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FORECASTING IMBALANCE PRICES IN THE SWISS POWER SYSTEM: COMPARING SKYTTE'S MODEL AND ALTERNATIVE METHODS

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Memory

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Abstract

This thesis aims to develop and evaluate a forecasting model to predict imbalance prices in the Swiss power market, with the ultimate goal of optimizing energy storage management strategies. The study leverages Skytte's model, originally designed for the Nordic power markets, and proposes an alternative linear regression model in case of missing variables. The methodology involves training both models on historical data and conducting simulations to assess their accuracy. The results indicate that while Skytte's model provides precise predictions by incorporating imbalance volumes, the alternative method, using only day-ahead prices, also offers reliable forecasts with minimal deviation. Statistical analyses, including residual clustering and interval prediction metrics, confirm the models' robustness. The automated application developed as part of this research demonstrates practical utility by autonomously forecasting imbalance prices, thus facilitating informed decision-making in real-time control of ADN.

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1 Introduction

The electricity commodity is unique due to its physical characteristics. Unlike other commodities, electricity cannot be stored efficiently in large quantities, which needs of real-time balance between supply and demand on the electrical grid. This balance is crucial to maintaining the stability of the grid's frequency, normally of 50 Hz in most countries. Any significant deviation from this frequency can lead to severe consequences, including grid instability or even widespread blackouts. Thus, the requirement for instantaneous balancing of electricity supply and demand introduces particular complexities to electricity markets, distinguishing them from other commodity markets.

1.1 Motivation

Users on the power grid engage in trading a specified amount of energy at a predetermined price (day-ahead price), established one day before the delivery time based on supply and demand. However, if a supplier or consumer fails to meet the before agreed amount of energy on the Energy-Only Market (EOM), the shortfall or surplus needs to be corrected to maintain system balance. This discrepancy between the expected and actual quantity of electricity is addressed through the imbalance market, where the cost of rebalancing is reflected in the imbalance price.

The imbalance price serves as a penalty for failing to adhere to the day-ahead agreements. This penalty exists because the rebalancing process incurs additional expenses, which impact the spot price of energy, making the imbalance market less economically efficient. Consequently, minimizing the need for adjustments on the imbalance market leads to a more efficient power market. This challenge of reducing imbalance penalties has been the focus of numerous studies lately.

During the year of 2023, the average day-ahead price traded on Swiss energy-only market has been at 107,49€/MWh [13], meanwhile on the imbalance market, participants that lead the grid into a deficit of energy, had to pay the missing energy at a price of 191,45€/MWh (known as Short price). [6] Same happened to the ones who lead the system to a surplus of energy, being paid 41,32€/MWh (known as Long price) for selling back their energy. The difference between these prices and the day-ahead ones is significant, leaving margin to develop solutions to optimize this process.

Managing Energy Storage Systems (ESS) can be advantageous for several reasons, including achieving independence from generation systems for a certain period. If both suppliers and consumers could utilize their own ESS instead of incurring penalties through the imbalance market, they could realize significant economic benefits. This would be possible by accumulating energy during periods with lower tariffs, thereby increasing income or savings.

Having prior knowledge of imbalance prices can facilitate this concept, as it would enable users to make more informed control actions in real time such as developing more effective storage management strategies. This is why this project tries to develop a forecasting model in order to lead to this optimization capability of the sector.

Since it's known that a high imbalance volume means that the power system is suffering, this actions that users could do, bring two benefits for the system; reducing the cost for the balancing group and helping the entire power system.

1.2 Literature review

Recent studies on imbalance market forecasting have attracted significant interest due to the challenges associated with the increasing integration of renewable energy sources into the power system. This integration leads to greater uncertainties and higher costs involved in real-time balancing. Several of these studies employ probabilistic models to determine imbalance prices. For instance, studies [10] and [5] utilize probabilistic forecasting techniques—such as Generalized Additive Models (GAMs) and Gaussian Processes respectively to model imbalance prices in the markets of Germany and Belgium. Also some studies focus on optimizing bidding strategies using machine learning algorithms. For example, studies [4] and [11] implement forest-based models and some algorithms to minimize imbalance costs in Spain and Greece. These strategies are crucial for markets with high penetration of renewable energy sources. Similarly, [1] explores strategic pricing forecasts in the GB market, really useful for real-time market participation. Furthermore, studies like [9] and [2] explore the impact of deterministic variables on market prices, using multiple-variable regressions and non-linear models to predict market behavior in the UK. Study [7] complements these studies by focusing on neural network architectures to forecast imbalance prices.

Study [15], is an example of how strategies that can be developed once the effective forecasting of imbalance prices becomes a reality. The paper "Risk-aware Participation in Day-Ahead and Real-Time Balancing Markets for Energy Storage Systems" proposes a two-stage optimization methodology for energy storage operators to participate in both day-ahead and real-time balancing markets in order to earn income from arbitrage. It incorporates risk management using Conditional Value at Risk to address price volatility due to renewable energy generation. This study is applied to the Belgian electricity market and it demonstrates improved profits compared to traditional methods. Having in consideration the similarity between power markets in all Europe, these studies applied on other countries can be very useful in order to see how the research in this field is currently.

However, a econometric analysis from 1999 made on the Nordic electricity market by Klaus Skytte [12], shows how to forecast the imbalance prices from knowing the real time day-ahead prices and imbalance volumes (amount of energy needed to bring back the balance to the system) in the Nord Pool market, the power exchange of the Nordic European countries.

Meanwhile it's observable that studies where done in most of the countries in Europe, no relevant studies could be found for the Swiss power market, revealing that a forecasting a study on Switzerland power market could be potentially beneficial for Swiss grid users.

Since it's true that the last commented study [12] was made in another power grid context more than twenty years ago, the context on Nordic countries and Switzerland when looking at type of generation on the electricity share have their similarities, suggesting that this method could potentially fit into the Swiss market.

For that reason, in this study, the from now on "Skytte model" is applied on the Swiss imbalance market, aiming to be a good market to apply the model to because of the hydro-electricity generation share that predominates in Switzerland and the Nordic countries back on the day of the study.

However, given that it is possible that the development of the forecasting model based on Skytte's could not fit the Swiss market, or some type of data could be missing, alternative methods are also developed in this thesis.

1.3 Objectives

This project develops a forecasting model to predict the imbalance energy prices on the Swiss grid through regression algorithms and analysis of its residuals. By effectively predicting the prices in the imbalance energy market, the study aims to provide insights that could lead to enhanced operational ESS strategies.

The ultimate goal is to lay the groundwork for future research and applications that could utilize these forecasts for better energy storage management, as proposed by [15].

Accurate forecasting could enable energy market users to make more informed decisions about when to store or release energy, potentially leading to significant economic savings and improved efficiency in energy utilization.

2 Background

The following section provides an overview of the Swiss electricity market, setting the stage for a deeper understanding of the concepts discussed in this thesis.

2.1 Context

Taking a look at the energy context in Switzerland, in 2021, this country operated 682 hydroelectric power stations, accounting for 62% of the nation's total electricity production. The country also maintains 220 dams, the highest density globally. [3]

The increasing penetration of renewable energy sources poses a significant challenge by introducing greater volatility into the electricity market. This heightened volatility comes from the difficulty in accurately forecasting renewable generation, leading to frequent deviations from dispatch plans and necessitating more active trading in the imbalance market to maintain grid stability. This is why, over the past two decades, many studies tried to find solutions to address this challenge, even the markets themselves have adapted to this challenge implementing measures like flexible pricing mechanisms.

2.2 Participants

The Swiss electricity market is composed by four different players. These are the suppliers, the final demand, the Transmission System Operators (TSO) and regulatory authorities. Suppliers or generators are the ones who own generation assets as power plants or storage systems. An important parameter of these power plants is the flexibility, that measures capability of response when imbalances occur. ESS can provide significant flexibility by storing excess energy during low-demand periods and releasing it during high-demand periods, thereby helping to balance the grid and manage imbalances effectively. ESS, however, can only transfer limited amount of energy. The final demand group or also known as load, is formed by the households and the industries. This last group has to be able to change their demand in a short interval of time. It is important to understand that to enhance communication and efficiency, generators and consumers are organized into Balancing Groups (BGs). A BG is a collection of various generators and consumers that collectively manage their electricity production and consumption. By coordinating within these groups, members can better balance their supply and demand, thereby minimizing imbalances and optimizing the overall stability of the power grid. Each BG is represented by a Balancing Responsible Party (commonly known as BRP), with the end of communicating between the transmission systems operators and the BGs, given that energy measurement is made at the BG level, not at generator or consumer level. The TSO is responsible for operating the transmission system and, thus, for maintaining reliability and stability of the electricity system. The regulatory authority provides and monitors the market environment. In Switzerland there are 3 different types of BGs. One is the standard BG, the major unit for measurement and billing, and two others for scheduling and accounting. (CH-15 and reserve BGs) Each of both CH-15 and reserve have to be linked

to a Standard BG. The 3 together form the accounting unit used for balance settlement. It's also important to know that the TSO in Switzerland is Swissgrid.

2.3 Markets

The electricity markets, depending on the country or region they operate in, can be slightly different. In Europe, the two main exchanges are the Nordic Power Exchange (NORDPOOL) for the northern Europe countries, and EPEX SPOT for central and southern Europe. Swiss markets are controlled by the latter, located in Paris. In order to address the reliability requirement electricity markets are organized in two different sub-markets. The energy-only market and the imbalance market. As the TSO is in charge of maintaining the stability of the grid, if overloading of lines in the grid can be foreseen, the TSO is allowed to adjust demand and supply schedules; a process called redispatching. Based on forecasts the Energy-Only Market (EOM) aims to equate expected demand and supply. Generators and demand actors bid energy into the market and the market maker equates these bids until the market is cleared. The EOM are categorized by the gate closure.

In Switzerland's case there are two types of EOM, which are the day-ahead auction and continuous intra-day trade.

- Day ahead: It opens 45 days before delivery time and is cleared the day before at 11:00. Given the day-ahead results as well as future and over-the-counter contracts, the BRP of buyer and seller, have to submit their schedules to the TSO (Swissgrid) until 14:30 the day before delivery.
- Intraday: Electricity is continuously traded after the market opens at 15:00 at the day before delivery time. Hourly, quarter-hourly, and base and peak contracts are traded.

Moving the gate closure closer to real time helps decreasing expected deviations of demand and supply, increasing reliability of the system in order to maintain system stability (redispatching). Redispatching occurs due to network problems and the TSO is not allowed to use reserve capacity for this purpose. It takes place before delivery time. It's important to know that balancing and redispatching are two separate processes. Balancing is necessary due to expected deviations in the demand-supply equation and occurs after delivery time.

2.4 Balancing

Imbalance is the demand for balancing energy, and this demand can be positive or negative. A positive balancing demand is a situation in which consumer demand unexpectedly exceeds electricity generation, causing a need for additional supply. In contrast, a negative demand situation requires a decrease in generation.

When actual demand and supply data becomes available, it often deviates from the forecasted values, leading to an imbalance. To ensure grid reliability, this imbalance must be corrected, which is managed through the imbalance market. Thus, imbalance markets are

cleared after the realization of supply and demand are known. Uncovered demand leads to a failure of the electricity system, this is why demand needs to be covered entirely by balancing facilities in every point in time. In order to address these imbalances, generation capacity is needed.

This supply of reserve energy, which is additional generation, needs to be procured before or simultaneously with the EOM, to ensure that the capacity is available and not blocked by the contracts of the EOM.

Balancing causes two type of cost: the cost of reserving the capacity and the cost of generating energy in the case of an imbalance. Imbalance pricing aims to solve an adverse hidden information problem: BRPs have private information about their demand and supply possibilities using costly forecast technologies.

2.5 Reserve capacity

This reserve of capacity generation is procured by the TSO in order to ensure against imbalances leading to system blackouts. But not all generators are able to be part of reserve capacitors. The generators have to fulfill the pre-qualification criteria set by the TSO.

Reserve generators are classified by their flexibility (their ability to deliver energy within a pre-defined amount of time):

- Primary Reserve or FCR: Primary control restores the balance between power generation and consumption within 30 seconds and lasts for a maximum of 15 minutes. During this operation, the frequency is stabilized within the permissible limit values. Activation takes place directly in the power stations by means of turbine regulators. In this phase, the grid frequency is monitored and, in the event of deviations, the primary control power needed is activated. All transmission system operators represented in the synchronous area must fulfill the requirements in their country in accordance with the ENTSO-E rules: the primary control power capacity which must be kept in reserve at all times is adjusted annually in November in accordance with ENTSO-E requirements (in Switzerland this is always approximately 70 MW with a frequency deviation of $\pm$200 mHz). It works within the solidarity principle, so the reserve energy can be provided from wherever, even outside the grid.
- Secondary reserve or FRR: Secondary control is used to maintain the desired energy exchange of a control area with the rest of the synchronous area, using simultaneous, integral support to maintain the frequency at 50 Hz. In the event of an imbalance between production and consumption, secondary control power in the connected power stations is automatically actuated by the central grid controller. As a prerequisite, these power stations must be in operation but must not be generating the maximum or minimum possible nominal capacity in order to meet the requirements of the central load frequency controller at all times. Secondary control is activated after a few seconds and is typically completed after 15 minutes. If the cause of the control deviation is not eliminated after 15 minutes, secondary control gives way to tertiary control.

- Tertiary reserve or RR: The Swissgrid dispatcher effectuates activation by sending special electronically transmitted messages to the providers, who must then intervene in power plant production to ensure the supply of tertiary control power. The supplier has to be fully available 15 minutes after the notification and up to an interval of 4 hours. The tertiary control reserve is primarily necessary for adjusting major, longer-lasting control deviations, particularly after production outages or unexpectedly long-lasting load changes.

Different problems like frequency changes, elevated costs to rebalance and other electrical challenges take place if this balance is not possible. That's why Swissgrid uses preventive and operative measures to maintain the stability of the transmission grid. The preventives measures are to predict the network status and 2 days before a potential problem, Swissgrid informs about congestion warning in certain regions and nodes. Power plants now can only produce energy up to what the maxim generation constraints established by Swissgrid let. If these production constraints are violated, all power plants have to pay a penalty of 10% of the day-ahead price for the excessive energy for possible redispatching extra costs. All these procedures are to avoid the process of redispatching. Operative measures are used when preventive measures are not able to stabilize the congestion situation. Generators do not only submit their scheduled supply but also a minimum and maximum amount of generation possible, so Swissgrid can calculate an efficient way to redispatch energy. In case after having traded at EOM, the grid is not perfectly balanced, it's possible to trade on the IBM.

2.6 Imbalance Pricing

In the Swiss electricity market, the processes of imbalance settlement and pricing are essential for ensuring that energy billing is accurate and for managing deviations between scheduled and actual energy deliveries. BRPs can adjust their schedules up until 5:00 PM the day after delivery, a period known as Post-Scheduling Adjustment. Swissgrid, the Swiss transmission system operator, then consolidates and verifies all schedules to calculate imbalances. These are measured on a quarter-hourly basis for each Balancing Group (BG) associated with a BRP, comparing scheduled against actual energy deliveries. The total imbalance for each BRP is calculated by aggregating the imbalances from all BGs, forming the basis for financial settlements. Swissgrid employs a two-price system for imbalance pricing to address the costs associated with energy overproduction or underproduction. For overproduction, the price (Long) includes a base price plus the maximum of the day-ahead price and the highest of the reserve prices. This is adjusted downwards to discourage excess generation. For underproduction, the price (Short) is calculated using a higher base price plus the minimum of the day-ahead price and the lowest of the reserve prices, adjusted upwards to cover the costs and risks associated with energy shortages.

This pricing mechanism is designed to mitigate financial risks for BRPs and maintain incentives for accurate scheduling and efficient market behavior. By linking imbalance prices to the reserve and day-ahead market prices, the costs of imbalances reflect the real-time value of electricity and the necessary expenditures to maintain system stability. This system also helps to discourage strategic bidding behaviors that could potentially destabilize the market.

3 Methodology

In order to forecast the imbalance prices, a model following the Skytte method is used [12]. In addition, an alternative method (as Skytte model, this second is also a lineal regression) is developed for when the imbalance data needed for the Skytte model isn't available in real time. These two methods are defined below in this section.

3.1 Skytte's model

This model is partially based on the Skytte model, developed by Klaus Skytte in 1999 [12], to originally predict imbalance energy prices (short price and long price) in the Nordic power markets. The paper posits that the cost of imbalance power is a quadratic function of the imbalance volume, distinguishing between the costs of up-regulation and down-regulation. It concludes that up-regulation costs are less sensitive to spot market prices but highly responsive to imbalance volume, which means that costs increase significantly during substantial power shortfalls, reflecting the high costs of securing additional power. On the other hand, down-regulation costs are more closely tied to spot market prices and less affected by the regulation volume, suggesting that reducing power output is typically less complex and costly.

This model's applicability to Swiss markets, where the majority of its electricity production comes from hydroelectric plants, should allow for precise predictions of imbalance prices, similar to what was achieved in the Nordic countries in the past

This paper provides the following equation: The regulating power price, denoted as PR, given the spot price P_t, the scheduled amount S_t, and the actual delivery D_t, is modeled using a segmented function. This model captures the dynamics based on whether there is excess demand or excess supply relative to the scheduled amount. The price function is defined as follows:

$$PR(P_t, S_t, D_t) = \phi \cdot P_t + \begin{cases} \lambda' \cdot P_t + \mu' \cdot (S_t - D_t) + \eta', & \text{if } S_t < D_t \\ \alpha' \cdot P_t + \gamma' \cdot (S_t - D_t) + \beta', & \text{if } S_t > D_t \end{cases} \tag{1}$$

where:

- ϕ is a scaling factor applied to the spot price P_t.
- λ' and α' are coefficients that represent the premium of readiness for down-regulation and up-regulation, respectively, influenced by the spot price level.
- μ' and γ' are coefficients reflecting the price sensitivity to the amount of regulation needed for down-regulation and up-regulation, respectively.
- η' and β' are constants that adjust the price for regulation, independent of the spot price or the volume of regulation.

The indicators $1_{S_t<D_t}$ and $1_{S_t>D_t}$ are characteristic functions that equal 1 when there is excess demand ($S_t < D_t$) and excess supply ($S_t > D_t$), respectively.

Once seen the mathematical method used in the paper which bases the model in a segmented function, a slight adaptation is done in the model created for this thesis. In order to get a non-segmented function and re-adapt the model to the data available, the equation used in this project for the application of Skytte's model on the swiss markets for both short and long imbalance prices is the following one:

$$y_{\text{short,long}} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \epsilon \tag{2}$$

where:

- $y_{\text{short, long}}$ represents the short and long imbalance prices.
- x_1 denotes the day-ahead price .
- x_2 is the imbalance volume.
- β_0 is the intercept.
- β_1 is the slope coefficient indicating the impact of spot prices on short imbalance prices.
- β_2 is the coefficient indicating the impact of imbalance volumes.
- ϵ is the residual or error term of the model, later used for statistical analysis and a better approximation.

This equation removes the segmented function of the Skytte model, which was made in order to differ the equation depending if there was a surplus or a deficit of imbalance regulation. In this new model this is differentiated based on the imbalance regulation sign. A positive sign on imbalance volumes means there's a surplus of energy and hence affects the long prices, and negative sign means there's a deficit of energy on the grid and affects on the short prices. Also the scaling factor is removed since it's not necessary. These nuances make this model more simple. To obtain the results of this model a Ordinary Least Squares regression is done, assuming the influences of the variables have on the imbalance prices.

3.2 Alternative method

This alternative method development comes from the problem there's in Skytte model when trying to apply it on real-time. The delay of imbalance volumes data is what makes the Skytte model not possible to be executed on real time, since this data variable is missing. In order to avoid this problem, the alternative method tries to foresee a relation between the day-ahead prices and the imbalance ones only, in order to have a running on real time model.

To forecast the imbalance prices with this alternative or simplified method, the same type of regression is done but now simpler because the missing variable. It is assumed that the

day-ahead price (the independent variable in this regression) influences the imbalance prices 'long' and 'short' (the dependent variables). This type of regression is selected for its simplicity and effectiveness in establishing a direct linear relationship, suggesting that changes in day-ahead prices directly and proportionally impact imbalance prices. In the following section, the equation for predicting the imbalance prices is presented, having the same procedure for short and long ones:

$$y_{\text{short, long}} = \beta_0 + \beta_1 x + \epsilon \tag{3}$$

Where:

- $y_{\text{short, long}}$ represents the short and long imbalance prices (dependent variable).
- x denotes the daily spot price (independent variable).
- β_0 is the intercept.
- β_1 is the slope coefficient indicating the impact of spot prices on short imbalance prices.
- ϵ is the residual or error term of the model, later used for statistical analysis and a better approximation.

This second and alternative method is simpler because the lack of the imbalance volume data as a variable. Although is not the objective of the thesis, the similarity of this method with the previous one makes an easier comparison between both, being the differences attributable to the missing variable in this second method. This can help on assessing how important the imbalance volume is for the accurate forecasting.

3.3 Statistical analysis of residuals

In addition to the linear regressions, a statistical analysis of the residuals of the methods seen above is performed to have a better approach of the results obtained by the model.

Residuals measure how much the observed values of the dependent variable deviate from the predictions made by the model. Ideally, residuals should be small and randomly distributed around zero if the model adequately captures the relationship between the variables.

A clustering and distribution of the residuals allow to identify patterns and group similar residuals together, which can help in understanding the structure and behavior of the data, lately improving it, as this analysis can reveal systematic deviations hidden at a first look. The clustering process is done using the K-means method [8], which groups data into k clusters by assigning each point to the nearest cluster center and then updating the centers until the clusters are stable. By grouping the weeks into clusters, it's possible to tailor a specific design or corrections to each group, leading to more accurate approximations and therefore the model itself. The exact same process is applied on both models, allowing to have a more accurate comparison between the two of them. All this statistical analysis returns an estimation within bounds depending on the cluster the simulated interval is in. Different clusters mean different

distribution of the residuals and therefore different upper and lower bounds. In order to evaluate how good this estimation is, the concepts PICP and PINAW are introduced. These two metrics help assess the reliability and precision of the intervals generated by the model.

Prediction Interval Coverage Probability (PICP)

The Prediction Interval Coverage Probability (PICP) is defined as the proportion of true values that fall within the predicted intervals. It measures the coverage accuracy of the interval predictions. The closer the PICP is to the desired confidence level, the better the prediction interval.

The equation for PICP is given by:

$$\text{PICP} = \frac{1}{N} \sum_{i=1}^{N} \mathbf{1}(y_i \in [\hat{y}_i^{\text{lower}}, \hat{y}_i^{\text{upper}}]) \tag{4}$$

where:

- N is the total number of observations.
- y_i is the true value at time i.
- $\hat{y}_i^{\text{lower}}$ and $\hat{y}_i^{\text{upper}}$ are the lower and upper bounds of the prediction interval at time i, respectively.
- $\mathbf{1}(\cdot)$ is an indicator function that equals 1 if y_i is within the interval $[\hat{y}_i^{\text{lower}}, \hat{y}_i^{\text{upper}}]$ and 0 otherwise.

PICP indicates how well the prediction intervals cover the actual values. An ideal PICP value should match the desired confidence level (e.g., 0.9 for a 90% confidence interval).

Prediction Interval Normalized Average Width (PINAW)

The Prediction Interval Normalized Average Width (PINAW) is defined as the average width of the prediction intervals, normalized by the range of the actual values. It measures the precision of the prediction intervals. A smaller PINAW indicates narrower and more precise intervals.

The equation for PINAW is given by:

$$\text{PINAW} = \frac{1}{N} \sum_{i=1}^{N} \frac{\hat{y}_i^{\text{upper}} - \hat{y}_i^{\text{lower}}}{y_{\max} - y_{\min}} \tag{5}$$

where:

- $\hat{y}_i^{\text{upper}} - \hat{y}_i^{\text{lower}}$ is the width of the prediction interval at time i.
- $y_{\max}$ and $y_{\min}$ are the maximum and minimum values of the actual observations, respectively.

PINAW indicates the average width of the prediction intervals relative to the range of the actual values. A lower PINAW represents more precise predictions.

Both metrics together provide a comprehensive evaluation of the prediction intervals. While PICP ensures that the intervals are reliable, PINAW ensures that they are not excessively wide.

In the implemented code, the intervals are generated by predicting the lower and upper bounds ($\hat{y}_i^{\text{lower}}$ and $\hat{y}_i^{\text{upper}}$). The PICP and PINAW metrics are then calculated to evaluate the quality of these prediction intervals. This approach ensures that the intervals provide a balanced trade-off between coverage probability and interval width.

Normalized Root Mean Squared Error

The Normalized Root Mean Squared Error (NRMSE) can also measure the accuracy of a predictive model. It is derived from the Root Mean Squared Error (RMSE), which is defined as follows:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{6}$$

where:

- y_i are the observed values,
- $\hat{y}_i$ are the predicted values,
- n is the number of observations.

The RMSE provides the square root of the average squared differences between predicted and observed values. However, to allow comparisons across different datasets or models, the RMSE can be normalized. The NRMSE is often normalized by the mean absolute value of the observed data. The NRMSE is given by:

$$\text{NRMSE} = \frac{\text{RMSE}}{\text{mean absolute value of observed data}} \tag{7}$$

Here, the mean absolute value of the observed data is defined as:

$$\text{Mean Absolute Value} = \frac{1}{n}\sum_{i=1}^{n}|y_i| \tag{8}$$

By normalizing the RMSE with the mean absolute value, the NRMSE provides a dimensionless measure of prediction accuracy. This facilitates easier comparisons across different models developed by studies in the same field and helps to assess the performance of the model developed in this thesis.

3.4 Models definition

In this part the two models developed in this thesis that are going to be compared are defined.

Skytte model

The "Skytte model" consists in the set of:

- The linear regression of imbalance prices on day-ahead prices and regulation volume following the Skytte model steps seen on [12].
- The statistical analysis of the residuals obtained after the regression.

Alternative method

The "Alternative method" consists in the set of:

- The linear regression done of imbalance prices on day-ahead prices only, obtaining a simpler regression.
- The statistical analysis of the residuals obtained after the regression.

It's important to know that the first part of each model (the lineal regression) is the part that is going to return an exact values for both of the future imbalance prices when the models are simulated. On the other hand, the statistical analysis as its name says gives a interval between and upper and a lower bound on every point the regression did forecast, leaving room for a probable error on every prediction.

This strategy was made to reach the best accuracy possible thanks analyzing the residuals the models left.

4 Simulation and results

Now that the methods to forecast the imbalance prices are known, two separated models are developed on Python programming language so the swiss market data can fit these models. The models divide in different main steps.

4.1 Data management and sources

The day-ahead prices of the swiss electricity market are uploaded on the ENTSO-E website [6] daily within a one-hour pricing intervals. The values of these prices are known a day before.

The imbalance prices, which are uploaded on the website 20 days after the closure of a month, can be found on the swiss TSO (swissgrid) website [13] within a 15-minute period. This leads into a delay of up to 50 days compared with the current moment.

The imbalance volume needed for the first model is uploaded hourly for the last hour also on swissgrid [14]. Its period is of 15-minute and because of upload timing can have a maximum delay of 1 hour and 15 minutes or 5 data steps. In the figure below (see Figure 1) the imbalance volume data used to train the Skytte model is represented.

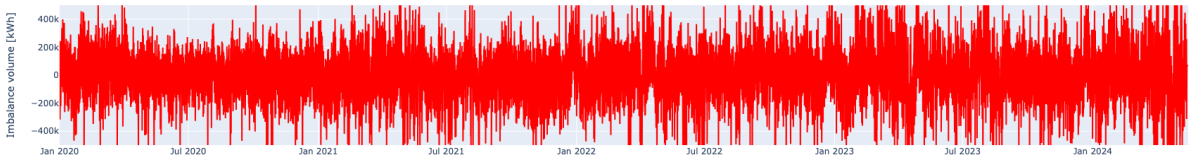

Figure 1: Imbalance volumes in kWh used to train the Skytte model

In the following charts, the day-ahead prices and imbalance ones are represented in the same charts. As can be seen in Figure 3, the day-ahead price is always between the Long and Short prices, thing that reflects the extra costs that rebalancing the grid has.

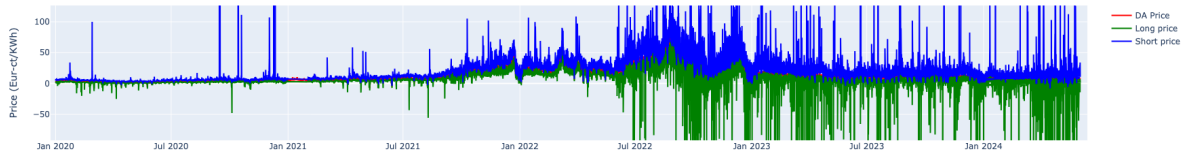

Figure 2: Day-ahead and imbalance prices available for the model

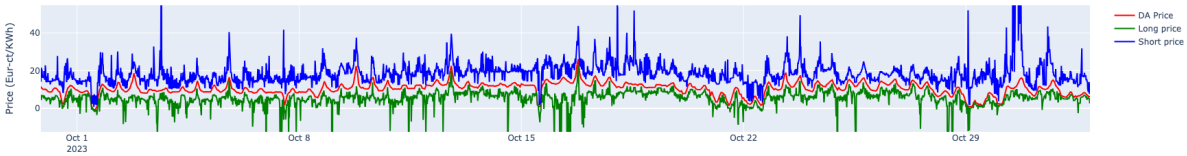

Figure 3: Closer view of prices data for a period of one month

The raw data needs to be cleaned and fitted for a correct management and running of the model. Once that is done, the three datasets are put in the same timelines and frequencies. This is a crucial step in order to later obtain accurate results. As can be seen, the imbalance prices suffer a large amount of intense peaks. These were not tried to be reduced, flattened or cut between certain amounts in order to have a more realistic and better trained model.

4.2 Models simulation

As there's data from prices available from several years ago and its behaviour changed on the last years, a training period for the model has been chosen after some tests trying to find the most accurate one. It's possible to see a normal behaviour excepting from September 2021 to July 2022, when prices went higher than expected. If these exorbitant prices are overlooked, two remaining intervals can be considered; before and after this event. Therefore, four intervals are tested on the linear regression model in order to find the most accurate one. These are:

- From January 2021 until August 2021.
- From September 2021 to July 2022.
- From July 2022 until December 2023.
- All available data; from January 2020 to December 2023.

After training them model with these four periods, the most accurate results for Long and Short prices model is the one from July 2022 until December 2023. Which actually could make sense because the last behaviour from the market until the month of June 2024 is similar to the one on the mentioned period. This eighteen month period of data is chosen to train both lineal regressions for the different models.

The summary of the models is the following:

Skytte model regression:

OLS Regression Results

Dep. Variable:	Short	R-squared:	0.734
Model:	OLS	Adj. R-squared:	0.734
Method:	Least Squares	F-statistic:	1.055e+04
Date:	Sat, 29 Jun 2024	Prob (F-statistic):	0.00
Time:	16:04:50	Log-Likelihood:	-50391.
No. Observations:	13154	AIC:	1.008e+05
Df Residuals:	13151	BIC:	1.008e+05
Df Model:	2		
Covariance Type:	HC3		

	coef	std err	z	P>|z|	[0.025	0.975]
const	5.5170	0.161	34.163	0.000	5.201	5.834
DA_Price	1.3099	0.009	145.215	0.000	1.292	1.328
Reg (kWh)	-1.218e-05	1.41e-06	-8.606	0.000	-1.5e-05	-9.4e-06

Omnibus:	33523.358	Durbin-Watson:	1.543
Prob(Omnibus):	0.000	Jarque-Bera (JB):	777987605.600
Skew:	28.555	Prob(JB):	0.00
Kurtosis:	1193.045	Cond. No.	2.60e+05

Figure 4: Regression summary on Short prices for Skytte model

OLS Regression Results

Dep. Variable:	Long	R-squared:	0.444
Model:	OLS	Adj. R-squared:	0.444
Method:	Least Squares	F-statistic:	1.017e+04
Date:	Sat, 29 Jun 2024	Prob (F-statistic):	0.00
Time:	16:04:50	Log-Likelihood:	-51388.
No. Observations:	13154	AIC:	1.028e+05
Df Residuals:	13151	BIC:	1.028e+05
Df Model:	2		
Covariance Type:	HC3		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-4.1823	0.208	-20.112	0.000	-4.590	-3.775
DA_Price	0.7442	0.007	113.248	0.000	0.731	0.757
Reg (kWh)	-1.353e-05	1.27e-06	-10.657	0.000	-1.6e-05	-1.1e-05

Omnibus:	31086.892	Durbin-Watson:	0.914
Prob(Omnibus):	0.000	Jarque-Bera (JB):	375644971.074
Skew:	-23.784	Prob(JB):	0.00
Kurtosis:	829.509	Cond. No.	2.60e+05

Figure 5: Regression summary on Long prices for Skytte model

Alternative method regression:

OLS Regression Results

Dep. Variable:	Short	R-squared:	0.726
Model:	OLS	Adj. R-squared:	0.726
Method:	Least Squares	F-statistic:	2.047e+04
Date:	Thu, 20 Jun 2024	Prob (F-statistic):	0.00
Time:	10:33:51	Log-Likelihood:	-50585.
No. Observations:	13154	AIC:	1.012e+05
Df Residuals:	13152	BIC:	1.012e+05
Df Model:	1		
Covariance Type:	HC3		

	coef	std err	z	P>|z|	[0.025	0.975]
const	5.4170	0.160	33.871	0.000	5.104	5.730
DA_Price	1.3177	0.009	143.084	0.000	1.300	1.336

Omnibus:	33332.257	Durbin-Watson:	1.514
Prob(Omnibus):	0.000	Jarque-Bera (JB):	736961990.703
Skew:	28.153	Prob(JB):	0.00
Kurtosis:	1161.208	Cond. No.	37.5

Figure 6: Regression summary on Short prices for alternative method

OLS Regression Results

Dep. Variable:	Long	R-squared:	0.426
Model:	OLS	Adj. R-squared:	0.426
Method:	Least Squares	F-statistic:	1.065e+04
Date:	Thu, 20 Jun 2024	Prob (F-statistic):	0.00
Time:	10:33:51	Log-Likelihood:	-51594.
No. Observations:	13154	AIC:	1.032e+05
Df Residuals:	13152	BIC:	1.032e+05
Df Model:	1		
Covariance Type:	HC3		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-4.2934	0.220	-19.532	0.000	-4.724	-3.863
DA_Price	0.7528	0.007	103.187	0.000	0.739	0.767

Omnibus:	30882.823	Durbin-Watson:	0.887
Prob(Omnibus):	0.000	Jarque-Bera (JB):	352687824.024
Skew:	-23.417	Prob(JB):	0.00
Kurtosis:	803.812	Cond. No.	37.5

Figure 7: Regression summary on Long prices for alternative method

As can be seen in the summary figures, on both models designed the Short one seems to be more accurate tan the Long one, having a higher R-squared score. Looking at the coefficients attributed by the regression on the variables and the constant, the model attributes an important correlation to day-ahead prices and not much to the imbalance volumes as can be seen in the figures above. This means that despite of having one more variable on the Skytte model, giving to that model more information, the results could be very similar given that among of that, the values of coefficients for both models are really similar.

So, in case of not having available a second variable to run the Skytte, the alternative method should be very similar and return very close results compared with the Skytte model making the second model a perfect alternative option.

When training these models with the data from the training period that will return a value from the variables input, these have a residual, which is differently distributed because of some factors for the two different models. The expected distribution for both models should be around zero. However, in the following figures the real distribution of the trained models can be appreciated.

In Figure 8 the residuals statistical distribution is plotted for the Skytte model. In blue, the distribution of the Long model is seen and the colour black is for the Short one.

The same can be seen but for the alternative method in Figure 9.

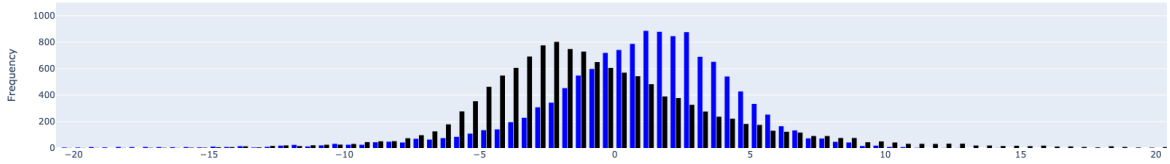

Figure 8: Histogram of residuals for the Skytte model.

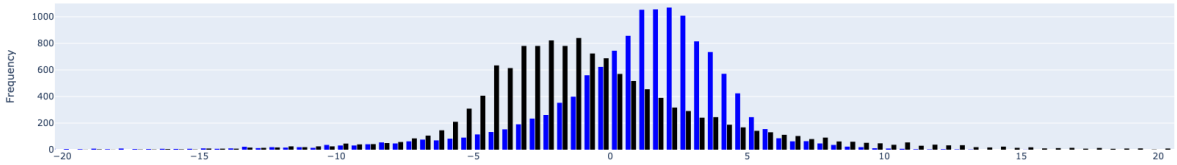

Figure 9: Histogram of residuals for the alternative model.

On both of the designed models, the statistical analysis step comes in. With the residuals being known, a clustering using k-means method is done and the days and weeks of the year can be classified in three different clusters. This clustering provides information about patterns in the residuals. This three clusters are probably related to the difference in the energy mix. In countries with a significant share of hydroelectric power, such as Switzerland, three main water cycles can be observed: the winter period, the melting season, and the summer period. Depending on the season the country is in, different behaviour of energy prices can be observed and hence different clusters. Below there's an example of how the weeks and days are attributed on a different cluster depending on their residuals behaviour. (see Figure 10)

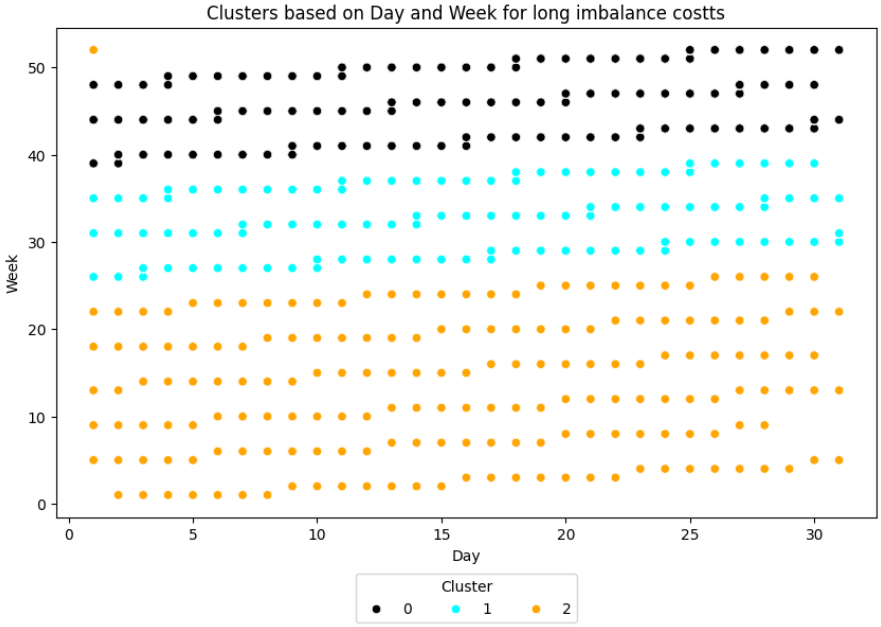

Figure 10: Clustering of residuals for the Skytte model on Long prices.

Knowing in which cluster the data is in, gives more information on the residuals when doing the probabilistic forecast or guessing between bounds, since what to expect from data from a certain period of the year is already more or less known because the historical data.

The simulations for forecasting these models are done during a past timeline in order to provide the best assessment possible for the results; the actual prices. Given that imbalance prices for the 2024 period are known, simulating in this period can be beneficial in terms of evaluating how good are the results and what to expect for future time intervals forecasts.

The simulation period of the imbalance prices forecast is between January and May 2024. These five months can provide enough results to know if the model works properly and accurately enough. It is important to remark that the simulation for the forecasting is done during a non-training period, because these could lead to over-performing and non-real results.

In order to assess the results, the PICP and PINAW are very useful metrics to know how good the probabilistic forecasting or guessing coming from the statistical analysis was. Below, in Table 1 and Table 2 these metrics in different bounds are shown for the average of the five months simulated.

In order to have a more clear idea and visual results, also a chart is designed, plotting the; actual prices (green), forecasted prices (blue) and lower and upper bounds of 10% and 90% (black). This type of charts can give a visual approach of how good the results are. In the following charts, a random selected week is shown for both models, the Skytte and the alternative one.

4.3 Results: Skytte model

Table 1: PICP and PINAW for the Skytte model

	PICP		PINAW	
	5-95	10-90	5-95	10-90
Long	0.85	0.73	0.06	0.04
Short	0.84	0.68	0.04	0.03

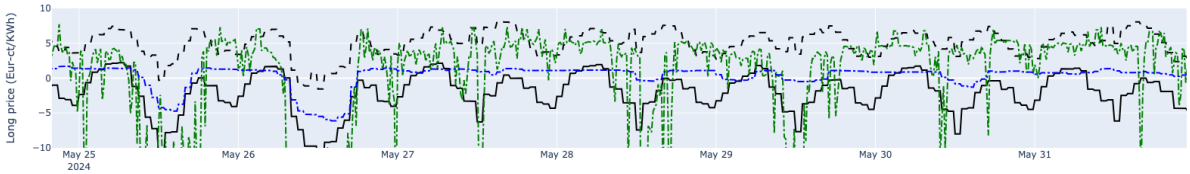

Figure 11: Results chart for Long prices on Skytte model

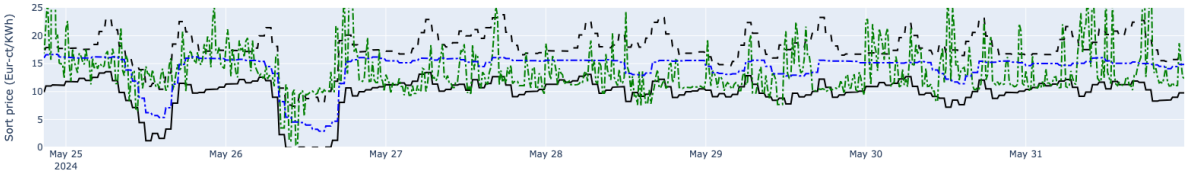

Figure 12: Results chart for Short prices on Skytte model

When calculating the NMRSE for the simulation period on the Skytte model, the results were the following:

- Long model: NRMSE = 39.35%

- Short model: NRMSE = 10.52%

4.4 Results: alternative method

Table 2: PICP and PINAW for the alternative method

	PICP		PINAW	
	5-95	10-90	5-95	10-90
Long	0.87	0.78	0.06	0.04
Short	0.83	0.69	0.02	0.03

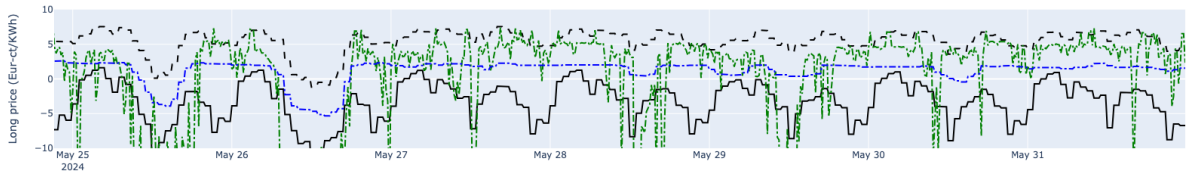

Figure 13: Results chart for Long prices on alternative model

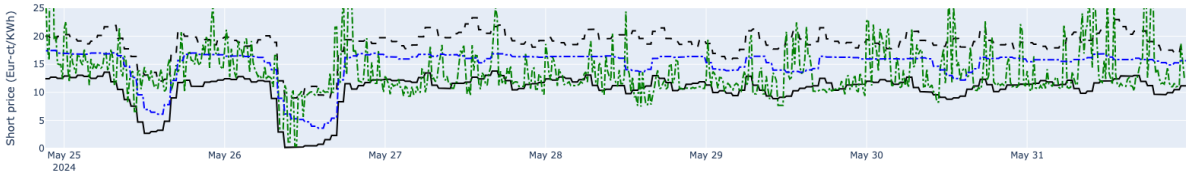

Figure 14: Results chart for Short prices on alternative model

When calculating the NMRSE for the simulation period on the alternative model, the results were the following:

- Long model: NRMSE = 39.76%
- Short model: NRMSE = 10.61%

4.5 Results analysis

In the Table 1 and Table 2 the PICP and PINAW average for both models designed and for the simulation period of five moths is calculated and shown. When calculating these metrics between percentiles, the expected value is known from these percentiles. In the 10% - 90% percentiles, the expected PICP should be 0.8, (80%), and the PINAW have an expected value of 0.2 (20%). Same happens with percentiles of 5% - 95%, where the expected values for PICP and PINAW respectively are 0.9 (90%) and 0.1 (10%). This metrics are the most analytical

ones this thesis has in order to assess the obtained results of the models and evaluating its accuracy.

In order to assess the results but in a more graphic or visual way the charts shown on Figure 11, 12, 13 and 14 show how's the behaviour of the forecasting compared to the actual values. A week far from the training period was randomly selected. This actual values are available because the forecasting was done on past months, in order to have available this comparison. The charts shown are forecasting the imbalance prices from the model trained in the training period, which are almost five months away from the closest trained point. In these charts is possible to see how good the model and the behaviour of the model is. When looking at actual prices, it's possible to see the little peaks the prices move on. However, when looking at the forecasted prices, these peaks are not possible to be predicted, making a way more flat line on the chart. These means the model is not capable of forecasting this little deviations ad little peaks that can be seen on the charts above. Also is possible to see how sometimes, the actual prices go out of bounds, meaning that the statistical guessing or forecasting wasn't capable of forecast the interval where the actual price finally was. However, it happens in rare occasions and for a very limited amount of time, for a few points.

When taking a look at closer months to the training period, a slightly different behaviour can be seen in the charts, also when looking the PICPs and PINAWs. When closer to training period, these metrics are closer to expected values.Table 3 shows the itemized by months the PICP and PINAW metrics for the different scenarios for every month. Both of the more far months from the training period (April and May) have the worst results for almost any scenario, whether it's Long or Short or between 10%-90% percentiles or 5%-95% percentiles.

However, it's not possible to confirm that the accuracy of the model is directly related with the distance from the training period.

Table 3: PICP and PINAW for Skytte and Alternative Models

Skytte Model						
	January		**February**		**March**	
	PICP	**PINAW**	**PICP**	**PINAW**	**PICP**	**PINAW**
Long 0.1-0.9	0.82	0.16	0.79	0.02	0.80	0.01
Short 0.1-0.9	0.63	0.01	0.68	0.05	0.75	0.02
Long 0.05-0.95	0.93	0.23	0.90	0.03	0.90	0.01
Short 0.05-0.95	0.78	0.01	0.82	0.07	0.87	0.03
	April		**May**		**Average**	
	PICP	**PINAW**	**PICP**	**PINAW**	**PICP**	**PINAW**
Long 0.1-0.9	0.60	0.00	0.63	0.00	0.73	0.04
Short 0.1-0.9	0.69	0.02	0.66	0.03	0.68	0.03
Long 0.05-0.95	0.73	0.01	0.78	0.01	0.85	0.06
Short 0.05-0.95	0.83	0.03	0.88	0.05	0.84	0.04
Alternative Model						
	January		**February**		**March**	
	PICP	**PINAW**	**PICP**	**PINAW**	**PICP**	**PINAW**
Long 0.1-0.9	0.83	0.16	0.87	0.02	0.85	0.01
Short 0.1-0.9	0.70	0.01	0.68	0.05	0.69	0.02
Long 0.05-0.95	0.94	0.23	0.93	0.04	0.93	0.02
Short 0.05-0.95	0.82	0.01	0.87	0.01	0.82	0.02
	April		**May**		**Average**	
	PICP	**PINAW**	**PICP**	**PINAW**	**PICP**	**PINAW**
Long 0.1-0.9	0.64	0.00	0.72	0.02	0.78	0.04
Short 0.1-0.9	0.72	0.02	0.66	0.03	0.69	0.03
Long 0.05-0.95	0.76	0.01	0.80	0.01	0.87	0.06
Short 0.05-0.95	0.82	0.03	0.81	0.04	0.83	0.02

5 Automated application

Once the forecasting model is designed and, as seen, is working with a certain amount of accuracy, an automatic running application is designed in order to automate the process seen before.

The model designed forecasts 24 hours of imbalance prices with the, named on this thesis alternative method, since it's not possible to have the imbalance volumes for the future, not even on present time because of the delay. So the application uses the alternative method model trained with the day-ahead prices variable and does a forecast for the next 24 hours autonomously.

This automation is done because it could lead to an autonomous ESS strategy decisions, where the decisions of store or deliver energy can be taken depending on the forecasted prices for the next day.

Below a resumed code used to create this application in order to implement the work done in this thesis can be found:

Algorithm 1 Daily Forecast and Upload Process

```
Require: Time: 9 PM daily
Require: Forecast model
Require: Database: InfluxDB
procedure DailyProcess
    while True do
        Wait until 9 PM
        Download day-ahead spot market price for the next day
        for each 15-minute interval do
            Predict imbalance price (Long and Short) using forecast model
            Calculate 10% and 90% percentiles of the prediction for each price
        end for
        Upload predicted prices and percentiles to InfluxDB
        Repeat next day
    end while
end procedure
```

The process follows the same steps when the simulation to assess the results of the trained models was done, but now automated.

To be sure that prices for the next day are available on the ENTSO-E website [6], he application waits until 9 PM every day to download the day-ahead prices spot prices. As prices are within 1-hour interval, data is transformed into 15-minute interval in order to suit better the imbalance prices forecast and have more frequency of data and hence more information during the forecasted day.

When predicting the Long and Short prices, the model uses the trained model, and forecasts the imbalance prices. In order to guess the Long and Short prices between percentiles of 10%

and 90%, the designed application thanks to the alternative model, attributes each day to a certain cluster before defined in the model also. This is what makes to be capable of returning a probabilistic forecast depending of the residuals distribution.

After returning all this data for both prices, these is uploaded on InfluxDB database automatically in the process.

6 Conclusions

This thesis has developed and evaluated two forecasting models to predict imbalance prices in the Swiss electricity market: the Skytte model and an alternative linear regression method. The key findings are the following ones:

The Skytte model, incorporating imbalance volumes among the day-ahead prices, has proven to be accurate in predicting imbalance prices in Switzerland despite being designed for the Nordic countries several years ago. The alternative model, based only on day-ahead prices, also provided reliable results, but with a very slightly reduced accuracy compared to the Skytte model when looking for the first 3 months of simulation. Taking a look at the PICP and PINAW of these three months since is where the higher accuracy in both models is found, the PICP for the Skytte model when expected values where 80%, these where 82%, 79%, 80% versus the 83%, 87%, 85% of the alternative method, being slightly more dispersed. Similar situation happens when expected values are 90%. It makes sense because of the lack of an entire variable, which actually brings a lot of information to the model.

Both models demonstrated that day-ahead prices have a significant correlation with imbalance prices, highlighting their importance for predictions

The ability to predict imbalance prices enables market operators and energy providers to make more informed decisions depending on the market and for example optimize their ESS strategies, potentially resulting in significant economic savings and improved operational efficiency. The statistical analysis methodology applied to residuals has provided additional information, giving reliable prediction intervals that can be used for risk management.

A major limitation is the availability and real-time updating of imbalance volume data, which affected the full implementation of the Skytte model. With the imbalance volumes data for the upcoming hours, the application would have been slightly more accurate.

Practically, the developed models can be integrated into automated systems for daily energy storage management, improving decision-making and economic efficiency. Theoretically, this research contributes to the existing body of knowledge on imbalance price forecasting, especially in contexts dominated by renewable energy sources and similar markets in Europe.

Future research with the same objective should focus on incorporating more predictive variables and improving model accuracy through advanced machine learning techniques or added information such as including aFRR bids on the day ahead in the forecasting model.

These conclusions highlight the value and applicability of the forecasting models developed in this thesis, while also recognizing areas for improvement and expansion in future research.

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