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Automated Machine Learning for Optimized Load Forecasting and Economic Impact in the Greek Wholesale Energy Market

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Abstract: This study investigates the use of automated machine learning to forecast the demand of electrical loads. A stochastic optimization algorithm minimizes the cost and risk of the traded asset across different markets using a generic framework for trading activities of load portfolios. Assuming an always overbought condition in the Day-Ahead as well as in the Futures Market, the excess energy returns without revenue to the market, and the results are compared with a standard contract in Greece, which stands as the lowest as far as the billing price is concerned. The analysis achieved a mean absolute percentage error (MAPE) of 12.89% as the best fitted model and without using any kind of pre-processing methods.

Keywords: ensemble-based model; automated machine learning; hyperparameter optimization; load forecasting



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1. Introduction

Accurate estimations of electrical demand stand as an essential component during the optimization of energy trading strategies that, alongside the estimation error, should always be taken into consideration during trading activities. Electrical load datasets typically form time series that display patterns in behavior, leading to variable fluctuations in the data due to seasonal shifts, economic fluctuations, and consumer habits, which add complexity to accurate load forecasting [1,2].

Conventional forecasting approaches often depend on manual intervention [3,4], are prone to errors, are time-consuming, and include detailed data pre-processing, a manual selection of features, and expertise in specific domains. However, this method not only costs time but also lacks scalability for large datasets or varied load profiles, particularly in energy portfolios that aggregate multiple time series for the final scheduling to the energy market. Additionally, the reliance on manual processes increases the potential for human error and may limit the ability to quickly adapt to changing market conditions, especially during optimization tasks [5].

Recently, AutoML frameworks have emerged as essential tools for overcoming the obstacles of traditional methods. These frameworks automate model selection, with pre-processing calculations on data, hyperparameter tuning, and feature engineering, significantly reducing the necessity for manual intervention [6]. This research focuses on evaluating the effectiveness of various AutoML frameworks for the prediction of a time series, domain-specific to the energy sector; this is followed by a comparative analysis to estimate their value in the Greek wholesale market using a stochastic optimization objective function for the diversification of the portfolio across different markets like conventional portfolio theory introduces [7,8].

Regarding the above-mentioned conventional approaches, Hyndman and Athanasopoulos [9] explored the application of ARIMA models in time-series forecasting, highlighting their effectiveness in capturing linear patterns in time-series data. However, they

also noted that these models often require extensive data pre-processing and a deep understanding of the underlying domain, which can limit their widespread adoption. This is why AutoML technologies have started to attract supporters. As demonstrated by Feurer [3], automated algorithms can automate the implementation of a forecast model, significantly reducing the need for domain-specific knowledge and making advanced statistical methods more accessible and efficient for practitioners in energy trading, as this study follows.

In a more recent study, Morais [1] examined the use of advanced neural networks, including recurrent neural networks (RNNs), bidirectional long-short term memory (LSTM), and gated recurrent unit (GRU) models for short-term load forecasting. They achieved substantial prediction accuracy, which was reflected in the low mean absolute percentage error (MAPE) values. Other studies also point to using LSTMs in the energy sector [2,10]. However, the adoption of AutoML—particularly through techniques like Neural Architecture Search (NAS) as discussed by Elsken [11]—could further enhance these outcomes by automating the design and optimization of complex neural network architectures. This would reduce the need for manual experimentation and enable more robust and scalable forecasting solutions in large-scale electrical power systems. Additionally, advancements in machine learning, such as transformer-based models, have shown great promise in electrical load forecasting due to their ability to capture complex patterns and long-term dependencies in time-series data [12], although, with the focus on simplicity, pretreatment methods on the dataset were avoided. This is why this study avoids the implementation of complex neural architecture and computationally intensive networks [13] and adopts automated machine learning workflows.

Building on these advances, Deng introduced a hybrid approach that combined statistical methods with machine learning techniques [14]. Their model utilized a new weighted multi-objective particle swarm optimization algorithm to optimize short-term load forecasting, effectively leveraging the strengths of both statistical and machine-learning methods. Automated procedures—particularly through the Sequential Model-Based Optimization (SMBO) that stands as an automated implementation methodology, as outlined by Hutter [15]—can address these challenges by automating the integration and optimization of diverse modeling techniques, simplifying the deployment of sophisticated hybrid models, and enhancing computational efficiency. The relevance and impact of AutoML in the context of forecasting are further supported, with accurate and robust implementations [16].

The aforementioned studies underscore the evolving complexity of forecasting methods on time series and also illustrate the critical role of AutoML, which could stand as crucial regarding the simplicity and robustness of these frameworks and their underlying methodologies. By automating model selection, tuning, and integration, AutoML not only mitigates the limitations of traditional approaches but also accelerates the adoption of advanced forecasting techniques, driving more efficient and accurate decision-making in the energy trading sector. It achieves this by using the forecasts for the allocation of an optimal energy mix across different markets under stochasticity due to the fact that in the specific case of load portfolios, there are always unpredictable factors for future allocations.

Beyond the forecasting procedures, there are also other factors of importance for the optimal aggregation to the energy market. The first consideration is the lowest possible cost of energy for a given time horizon, and the second stands as the risk involved for the above-mentioned allocated price. Different studies [17,18] depicted the conjunction of stochastic optimization problems in the energy sector. Additionally, inspired by risk quantification practices from the traditional finance sector, it is crucial to consider the correlation among different markets for the same product. This interdependence should be accounted for when analyzing and forecasting market trends and behaviors [19]. Additionally, other studies have emphasized the significance of forecasting in high-frequency markets, underscoring the critical role of automated prediction techniques in enhancing accuracy and decision-making [20].

The purpose of this paper is to create an industry-viable approach to forecasting as well as the conjunction of these forecasts with an energy procurement optimization

framework, which combines different energy markets and involves the financial risks of these markets. As depicted by Liu [21], it is viable to approach the energy management of a microgrid and beyond that under a portfolio entity as this manuscript proposes, so as to manage risks and be able to receive decisions under a strategic way of energy procurement. Therefore, it addresses the existing scientific gap of by introducing an agnostic way to integrate the forecast error into the energy trading strategy until the optimal energy mix, as far as the cost and risk of the current market state, is defined. The shortfall costs of the energy are taken into account for each time period, which is the imbalance between the acquired energy and the real consumption.

The rest of this manuscript is organized as follows: Section 2 presents the methodologies, Section 3 the implementation of AutoML frameworks, and finally, Section 4 illustrates two simplified scenarios of the implementation of the framework as well as a comparison with a standard contract located in the Greek energy market.

2. Methodology

The Methodology Section outlines the steps and techniques employed in the study to forecast electrical loads using automated machine learning (AutoML) frameworks. This approach is designed to assess the effectiveness of these frameworks in predicting electrical loads without heavy reliance on pre-processing methods or manual feature selection. While previous studies, such as that by Chen and Su [22], have successfully applied other types of techniques like deep reinforcement learning for forecasting in local energy trading contexts, this study aims to explore the potential of AutoML frameworks in optimizing electrical load forecasting at a larger scale within the wholesale market. By automating model selection or creation and hyperparameter tuning, AutoML can potentially replicate the success seen in local energy markets on a broader, more complex scale.

2.1. Data Collection and Pre-Processing

The first step involved collecting historical electrical load [23]. This dataset includes various features that could influence load patterns, such as the time of day, day of the week, seasonal variations, and economic indicators. The data were then split into training and testing sets to evaluate the performance of the models. In some cases, the AutoML frameworks themselves performed the train–test split based on their internal algorithms to ensure optimal model training and evaluation. These data were selected due to the unpredictable behavioral patterns of an industrial load profile, making this profile a suitable candidate to test the robustness of the forecasting models. For simplicity, the data are treated as univariate.

2.2. Automated Machine Learning Framework Selection

Several AutoML frameworks were selected for evaluation, including AutoML by H2O [24]: a general-purpose AutoML tool known for its flexibility and ease of use. The second framework is FlaML [25]: a lightweight and efficient AutoML library from Microsoft Research, designed for quick deployment and resource optimization. Other frameworks were considered to ensure a comprehensive analysis, focusing on their ability to handle time-series data and integrate with automated prediction methods like AutoTS [26].

2.3. Ensemble Model Creation

Given the complexity and variability of the electrical load data, ensemble models were created to enhance predictive accuracy. Ensemble methods combine the predictions of multiple models to reduce overfitting and improve the overall resilience and accuracy of the resulting model. The AutoML frameworks were utilized to automate the creation and tuning of these ensemble models, based on the settings of each framework.

Several methods for making ensemble models exist, with different approaches as far as the final resulting model is concerned, as mentioned in [27].

Bagging is a method that involves training multiple instances of the same model on different subsets of the given dataset. These subsets are created through bootstrapping, a process where random samples are drawn with replacements from the original data. The purpose of bagging is to reduce variance and improve the accuracy of predictions. In the case of regression, the final prediction is the average of the individual model predictions, while for classification tasks, it is determined by a majority vote among the models.

Boosting is an ensemble technique that sequentially trains models, with each new model in the sequence focusing on correcting the residual errors made by the previous models. Unlike bagging, where models are trained independently, boosting models work together in a dependent manner, where each model improves upon the mistakes of its predecessor. This approach helps in reducing bias and improving the overall accuracy of the model, always with respect to the previously trained model.

Stacking is an ensemble method that combines predictions from multiple models, known as level 0 models, using a meta-model, or level 1 model. In this technique, the meta-model is trained on the predictions generated by the base models rather than on the original training data. The meta-model then learns how to best integrate the outputs of these individual models to generate a final prediction. Stacking leverages the strengths of different models to improve predictive performance, often yielding better results than using a single model alone.

Automated Feature Engineering involves the automatic generation, selection, and transformation of features from raw data to enhance model performance. This method leverages domain knowledge and data patterns to create new features that can be more informative for the predictive model. By automating this process, AutoML systems can identify complex relationships within the data and produce features that significantly improve the accuracy and robustness of machine learning models [28].

Hyperparameter optimization is a crucial component of AutoML, focusing on the automatic search for the best set of hyperparameters that enhance model performance. The process involves exploring various configurations of hyperparameters, such as learning rates, regularization parameters, and tree depths, to identify the optimal combination for a given model and dataset. By automating hyperparameter tuning, the frameworks can achieve significant improvements in model accuracy and efficiency without requiring extensive manual intervention [29].

Mathematical Formulation

As studied in [30], one form of AutoML includes the ensemble method creation by aggregating predictions from several base models to form a final prediction. This generic approach is applicable to various ensemble techniques, particularly those that use weighted averaging of model outputs. Let $f(x_1), f(x_2), \dots, f(x_n)$ represent the set of predictions from n different base models for a given input x .

The combined prediction $F(x)$ of the ensemble model can be represented as follows:

$$F(x) = \sum_{i=1}^n w_i \times f_i(x) \quad (1)$$

where $f_i(x)$ is the prediction from the i -th base model for input x ; w_i is the weight assigned to the i -th base prediction of the model. The weights w_i are non-negative values with summation: $\sum_{i=1}^n w_i = 1$.

The weights $w_1, w_2, \dots, w_n$ can be optimized to the mean absolute percentage error (MAPE) [31] of the ensemble model. The MAPE-based optimization can be formulated as a constrained optimization problem as follows:

$$\min_{w_1, w_2, \dots, w_n} \frac{1}{m} \sum_{j=1}^m \left| \frac{y_j - \sum_{i=1}^n w_i \times f_i(x_j)}{y_j} \right| \quad (2)$$

where y_i is the actual value of the $j - th$ observation; $f_i(x_j)$ is the prediction from the $j - th$ observation; w_i is the weight assigned to the $i - th$ base model; and m is the number of observations. It is constrained to $\sum_{i=1}^n w_i = 1$ as well as $w_i \geq 0, \forall i$.

After generating the results of an energy forecast model for a future time horizon, the main goal of an energy trading entity is to minimize the total cost of procuring energy across all hours while also minimizing risk [32]. The total cost occurs after accounting for all the revenues of the underlying markets [33]—such as the Day-Ahead Market, Real-Time Market, Futures Market, Demand Response programs [34], and the penalties for energy shortfalls during the trading procedures [35] as well as the standard deviation minimization in the second term of (3)—to introduce the risk-aversion factor and the correlations of markets. Previous studies regarding futures hedging in electricity retailing [36] depicted benefits of hedging against the volatile spot prices in the future markets [37] and, following this context, the next mentioned objective function could result in an energy mix optimal to the market conditions at each time slot of the market. The cost of energy for a given hour is calculated based on the first term of (3) since the prices at each of the markets consist of a forecast for the future, which is why we should take into consideration the volatility of them based on past data. Summarizing, the primary objective, $\min Z$, targets to minimize both the expected costs and the exposure to price volatility. The summation of a and b to 1 ensures a proper balance between cost and risk.

$$\min Z = a \sum_{t=1}^h \left\{ P_t^D \times E_t^D + P_t^R \times E_t^R + P_t^F \times E_t^F - P_t^{DR} \times E_t^{DR} + \lambda_t \times S_t \right\} + b \sum_{t=1}^h \left\{ z_t^T Cov z_t \right\} \quad (3)$$

Constrained to the following:

$$E_t^D + E_t^R + E_t^F - E_t^{DR} = F(t), \forall t \in h \quad (4)$$

$$E_t^D \geq 0, E_t^R \geq 0, E_t^F \geq 0, E_t^{DR} \geq 0 \quad (5)$$

$$a + b = 1 \quad (6)$$

where Cov is the covariance matrix of prices; $z_t^T = [E_t^D E_t^R E_t^F E_t^{DR}]$ is the vector of energy allocation of each market; t : the time index (for each hour on market time unit); h : the number of hours in the optimization horizon; $F(t)$: the energy demand for hour t output of the AutoML (MWhr); P_t^D : the price of energy in the Day-Ahead Market (DAM) at hour t (in EUR/MWh); P_t^R : the price of energy in the Real-Time Market (RTM) at hour t (in EUR/MWh); P_t^F : the price of energy in the Futures Market at hour t (in EUR/MWh); P_t^{DR} : the price of energy in the Futures Market at hour t (in EUR/MWh); P_t^{DR} : the revenue from Demand Response at hour t (in EUR/MWh reduction); E_t^F : the energy provided through the Futures Market at hour t (in MWh); E_t^D : the energy procured in the Day-Ahead Market at hour t (in MWh); E_t^R : the energy procured in the Real-Time Market at hour t (in MWh); E_t^{DR} : the demand reduced through Demand Response at hour t (in MWh); λ_t : the penalty for energy shortfall or deviation from demand at hour t (in EUR/MWh); S_t : the energy shortfall at hour t (in EUR/MWh); a : weight for the cost of across markets and shortfall components; b : weight for the risk component; σ_t^F : standard deviation (or variance) of the forecasted price in the Futures Market at hour t ; σ_t^R : standard deviation (or variance) of the forecasted price in the Real-Time Market at hour t ; σ_t^D : standard deviation (or variance) of the forecasted price in the Day-Ahead Market at hour t ; σ_t^{DR} : standard deviation (or variance) of the forecasted price in the Demand Response Market at hour t .

The next flowchart, in Figure 1, proposes an energy aggregation framework for the automated bidding mechanism [38] to the energy market:

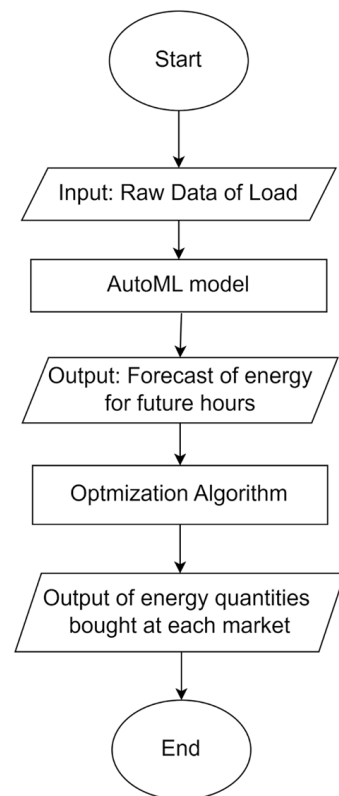


Figure 1. Flow of information for the final definition of energy mix.

Each round of forecasting and optimizing the energy quantities on the market is conducted after the publication of new raw data.

3. Implementation

The ensemble models for electrical load forecasting were implemented using three separate AutoML frameworks: FlaML, AutoML by H2O.ai, and AutoTS—a past winner of the Makridakis Competition [39]. Each framework automated the selection and tuning of the models in a distinct manner, allowing for a comprehensive comparison of their effectiveness. To focus solely on the predictive power of the time-series models and to avoid the complexity introduced by additional parameters, a univariate time series was chosen for this study. This approach ensured that the analysis remained centered on the time-series data itself, without the influence of external variables. For this study, a time series without a concise behavioral pattern was selected to make it harder for the framework to forecast. The next line plot, in Figure 2, presents the selected load profile, which is a dataset of 22 months range in hourly granularity.

The first implementation involves the use of AutoTS, a framework specifically designed for time-series forecasting. AutoTS automates the generation and tuning of time-series models and supports various ensemble-based techniques tailored to sequential data. The primary method used in AutoTS involves model averaging or weighted averaging, where the predictions from different time-series models (including ARIMA, machine learning models, and deep learning models like LSTMs) are combined to produce a final forecast. While AutoTS can support stacking, its strength lies in capturing various patterns in time-series data through model selection and averaging. The weights of the base models were fine-tuned to reduce prediction errors, and the model's performance was assessed using the MAPE metric. AutoTS uses backward cross-validation as the default, a method that validates models on consecutive chunks of recent data, making it suitable for time-series data.

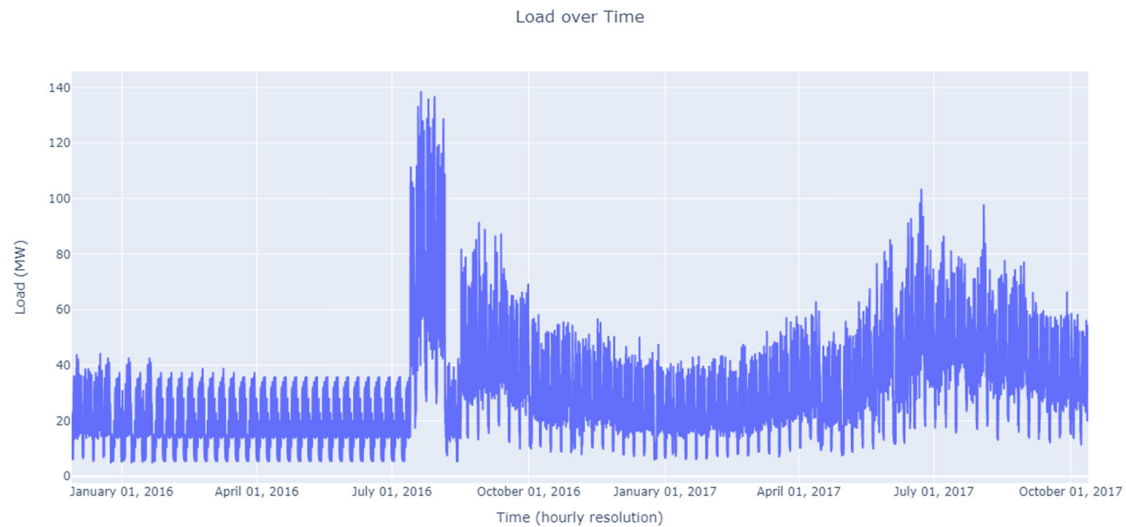


Figure 2. Industrial load profile.

In the second implementation, FlaML was employed to automate the generation of multiple base models and optimize their weights. The approach of this framework centered on efficiently searching through various model configurations to quickly identify optimal models with minimal computational cost. Although FlaML is primarily focused on single-model optimization, leveraging the optimization of hyperparameters, it can support basic ensembling methods like bagging (Bootstrap Aggregating) if explicitly configured by the user. However, FlaML does not inherently emphasize complex ensemble strategies. The optimized ensemble model was then evaluated on the testing set using the mean absolute percentage error (MAPE) metric, which provided a clear measure of prediction accuracy.

This tool automatically selects a resampling strategy based on the dataset size and time budget, with five-fold cross-validation as the default when cross-validation is selected.

The third and final implementation utilizes the AutoML framework by H2O.ai. This tool is known for its robust ensemble-based techniques, particularly its use of stacked ensembles. AutoML automatically trains a range of models, including GLMs, random forests, gradient-boosting machines, and deep learning models, and then creates ensembles using stacking. In this approach, the base models (level 0 models) are combined using a meta-learner (level 1 model), often a generalized linear model (GLM) or a gradient-boosting machine (GBM). This meta-learner is trained to optimally combine the outputs of the base models, thereby improving predictive performance. AutoML may also incorporate bagging and boosting techniques within its workflow. The performance of the optimized model was again evaluated using the MAPE metric on the testing set. By default, this framework automatically decides between a number of folds for the cross-validation on the dataset.

By conducting these separate implementations with the above-mentioned tools, this study was able to explore and compare the effectiveness of different frameworks in automating the ensemble modeling process for electrical load forecasting. The use of the MAPE metric across all implementations ensured a consistent basis for comparison, highlighting the strengths and potential limitations of each framework's approach to ensemble creation within this specific application domain.

The performance of the frameworks was evaluated using the mean absolute percentage Error (MAPE) as the key metric. AutoML by H2O.ai demonstrated the best performance with a MAPE of approximately 12.89%, indicating its strong accuracy in predictive tasks. FlaML followed closely with a MAPE of 13.95%, offering a competitive balance between accuracy and efficiency. AutoTS, while slightly less accurate, achieved a MAPE of 14.01%, making it a viable option depending on the specific requirements of the application. These results, presented in Table 1, highlight that while all three frameworks are effective, AutoML by H2O.ai may be the preferred choice when precision is critical. Moreover, despite the

volatile energy consumption of the forecasted load, these frameworks could also create viable predictions as far as the energy trading business boundaries are concerned.

Table 1. Results of different AutoML frameworks.

Framework	Model Category	MAPE (%)	Time (s)
AutoTS	Model Averaging	14.01	14.4
FlaML	Hyperparameter Optimization	13.95	13.3
AutoML by H2O	Bagging, Boosting, Stacking, Hyperparameter Optimization	12.89	16.8

The prediction of the H2O.ai tool is presented in Figure 3.

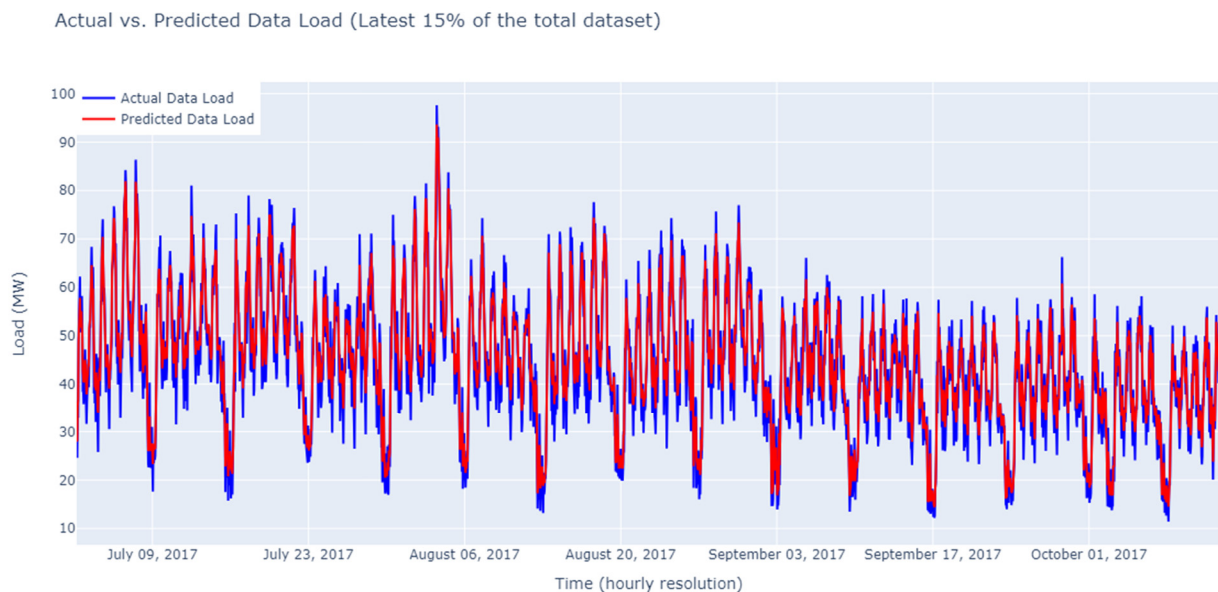


Figure 3. Actual and predicted values.

4. Use Case in the Energy Wholesale Market

4.1. Integrating Forecasting Error into Energy Procurement Strategy

In this use case, the challenge of mitigating risks associated with the mean absolute percentage error (MAPE) in electrical load forecasting was addressed by incorporating MAPE into our energy procurement strategy. Specifically, the MAPE have to be taken into consideration to evaluate potential forecast inaccuracies and adjust the energy procurement accordingly. This conservative strategy involves purchasing additional energy beyond the forecasted load as a countermeasure for potential shortfall deviations.

Moreover, two different scenarios will be assessed to compare [40] their outcomes with the standard contract in the Greek energy market. The first scenario will explore an isolated Spot Market aggregation of the portfolio, while the second will take a more feasible approach to account for forecast uncertainty including the Futures Market. Both scenarios will be evaluated against a typical contract framework in the Greek market, factoring in the costs and risks associated with Real-Time Market fluctuations. The primary objective remains to minimize the likelihood of incurring penalties or purchasing missing energy quantities at higher prices in the Real-Time Market, which is generally far more expensive than the Day-Ahead Market (DAM), as well as that the portfolio is always balanced against energy shortfalls. This dual-scenario analysis will offer a comprehensive comparison to ensure a robust and cost-effective strategy in conjunction with the added or lost value in comparison with the selected contract in Greece.

4.2. A Standard Retail Contract in the Greek Energy Market for a Comparative Analysis

In the Greek market, there is an offering of a specific standard contract (7), which follows the Spot Market and could be used as a reference for comparative analysis [40]:

$$\text{Standard Contract Revenue} = \sum_{i=1}^N 1.159 \times (TEA \times (1 + \text{Losses})) \times E_i \quad (7)$$

where TEA is the scaled-out price from the Spot Market to Low/Medium Voltage (~11% increase from the DAM price, annual estimation for 2023 based on IPTO data) and the Losses factor equals 0.01357 of the low voltage, publication from the Greek DSO.

The TEA is not included in the calculation for the added value of this contract in comparison to the DAM price since it contains the disaggregation from the high to the low-medium voltage; this is why, based on (7), it will be a fixed cost at the final billing price, which is why it is excluded. Therefore, the added value results in 17.4% from the wholesale market. The hypothesis is that the retailer responsible for (7) buys all the energy from the DAM price without diversification of other markets.

Scenario 1

The first strategy involves purchasing an additional 12.89% of energy based on the resulting MAPE of our automated machine learning model to mitigate the risk of penalties due to under-supply. The portfolio participates only in the Spot Market, and there are no hedging techniques during procurement. Additionally, an assumption is that the excess of the bought energy will be sold in the Real-Time Market, for the minimization of energy deviations ($S_t = 0$), at a zero price as well as the factor a being set to zero.

$$\text{Total Revenue} = \sum_{i=1}^N P_t^D \times E_t^D - P_t^R \times E_t^R, \quad (8)$$

where P_t^D : day-ahead price for the i -th time slot of the trading day and $i \in \{1, 2, \dots, 24\}$; and E_t^D is the overbought amount of energy for each time slot based on the MAPE, here it is 12.89% more than the predicted one, so $E_t^D = (1 + \text{MAPE}) \times F(t)$.

This scenario assumes that the excess energy would be resold to the real-time Market for zero price ($P_t^R = 0$), so the market absorbs the excess and minimizes the shortfall to zero. Moreover, the risk-aversion factor is $b = 0$.

This simplified approach was compared against a standard contract commonly used in the Greek market, which was consistently 17.4% more expensive than the Day-Ahead market prices. The worst-case scenario using this approach is that during the overbought condition of the market, less energy than forecasted will be used, and this is why an energy shortfall of twice the MAPE will occur. This results in 25.78% more expensive energy and there is a negative margin in comparison with (6) at 8.38%.

Scenario 2

In this scenario, the strategy aims to minimize costs without minimization of the risk, using Futures contracts. These financial assets offer the securing of energy quantities at a fixed price for a dedicated amount of market time slots. The energy retailer buys an amount of energy in the Futures Market, E_t^F , and the remaining amount is exposed to the volatile Spot Market as E_t^D . The total energy demand for hour t is $F(t) = E_t^D + E_t^F$.

Each market is cleared at price P_t^D and P_t^F for hour t for the wholesale and Futures markets, respectively. For the definition of an equilibrium between this energy aggregation strategy and the standard contract of (7), Equation (9) sets an increase of 17.4% to the DAM price and compares it with the total revenue accordingly.

$$\sum_{t=1}^N P_t^D \times E_t^D + P_t^F \times E_t^F = \sum_{t=1}^N P_t^D \times 1.174 \quad (9)$$

The revenue of the Real-Time Market is always set to zero due to ($P_t^R = 0$) to minimize the energy shortfalls ($S_t = 0$). The exposure of the forecast error to the Spot Market, due to the hedged amount in the Futures Market, decreased. For the calculation of the

aggregated energy to the Spot Market, we can outline the next formula to define the MAPE exposure to the market manually. The risk aversion factor: $b = 0$.

$$E_t^D = (1 + 0.087) \times (F(t) - E_t^F) \quad (10)$$

The 8.87% is the reduced MAPE, which in the worst case of Scenario 2 adds a value of 17.4% to this specific procurement strategy; this is equal to the above-mentioned existing contract of the Greek market (7) and the comparative analysis result in the 0 margin between the existing and proposed contracts.

Both scenarios, which are represented in Figure 4, do not participate in any kind of Demand Response program, which could create extra value for the total revenue, and there is no profitability of the resold energy in the Real-Time Market. The zero revenue on the Real-Time Market stands as the trade-off between cost and balancing for the avoidance of financial penalties due to estimation errors. Finally, both scenarios do not include any risk-aversion optimization across different markets.

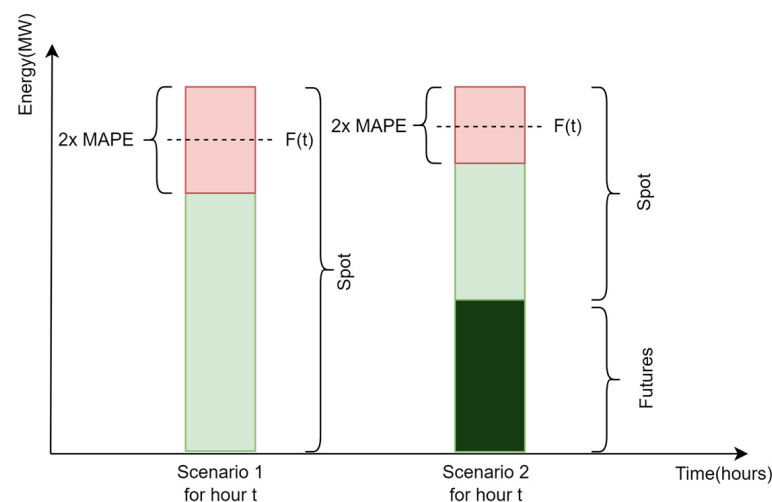


Figure 4. A qualitative visual representation of the allocated mix of both scenarios.

4.3. Lower Operational Expenditures Through Simplified AutoML Implementation

Vakhrushev [41] mentions the significant benefits of (AutoML), particularly in terms of cost and time savings in model development. The researchers highlight that by automating the complex and time-intensive processes traditionally handled by data scientists, AutoML techniques can substantially reduce Operational Expenditures (OPEX). This reduction is achieved through the minimization of the need for specialized human resources and the reduction in computational infrastructure costs. Moreover, the automation allows for the rapid deployment and adaptation of models, making it a cost-effective solution for scaling energy portfolio aggregation. These advantages enhance the economic feasibility of procurement strategies, ensuring that organizations can more efficiently manage and scale their operations while maintaining flexibility in their response to changing market conditions.

4.4. Operational and Financial Impact of Worst-Case Scenario

The decision to purchase additional energy at a higher cost, based on a worst-case scenario approach, carries significant operational and financial implications. From an operational standpoint, over-purchasing ensures a balanced load portfolio, which enhances the entity's stability even in the most challenging conditions. This strategy is designed to prevent supply shortfalls with minimal additional effort, thereby safeguarding continuous operations. Financially, while this approach does increase costs, it is a calculated measure to avoid potentially severe penalties. By planning for the worst-case scenario with a straightforward strategy, the entity can maintain financial resilience and ensure ongoing

operational continuity despite adverse market conditions. Additionally, as highlighted in the work of Tanrisever [36], the efficiency of risk management strategies like hedging can be significantly improved by minimizing forecasting errors, such as MAPE, thereby further reducing exposure to market risks. Reduced estimation error is beneficial for both utility companies and energy consumers. For utility companies, a lower MAPE means better accuracy in predicting electric load, which enables more efficient aggregation in the energy market. This accuracy helps the company remain competitive, avoiding significant cash flow disruptions that can arise from unexpected price fluctuations. On the other hand, end users benefit from more stable and potentially lower billing prices as accurate load forecasts help reduce the costs associated with energy procurement and generation, which are closely linked to market prices. The investment costs also play a crucial role in the initial investments for business domains that are affected by uncertainty, especially in the energy sector, as seen in other studies that leverage stochastic optimization approaches [42]. Please note that for the needs of this study, no further diversification was researched because the focus was invested in the benefits of AutoML methodologies for their usage in the energy trading sector.

5. Discussions of Results and Future Work

This use case illustrates how integrating a 12.89% MAPE into energy procurement strategies, through the deliberate over-purchasing of energy at a potentially higher cost, effectively addresses the worst-case scenario in the Greek wholesale energy market. By adopting this conservative approach without additional effort for risk hedging, and comparing it against a more expensive standard contract—which also follows the wholesale prices—the trading entity ensures compliance, maintains a balanced load portfolio, and avoids the financial penalties associated with under-supply. Additionally, by leveraging AutoML with minimal pre-processing, the strategy offers the added benefit of lower CAPEX for energy portfolio aggregation, making it a cost-effective and scalable solution in volatile market environments. This comparison offers valuable insights into optimizing procurement strategies in volatile markets, highlighting the trade-offs between cost, risk management, and flexibility.

Finally, this work could be further extended using real market data from the Greek energy market to define the real equilibrium of energy cost at each hour. This equilibrium could create a detailed and robust approach as far as the profit margins and risk factors that come with energy aggregating portfolios in the specified market. As an agnostic framework for the quantification of value, it could extend to a variety of energy markets worldwide. Possible integrations in the future include detailed regulatory compliance research for the effective definition of factors, such as the shortfall costs of these kinds of portfolios. Additionally, exogenous variables for the load prediction could be adopted such as weather conditions, National Holidays, and sudden events as well as the geolocation of each consumer, which stand as reasonably correlated variables. More advanced data pre-processing methods could also be implemented, as past studies have depicted [43].

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