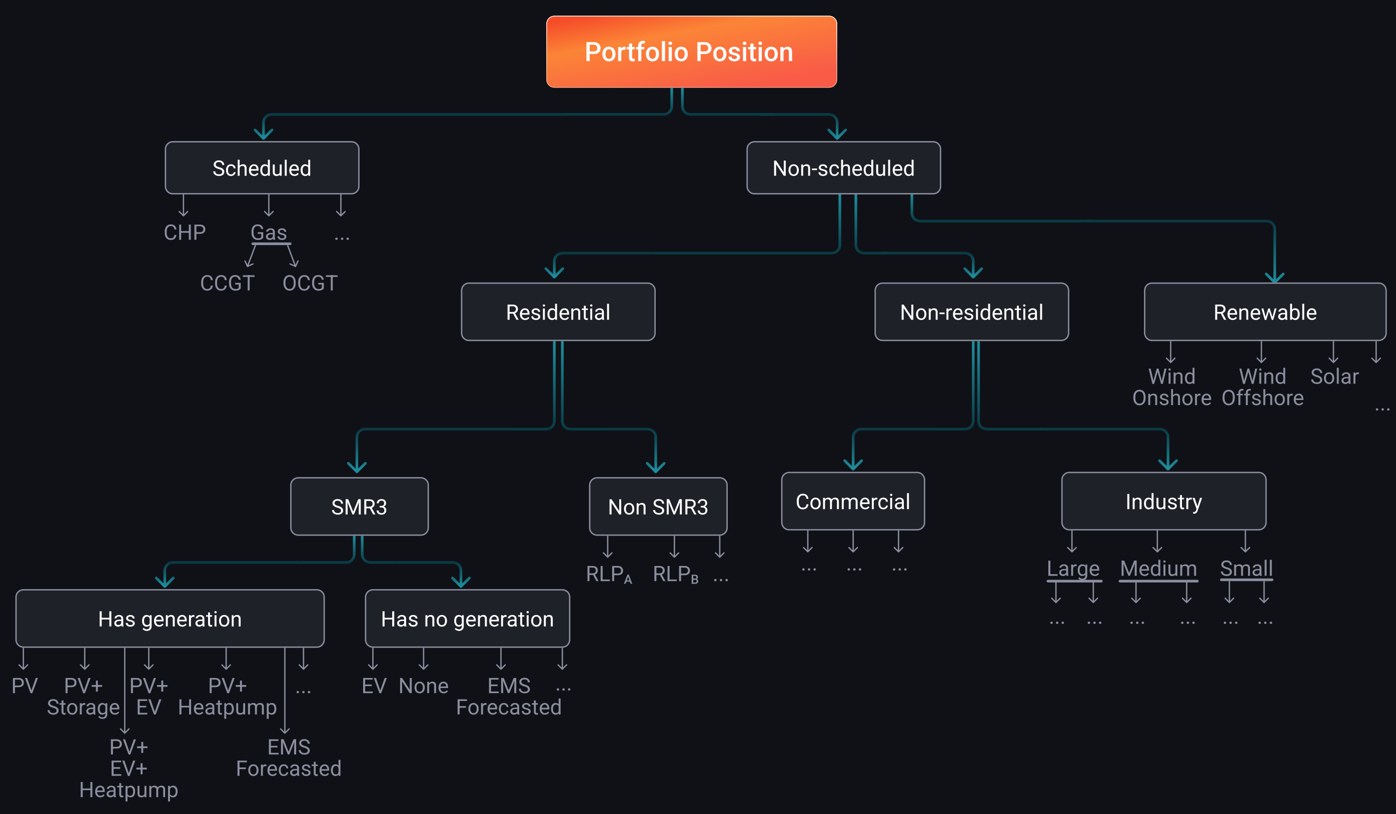

Figure 2: Example of hierarchical segmentation where forecasting can occur at any level. Of course any tree suited for your approach or needs can be created.

In the next phase, various Machine Learning (ML) techniques can be used to improve the segmentation. This can be achieved by automatically enriching the master data, or by applying dynamic clustering techniques to further analyse and group the load profiles. For instance, a classifier can be trained to identify the presence of EVs, heat pumps etc. based on consumption patterns, effectively augmenting the master data. As figure 3 below illustrates, different load profile characteristics can be identified for various assets.

When the master data lacks detail or can't be enriched in a valuable way, clustering algorithms can be further employed to analyse the underlying load profiles to uncover hidden patterns in consumption and production behaviours. Clustering techniques excel at discovering and grouping clients or assets with similar load characteristics, even when these patterns are not evident from master data alone. For instance, within the segment "SMR3[1] – EV" a further segmentation can be done by further clustering this segment into groups such as those who primarily charge in the morning, in the evening, or those who use their charging station rarely.

The automated segmentation combines clustering on master data with clustering on load profiles and will continuously and automatically move customers in the right segment when new master data or metering data becomes available. This dynamic updating ensures that segmentation structures remain relevant and reflect the latest customer and asset behaviours.

Hierarchical forecasting

Intuitively, granular data on specific assets or segments should provide more precise insights, leading to better forecasts. Yet, paradoxically, forecasts made at an aggregate level tend to be more accurate than aggregating individual forecasts.

This phenomenon can be attributed to the superior ability of aggregated data to smooth out anomalies and capture broader, underlying trends. Nevertheless, this implies that valuable, detailed information is not being fully exploited to optimize forecasting performance.

To reconcile the benefits of both granular and aggregate data, a hierarchical forecasting approach can be employed. This technique, which leverages multi-task learning, enables forecasting across multiple levels of granularity, simultaneously capturing both specific details and overarching trends.

| [1]Smart Metering Regime 3 enables 15' measurement readings

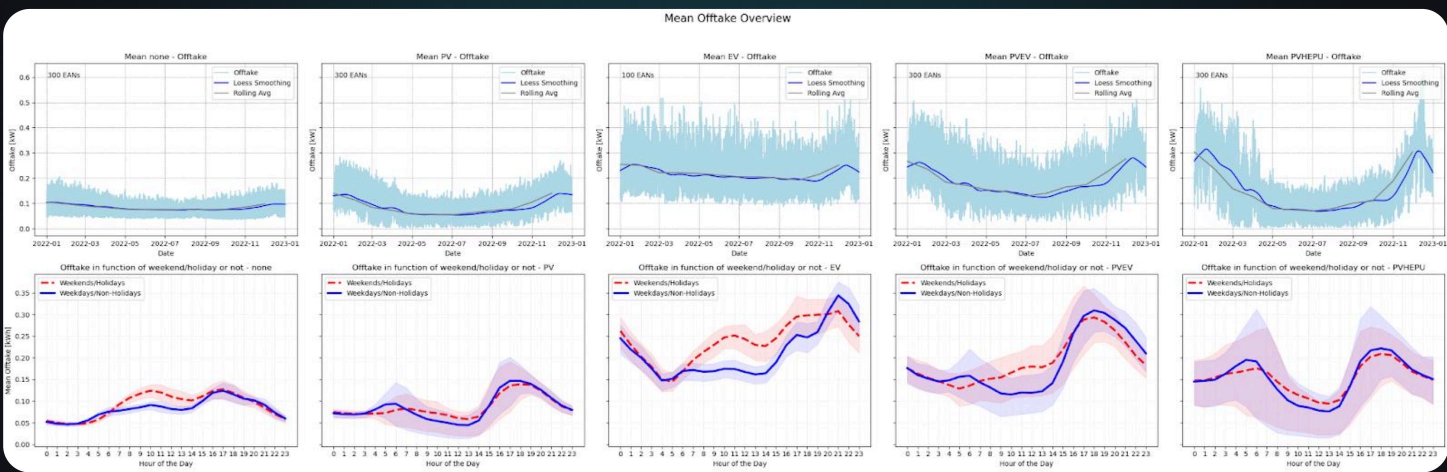

Figure 3: Illustrating the distinct behavioural patterns of different asset categories (classic consumer | PV | EV | PV+EV | PV + Heat Pump). The upper row shows the mean offtake trends over a year, while the lower row highlights the variability in offtake during weekdays versus weekends/holidays. These illustrate the differences in behaviour, but also highlights the variation in consumption magnitudes per asset.

3. Integration of a near-real-time forecasting system

Most BRPs succeed in generating actionable forecasts of their portfolio. However, the transition to an automated system with near-real-time forecasts across a wide set of variables presents significant challenges. As the number of forecasted variables increases, managing and maintaining models becomes more complex and time-consuming. Without proper orchestration, model versioning, and tracking, the risks of failure and undetected errors rise exponentially. Addressing this requires a shift from traditional model development to a more comprehensive ML system development approach.

Key aspects of an automated forecasting system

Adhering to advanced MLOps best practices is essential for building and maintaining an effective automated forecasting system. This includes:

- **Automated and Orchestrated Pipelines**
  Transitioning from manual workflows, such as notebooks and scripts, to automated pipelines ensures scalability and reliability. This shift allows data science teams to handle complex requirements with less manual intervention.
- **Experiment Tracking and Artifact Versioning**
  Experiment tracking enables teams to record changes, results, and metadata across iterations, helping to prioritize the best approaches. Versioning artifacts such as data, models, and code provide full observability, fostering trust and making it easier to identify the source of performance shifts or anomalies.
- **Handling Interdependence of Forecast Variables**
  Forecasted variables often have interdependencies that require advanced techniques like hierarchical and multivariate forecasting models. Hierarchical models ensure consistency across levels of aggregation, while multivariate models benefit from automated hyper-parameter tuning and experiment tracking. An automated ML system orchestrates these processes, significantly reducing complexity.

Integrating forecasting into operations

To fully leverage AI in BRP portfolio management, it is essential to integrate forecasting into operational processes effectively. This includes:

- **Segment-Specific Forecasting**
  Applying different forecasting models based on customer segmentation improves accuracy. However, frequent updates and an increasing number of segments can lead to model proliferation. Proper model management tools and processes are essential to prevent maintenance burdens from overwhelming data science teams.
- **Model Training and Deployment:**
  - **Model Training:** Leveraging historical data to train models ensures they are updated regularly for accuracy.
  - **Operational Forecasting:** Real-time data integration is critical for operational processes. Automated data validation and mitigation techniques address challenges like lagging inputs or missing values.
- **Post-Processing and Enhancement**
  Forecasts must be actionable and accurate through steps such as data quality checks, aggregation of forecasts, and validation against business rules. Handling uncertainty through probabilistic methods ensures that forecasts remain reliable, even in challenging conditions.

Integrating AI-driven forecasting into BRP operations provides a systematic, reliable way to enhance decision-making. Figure 4 represents a reference functional component diagram that provides an overview of the different aspects supporting the integration of AI models into operational processes, ensuring the smooth flow of data from input to actionable forecast output.

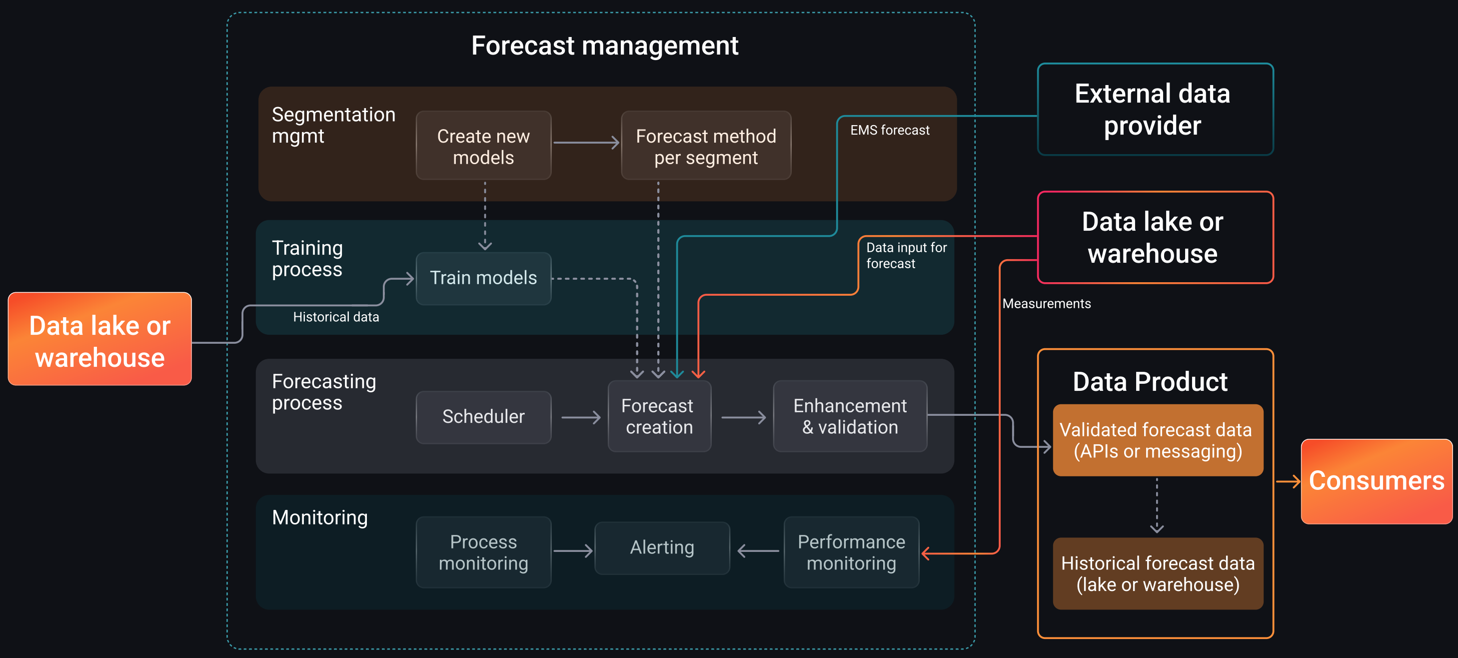

Figure 4: Reference functional component diagram for integrating forecasting into operations

Near-real-time forecasting challenges

One major challenge with near-real-time forecasting is the availability of real-time data inputs. Delayed inputs can disrupt forecasting systems, requiring strategies to balance latency and accuracy:

- **Data Imputation:** Techniques like record-based or time-based imputation can fill gaps, but recent data often has a higher impact on predictions, making this approach less reliable.
- **Residual forecasting** splits forecasting into two stages. General trends are predicted using older, complete data, while a residual forecast based on the most recent data is used to fine-tune these trends. This technique helps capture finer details without over-reliance on potentially unreliable imputations.
- **Dynamic latency thresholds** can dynamically delay forecasts by a tolerable amount of time to ensure higher data quality, especially when critical inputs are missing. During the delay, older forecasts can be served to ensure system continuity.
- **Probabilistic forecasting** methods quantify the uncertainty of the forecasts based on missing data, allowing for informed decision-making even in the presence of incomplete data.

By addressing these challenges, automated systems enable the transition to near-real-time forecasting through streaming data ingestion, automated evaluation, and online model deployment. Such systems provide a systematic, reliable way to enhance decision-making, ensuring the smooth flow of data from input to actionable forecast output.

4. Conclusion

In conclusion, we recommend the implementation of **an automated segmentation and forecasting system** to improve forecasting accuracy and operations. Advanced portfolio forecasts allow for accurate sourcing across different timelines and can deliver insights into the flexibility of non-scheduled assets. When additionally applying these forecasting techniques to predict wholesale and imbalance prices, optimal asset scheduling and real-time imbalance steering become readily available.

As outlined in the paper, we consider it necessary to apply automated classification and clustering techniques allowing for a smart segmentation of your portfolio and to leverage the benefits of combining granular and aggregated forecasting models.

As the number of forecasted variables and requirements for near-real-time results increase, a proper forecasting system setup is required to manage complexities and integration into operational processes.

We believe that when a mature forecasting setup is in place, it will **create significant value** for BRPs by leveraging an accurate forecasted portfolio for imbalance cost reduction and other forecast-based value streams.

Together, **Nodis Consulting and ML6** bring a unique offering of deep expertise in energy markets and artificial intelligence, and enable customers to rapidly and incrementally **implement a roadmap to bring forecasting capabilities to the next level**.

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