Day-ahead Electricity Price Forecasting of Elspot Markets in Norway

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***Abstract*—Forecasting day-ahead electricity prices from the Elspot market holds essential importance for various stakeholders, primarily electricity producers. These producers depend on precise price forecasts when placing supply bids and fine-tuning their dispatch schedules. This paper delves into this vital area, emphasizing day-ahead Electricity Price Forecasting (EPF). Following a comprehensive assessment of EPF techniques, we have experimented with three methods: a heuristic approach, Extreme Gradient Boosting (XGBoost), and the Long Short-Term Memory (LSTM) network. We have carried out unified comparisons among these three approaches across all six Elspot markets of Norway. Our results indicate that the LSTM outperform the other models in three of the six zones, which indicates the superior efficacy of the LSTM model. We have also noticed the impact of data variance on model performance, and hence improving model generalization will be our subsequent research endeavors.**

***Index Terms*— Electricity Price Forecasting, Elspot prices, XGBoost, LSTM.**

I. Introduction

Accurately forecasting market trends and price fluctuations is of paramount significance for a diverse range of stakeholders, including investors, businesses, and policymakers. This importance is particularly pronounced in the context of electricity markets, which serve an integral role in modern society and have experienced substantial transformation through deregulation and the integration of renewable energy sources [8] [12] [14] [29]. Recent disruptions in European electricity markets further underscore the growing imperative for precise Electricity Price Forecasting (EPF). Such predictions are crucial for electricity producers, consumers, and market operators to effectively plan their production, consumption and trading activities [1].

The NordPool spot (Elspot) market is a day-ahead market, where the price of power is determined by supply and demand. Such spot prices are actual price for electricity the next day, which will be set at Nordpool Elspot. Our primary focus is on day-ahead price forecasting using known spot prices. This forecasting directly informs bidding strategies for the upcoming day [17]. Due to the distinct characteristics of electricity markets, each forecasting challenge is unique across different markets and necessitates bespoke model developments [22]. We propose a framework for evaluating forecasting methods for all six Elspot markets of Norway while comparing three different numerical approaches to the problem of extrapolating prices in both univariate and multivariate configurations, facilitating the identification of region-specific models and model configurations.

In essence, this paper addresses the pressing need for accurate EPF in an evolving energy landscape, providing a systematic framework for evaluating and comparing forecasting methods across multiple markets in Norway. In Section 2 we dive into electricity markets and existing literature on EPF, Section 3 present the methodologies employed, Section 4 discuss the conducted experiments and in Section 5 we conclude in an analysis of the obtained results.

II. Background and Literature Studies

In this section we review the various market mechanics characterizing electricity markets and existing literature concerning EPF.

A. Background

Electricity is produced only moments before consumption, so unlike other commodities, electricity must be balanced between production and consumption at all times [15]. In a deregulated market environment, determining the unconstrained Market Clearing Price (MCP), commonly referred to as the spot price of an electricity pool typically involves the following steps:

Figure 1: MCP bidding process.

- Generating companies bid prices for supplying energy, creating a supply curve.
- The demand curve may be set at a value derived from a forecast of the load due to short-term inelasticity for demand of electricity, resulting in a vertical line at the forecasted load value.
- Spot price is found where supply and demand curves intersect, signifying the market equilibrium.

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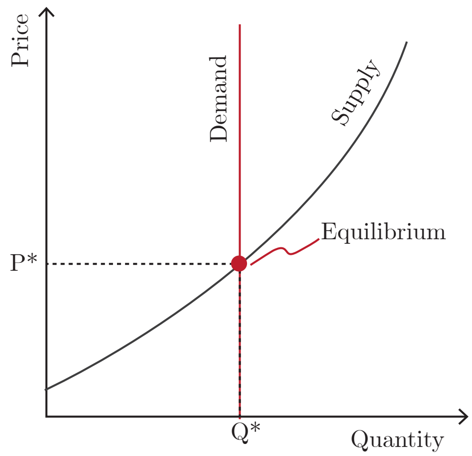


Figure 2: Equilibrium curve to determine the MCP of a bidding-pool.

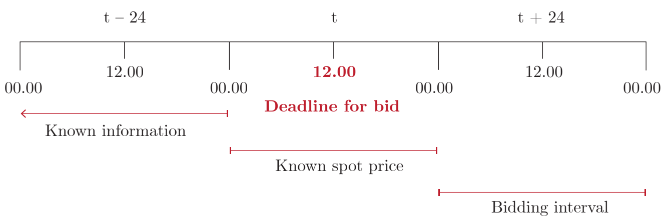


Figure 3: Deadline for bids in the Elspot markets.

The spot price is set at the equilibrium between supply and demand as seen in Figure 2 for each hour of the following day after accounting for the bids received within the deadline as illustrated in Figure 3 [12].

A time series is defined as a series of data points indexed in time order [32]. Commonly expressed as:

$$X = X_{t\,t=1}^{\infty} = (X_1, X_2, \ldots) \tag{1}$$

where X_t denotes the observation at time t, and the sequence of observations is indexed by t ranging from 1 to infinity.

Accurately extrapolating the future poses unique challenges due to several constraints imposed by time order. Some of these constraints include look-ahead bias, stationarity, autocorrelation, seasonality, trend and noise. Time-series data, characterized by sequential observations over time, requires specialized methodologies that can capture temporal dependencies and patterns. Additionally, the electricity market is influenced by a multitude of factors, including supply and demand dynamics, changing industrial and household consumption, multiple seasonality, weather conditions, regulatory policies, fuel prices, the integration of renewable energy sources, and the rapid diffusion of price-anomalies [1] [8] [12] [14] [29]. Understanding the key drivers of price movements aids in feature selection for predictive models. For instance, if weather patterns or economic variables significantly affect prices, incorporating these into a model may improve accuracy. The choice of methodology should also consider the nature of price drivers, as incorporating these considerations guides model selection. Furthermore, accurate price forecasts coupled with an understanding of their drivers provide valuable market insights.

B. Literature Studies

In the domain of EPF, selecting appropriate input variables, historical data duration, and modelling techniques is crucial. Most efforts that focus on forecasting day-ahead prices typically include an inference horizon of 1-4 weeks [2] [3] [10] [11] [13] [17] [18] [22] [23] [26] [30] [33]. Historical data spanning at least a year is commonly employed to capture yearly seasonality [2] [13] [18] [24] [33]. Input variables encompass a range of factors, including past prices [2] [3] [5] [6] [9] [10] [11] [13] [16] [17] [18] [21]- [27] [30] [33], system loads [13] [17] [21] [23]- [26] [30], weather variables [5] [13] [18] [24] [31], fuel costs [3] [5] [19] and sector indices [28]. Preprocessing and data transformations are essential to handle missing values and outliers, which can affect model performance. Techniques like normalization [5] [6] [30], decomposition [6] [10] [18] [23] [25] [33], and differentiation [11] are used to improve data quality and model accuracy. Statistical models, such as econometric methods, like Linear Regression [13] [21] [23] [31] and Auto-Regressive models [3] [10] [11] [13] [16] [18] [30] [33], offer interpretability and insights into correlations. Algorithmic models like Deep Learning (DL) [6] [13] [16] [17] [19] [21]- [25] and Ensemble models [3] capture complex and nonlinear patterns. Overall, the process of building a forecasting model involves decisions on input selection, preprocessing, model choice, parameter estimation, and accuracy evaluation. However, guidelines for navigating these complexities are limited, with much variation in reported approaches. Given the specific nature of EPF, establishing baselines and ensuring rigorous reporting is critical for advancing research in this field.

III. Proposed Methodology

In this research, the methodology centres around two key aspects of EPF: input variables and forecasting methods. The approach begins with selecting a baseline method that is heuristic-based. Building upon this baseline, the study conducts an empirical-driven progression to develop previously proven forecasting models in both univariate and multivariate configurations. Three distinct approaches are explored: a heuristic method, an algorithmic ensemble approach, and a DL approach. This methodology is designed to ensure objectivity and standardization in the evaluation process. Given the unique and inconsistent nature of electricity markets, EPF challenges vary significantly across locations and time frames, rendering cross-study evaluations potentially misleading and universal benchmarks logically unsound for this domain. Therefore the methodology involves systematic steps, including literature review of related work, data collection and preparation, model development and rigorous testing against real-world outcomes. All the data-handling, -visualization and model-implementation and -evaluation was done using Python software.

A. Heuristic Baseline

The persistence forecast is utilized as a baseline for this study. This approach involves using the last observed value of the time series as the forecast for the corresponding day-ahead time step. In the context of day-ahead electricity price forecasting, this would mean using the most recent price value as its prediction for the same hour the next day. Assuming we have a time series of electricity prices $p_t, p_{t+1}, p_{t+2}, ..., p_{t+n}$ where t is the current time step, the persistence model predicts the current price 24 hours ahead for each time step. In the context of day-ahead EPF, the persistence model serves as a sensible baseline. While more complex modelling methods may exhibit reasonable accuracy, they must be able to generalize beyond the explicit information provided in the input data. As a baseline the heuristic provides a reference point against which more advanced models can be evaluated, ensuring that they genuinely contribute to improved forecasting performance. We can express the persistence model in mathematical notation as follows:

$$\hat{P}_t = P_{t-24} \tag{2}$$

where $\hat{P}_t$ *denotes the predicted electricity price at time t and* P_{t-24} *is the observed value of the electricity price 24-time steps earlier.*

B. Algorithmic Ensemble

Extreme Gradient Boosting (XGBoost) is a popular gradient-boosting algorithm that is commonly used in machine-learning applications for both classification and regression tasks. It is an ensemble algorithm that combines multiple weak models (decision trees) to make a strong prediction. XGBoost learns from examples by building a series of decision trees. Each tree tries to correct the mistakes made by the previous trees reducing the risk of overfitting, and leading to a more accurate prediction [7]. The objective function for XGBoost can be written as:

$$\mathcal{L}(\Theta) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \tag{3}$$

where Θ *represents the set of model parameters,* n *is the number of training examples,* y_i *is the true value of the* i*-th example,* $\hat{y}_i$ *is the predicted value,* $l(y_i, \hat{y}_i)$ *is the loss function,* K *is the number of weak models,* f_k *represents the* k*-th weak model, and* $\Omega(f_k)$ *is the regularization term.*

The weak models used in XGBoost are decision trees, which can be expressed as:

$$f(x) = \sum_{t=1}^{T} w_t q_t(x), \quad w \in \mathbb{R}^T, \quad q : \mathbb{R}^d \to \{1, 2, \ldots, T\} \tag{4}$$

where x *is the input features,* w *is the vector of weights associated with each leaf node of the tree,* T *is the number of leaf nodes, and* $q(x)$ *is the function that maps the input features to the index of the corresponding leaf node.*

C. Deep Learning

Long Short-Term Memory (LSTM) is a type of Recurrent Neural Network (RNN) that is commonly used for time-series forecasting. Unlike traditional RNNs, LSTM networks are designed to overcome the problem of vanishing gradients, which make it difficult for the network to learn and remember long-term dependencies in the data. In simple terms, the LSTM network is like a specialized memory unit that can selectively remember important information from the past and use it to make predictions about the future. It achieves this by using a system of gates, which are like control switches, to control the flow of information within the network.

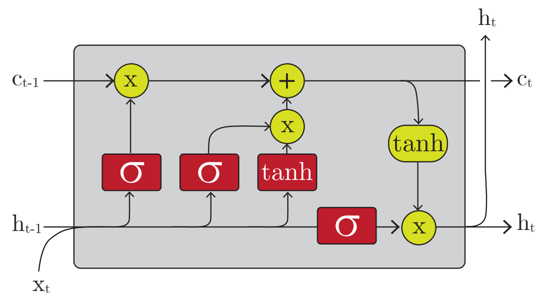


Figure 4: Long Short-Term Memory (LSTM) Network Diagram.

The LSTM network has three main types of gates as visualized in Figure 4: input gates, forget gates, and output gates. These gates allow the network to decide which information is important to keep, which information to forget, and when to output its predictions [20].

IV. Experiments and Discussion

This section covers the datasets used, the experimental setup, and the ensuing presentation and discussion of results.

A. Dataset and Description

The data, including unit measures, granularity and data sources are described in Table I. A total of six data-sets were created, each comprising time series data from one of the six bidding zones. The data-sets consist of 14-16 variables each, with the amounts of variables varying depending on the number of exchange connections to neighbouring zones.

Missing values occurred due to multiple reasons, such as changing time zones, observations at a lower frequency than

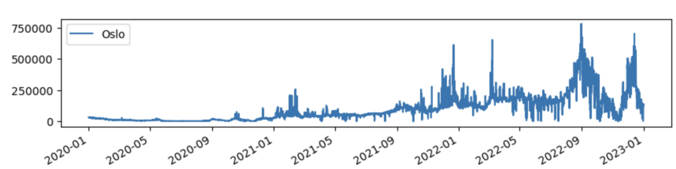


Figure 5: Historical Elspot prices for Oslo (NO1).

TABLE I: DESCRIPTION OF DATA (TARGET*).

Variable (units) [granularity]	Source
Elspot price (NOK/MWh) [h]	Nord Pool
Day-ahead Elspot price (NOK/MWh)[h]*	Nord Pool
Power production (MWh) [h]	Nord Pool
Power production prognosis (MWh) [h]	Nord Pool
Power exchange (MWh) [h]	Nord Pool
Power consumption (MWh) [h]	Nord Pool
Reservoir levels (GWh) [w]	Nord Pool
Reservoir capacity (GWh) [w]	Nord Pool
Gas price (NOK/mmbtu) [d]	Yahoo-finance
Oil price (NOK/barrel) [d]	Yahoo-finance
OSEBX price (NOK/OSEBX) [d]	Yahoo-finance
Air temperature (mean/degC) [d]	MET
Wind speed (mean/ms) [d]	MET
Percipitation (sum/mm) [d]	MET

the target values and stock exchanges being closed during weekends. Missing values due to these occurrences were appropriately imputed using interpolation, backward-fill or forward-fill.

The data is split into two sections, the first contains three years of data with 26 000+ price-observations and is allocated for training and validation, the second is separated from the first and contains 4 months of recent and unseen data allocated for testing and evaluation. The date ranges are the following, 01.01.2020 00:00 - 29.12.2022 23:00 for train and validation, and 01.01.2023 00:00 - 30.03.2023 23:00 for the hold-out test set. Essentially, the train-test split contains the original time order and is not shuffled or re-ordered. Data is normalized using min-max scaling, this is done separately for the two sections in order to prevent introducing look-ahead-biases encoded in the scaling.

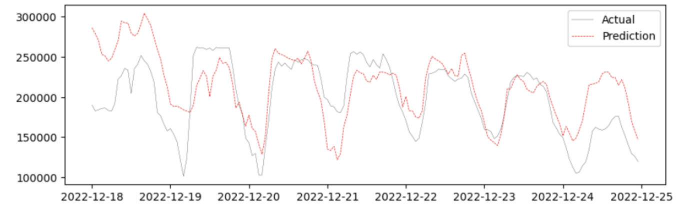
B. Experiments

The experiments include a heuristic baseline and are compared against each other as opposed to previous experiments from related work. First, the models are validated in the task of predicting the day-ahead hourly elspot prices on the validation set using a rolling forecast cross-validation (RFCV) scheme presented in Table II.

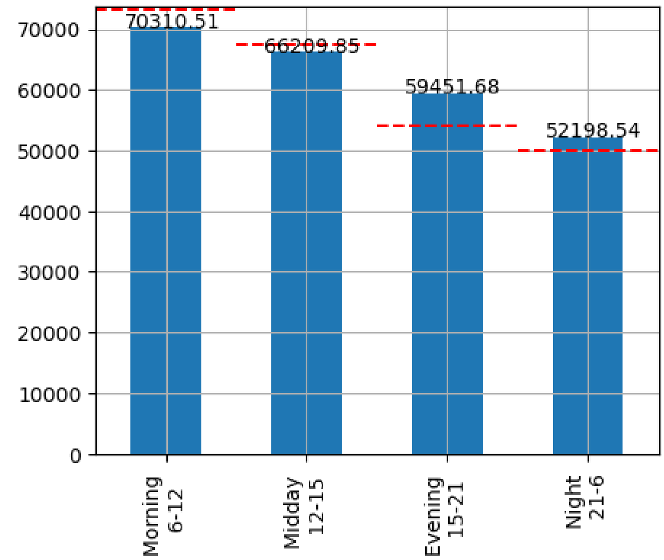
TABLE II: RFCV SCHEME (YYYY-MM-dd hh).

Fold	Train Start	Train End	Val Start	Val End
1	2020-01-01 00	2021-12-31 23	2022-01-01 00	2022-01-01 23
2	2020-01-01 00	2022-01-01 23	2022-01-02 00	2022-01-02 23
3	2020-01-01 00	2022-01-02 23	2022-01-03 00	2022-01-03 23
...	...	...	...	...
365	2020-01-01 00	2022-12-28 23	2022-12-29 00	2022-12-29 23

These experiments provide information about the models' performance on a full year of daily-predictions with daily retraining. During validation, the error of the models is measured using Root Mean Squared Error (RMSE). The errors are averaged by time of day; mornings (hours 6-12), mid-days (hours 12-15), evenings (hours 15-21) and nights (hours 21-6). An example of results from rolling forecasts origin validation with visualization from a sample period of 1 week including bar charts of aggregated time-of-day scores from the entire year are presented in Figure 6 (baseline results of aggregated RMSE are marked with red dashed lines for comparisons).



(a) Actual vs. prediction (18.12.2022 00:00 - 24.12.2022 23:00).



(b) Aggregated RMSE (01.01.2022 00:00 - 29.12.2022 23:00).

Figure 6: Rolling Forecast Origin Cross-validation of multivariate LSTM for Kristiansand (NO2).

After validating the models on the last year of the train-set, they are then are evaluated in their ability to extrapolate 24 time-steps ahead from the known spot-price during a 4-month out-of-sample period on a recent hold-out test-set from all the bidding-zones, with their weights and hyperparameters determined from training and tuning on the previous 3 years of data. The results of these experiments are presented in Table III, allowing for comprehensive analysis and review of the different modelling approaches in relation to the bidding zones and the addition of exogenous variables. The evaluation scheme of model performance consists of four different error terms; Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Average Percentage Error (MAPE) and Residual Sum of Squares (RSS). To gain a comprehensive understanding of the models' capacity for generalization and their ability to navigate the bias-variance trade-off, we seek to offer diverse viewpoints on the models' performance.

C. Discussion

Predictions from validation seem to be more accurate during mornings (6-12) and middays (12-15) as illustrated by the RMSE scores in Figure 6. However, none of the models consistently outperform the heuristic baseline across bidding

TABLE III: RESULTS FROM OUT-OF-SAMPLE EVALUATION (01.01.2023 00:00 - 30.03.2023 23:00).

		RMSE		**MAE**		**MAPE**		**RSS**	
	Model	endog	w/ exog	endog	w/ exog	endog	w/ exog	endog	w/ exog
NO1	Heuristic	29469	/	19946	/	**25.19%**	/	$18.7e^{11}$	/
	XGBoost	29156	27052	20268	**18838**	26.22%	26.92%	$17.9e^{11}$	$\mathbf{15.5e^{11}}$
	LSTM	29174	**21109**	21035	20134	29.21%	26.69%	$17.9e^{11}$	$17.9e^{11}$
NO2	Heuristic	29474	/	19943	/	25.19%	/	$18.7e^{11}$	/
	XGBoost	29545	27259	20715	19266	26.77%	26.19%	$18.4e^{11}$	$15.7e^{11}$
	LSTM	28354	**26431**	20317	**18173**	29.09%	**24.81%**	$16.9e^{11}$	$\mathbf{14.9e^{11}}$
NO3	Heuristic	30448	/	21069	/	37.58%	/	$20.0e^{11}$	/
	XGBoost	28469	29069	19687	19666	35.79%	31.79%	$17.1e^{11}$	$17.8e^{11}$
	LSTM	28438	**28381**	20462	**19228**	40.91%	**31.29%**	$17.1e^{11}$	$\mathbf{16.6e^{11}}$
NO4	Heuristic	21456	/	11705	/	25.28%	/	$99.4e^{10}$	/
	XGBoost	20592	23149	11424	12507	25.43%	29.35%	$89.6e^{10}$	$11.3e^{11}$
	LSTM	**19448**	21675	**10519**	13155	**22.76%**	28.05%	$\mathbf{79.9e^{10}}$	$96.1e^{10}$
NO5	Heuristic	25240	/	**16953**	/	**15.75%**	/	$\mathbf{13.7e^{10}}$	/
	XGBoost	24950	**24156**	17137	17018	16.27%	15.94%	$13.1e^{11}$	$12.3e^{11}$
	LSTM	25427	24584	18391	18189	17.80%	17.49%	$13.6e^{11}$	$12.9e^{11}$
NO6	Heuristic	30448	/	21069	/	37.58%	/	$20.0e^{11}$	/
	XGBoost	28469	**28326**	19687	**19532**	35.79%	**31.70%**	$17.1e^{11}$	$\mathbf{16.9e^{11}}$
	LSTM	28438	30100	20462	22870	40.91%	48.58%	$17.1e^{11}$	$19.1e^{11}$

zones and time-of-day during these experiments. This could be attributed to the highly volatile and disruptive prices witnessed in the year 2022 as illustrated in the historical elspot prices in Figure 5, which is the year allocated for validation, making it difficult for the models to fit the data comprehensively.

Results from the out-of-sample evaluation exhibit more promising improvements over the baseline. As seen in Table III, the LSTM and XGBoost models outperform the baseline across all evaluation criteria for most of the bidding-zones, meaning that they are able to balance between capturing price nuances while maintaining robustness to outliers. These results ultimately emphasize the potential of DL and ensemble ML techniques for capturing the complexities of EPF. Specifically, the LSTM model in its multivariate configuration achieves this feat during out-of-sample evaluation on the data-sets for bidding-zone NO2 and NO3. Surprisingly, the univariate LSTM outperforms the other models in all aspects of error for the bidding-zone NO4. The final model to outperform all other models for all aspects of error is the multivariate XGBoost model for the bidding-zone NO6. For the remaining bidding-zones NO1 and NO5 there is no clear contender for best model performance. The variability in results across the different data-sets highlights the presence of unique characteristics for the distinct bidding-zones, with varying predictability, model-performances and optimal model-configurations.

V. Conclusion and Future Work

Forecasting day-ahead electricity prices plays a pivotal role in strategizing and balancing the supply and demand for the subsequent day, making it an essential area to delve into. In this paper, we introduce a framework to assess forecasting techniques across all six Elspot markets in Norway, intimidating heuristic methods with advanced XGBoost and LSTM deep learning networks. Results consistently showcase the superiority of LSTM model over its counterparts in out-of-sample evaluations across most bidding zones. Specifically, the LSTM model in its multivariate configuration outperforms all other models for all aspects of error in bidding-zone NO2 and NO3. The univariate LSTM outperforms the other models in all aspects of error for the bidding-zone NO4. This is notable due to capability to capture price variance temporally, as well as a notable merits of robustness against outliers. Concurrently, the XGBoost model has also marked its presence by performing admirably in the bidding-zone NO6, also outperforming the other models for all aspects of error. This feat could be attributed to the simplicity of the XGBoost model as opposed to the more complex LSTM, making it less likely to overfit on data that exhibit less intricate and complex patterns. The variability in results across the different data-sets highlights the presence of unique characteristics for the distinct bidding-zones, therefore, model generalization will be the focal point of our future research endeavors.

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