UK Intraday Power Trading Using Changes in Expected Wind Speed and Price Momentum

Economic Rationale

Over the past decade, renewable energy sources, such as wind and solar power, have significantly increased their contribution to electricity generation. In the United Kingdom, wind energy has grown from virtually no contribution in 2007 to around 28.1% of electricity generation in 2023 (Department for Energy Security and Net Zero, 2024).

The availability of renewable energy, especially wind, impacts electricity prices. Xiao and Mu (2024) analyzed 30-minute wholesale electricity prices in the UK and found that increased wind energy production throughout the day significantly decreased electricity prices during peak hours (8:00 to 20:00). Their work was built upon Green and Vasilakos's (2010) hourly equilibrium price simulations conducted with wind data from 1993 to 2005. Following these findings, this paper aims to understand the effect of wind speeds on a more granular level of intraday electricity price setting, to create a trading algorithm that can take advantage of inefficiencies in the intraday market.

Electricity prices are determined by the balance between supply and demand. Each day suppliers and users of electricity trade in the day-ahead market, locking in their price of electricity for the next day at hourly and half-hourly intervals for each settlement period. As electricity in essence is a non-storable commodity (batteries and pumped hydro are minor parts of the grid), high-frequency supply-demand adjustments must be made during the day. These adjustments happen in the continuous intraday market and balancing market, the first being the focus of our paper.

Method of model

Our model fundamentally attempts to understand whether the price of a specific intraday 30-min forward contract at a given point in time is priced lower or higher than the expected last closing price. In an attempt to understand this, we began by reviewing each continuous intraday trade conducted since 30-12-2023, totaling c. 16m observations, spanning all 48 settlement periods ("SP") (in essence each of the 48, 30-min, settlement periods per day are different forward contracts). The initial analysis was conducted on SP27, which is the contract for delivery from 13:00-13:30 each day. Indicative analysis focusing on trend, seasonality, cyclicality, and partial autocorrelation yielded limited results. Only the PACF shows any statistical significance, with the interpretation being that a given intraday price is dependent on the previous observation. Next, we tested the correlation between intraday prices and a variety of factors. We found that the strongest correlation (ignoring the intraday time lags), albeit still quite weak, is the one between intraday prices and day-ahead prices (the price traded the day before for the specific SP).

Our basic hypothesis involved whether the deviations between expected wind speeds at the timing of the day-ahead trade and the realized wind speeds throughout the intraday could, to some extent, predict fluctuations in price. To understand this, we set up a database consisting of the 30 largest offshore wind farms in the UK, after which we matched the coordinates of the wind farms to weather stations. The database of all the wind farms' expected wind speeds (at t-1) and realized wind speeds totaled c. 13m observations. Using the hourly deviation of wind speeds for each wind farm, we set up a combined capacity (MW) weighted factor to use in our price model.

Given the difficulties in predicting the intraday prices, we decided on an iterative model approach. Based on our initial analysis the following independent variables were used in the model: day-ahead price, last hour's average price, intraday price lags 5 & 10, wind factor lag 1, average volatility day before, and volatility until t-10min. We applied an extreme gradient boosting ("XGBoost") machine learning algorithm on the dataset. The algorithm was originally designed for image recognition, but in essence, it is an iterative decision tree algorithm that continuously tests its predictions against an evaluation dataset to achieve the best features. The algorithm essentially clusters and weighs a set of weaker prediction features into a combined model (Ahmetoglu & Das, 2022). The issue with this approach would be overfitting as it continuously evaluates performance, and while the XGBoost algorithm already has countermeasures against this, we decided to split our dataset into training (60%), testing (20%), and trading (20%), to not overinflate our final trading data outputs. Based on the model, the features with, by far, the largest weighting (importance) were last hour's average price (71%) and intraday price lag 5 (26%). Unfortunately, our hypothesis concerning the wind data did not hold, with the wind factor only contributing to 0.3% of the model's predictive power. The interpretation instead is that the model primarily calculates price momentum, i.e., if the previous price increases it probably will again and vice versa.

The same procedure as above was conducted for the remaining 47 SPs and the ineffective models (which could be due to data issues) were discarded, this left us with models for SPs: 1, 3, 6, 8, 9, 11, 12, 14, 18, 20, 21, 22, 23, 30, 36, 42, 44, 47. The trading performance (more on this in the next section) of each model was then calculated using the trading dataset, after which the minimal variance portfolio of models was determined by calculating expected returns, covariance, and variance. The final portfolio weights of the trading strategy can be found below.

SP model	1	3	6	8	9	11	12	14	18	20	21	22	23	30	36	42	44	47
Weight	11%	12%	9%	-	-	-	7%	1%	6%	1%	-	9%	11%	0%	-	14%	6%	13%

Table 1: Portfolio weighting of SP trading strategies.

Investment strategy

Based on our model for each SP a long-short trading simulation was set up. The strategy essentially works as a four-step process:

1) The model starts with a capital of £1,000
2) Due to the short-term nature of the forward electricity contracts, i.e., they are traded the same day they are delivered, no position is held at the beginning of the day.

3) Throughout the day, the simulation evaluates the following:
    a. At the time, t, the information available to the model (all information leading up to t minus 1 minute) is used to ascertain: 1) Expected current intraday trading price ("CIT"), 2) Expected last intraday trading price ("LIT") (the price at gate-closure). For each t the model runs through the below conditionals, which are essentially determining whether to long, short, or close the position.
        i. If at t-1 the actual intraday price is less than or equal to zero, all positions are closed (analysis showcased extreme discrepancies in the model's understanding of negative prices as they are quite rare) and the model goes on to the next t (only one action for each model is assumed to happen for each period of t)
        ii. If at t-1 the actual intraday price times the absolute position held (long or short) exceeds 20% of the current capital the position is closed (a form of stop-loss / take-gains mechanism) and the model goes on to the next t.
        iii. If at t, $\mathrm{abs}(\mathrm{CIT} - \mathrm{LIT}) < \mathrm{abs}(\mathrm{transaction\ costs})$ the model goes on to the next t.
        iv. If at t, $\mathrm{CIT} - \mathrm{transaction\ costs} < \mathrm{LIT}$ and the current position is not negative, the model purchases one unit (one MWh) of electricity at the actual intraday price (at t). This purchase is added to the position (pos/neg position for long/short cumulative positions, the model cannot be long and short at the same time)
        v. If at t, $\mathrm{CIT} - \mathrm{transaction\ costs} > \mathrm{LIT}$ and the current position is not positive, the model shorts one unit of electricity at the actual intraday price.
        vi. If the model wanted to be long or short, but was not able to as the current position held was the opposite, then the position is closed, and the model goes on to the next t.
4) At the last trading period for each day (the last trade for the different settlement periods happens at different time points throughout the day) all positions are closed.

As mentioned previously our final strategy was a weighted portfolio of models for different settlement periods. This means the above strategy was simulated for each of the individual models, after which their results were weighed and included in our final performance. An important caveat is that the portfolio optimization was conducted on a simulation with nil transaction costs, as most of the simulations did not yield positive returns when including transaction costs. However, our final result which includes transaction costs, assumes costs for both going long, short, or closing a position.

Associated transaction costs, cost of capital, and volume

Continuous intraday trading of electricity primarily happens on EPEX Spot, which is also where we have received our information, the exchange has execution costs. These execution costs will vary for different market participants, often based on their size and liquidity provision, there is no set rate card for all participants. Upon consulting with industry experts, including both brokers and traders. We were able to gather that the transaction cost to execute a trade in the intraday continuous market is approximately £0.07/MWh. We have worked under the assumption that this level of costs would be applied to each of our trades.

In general, power trades are cleared via European Commodity Clearing (“ECC”), the ECC clears and settles trades using both initial and current margins (European Commodity Clearing AG, 2024). The calculation of these margins depends on a few different factors, with an underlying importance of time to settlement and timing of exposure. However, given the nature of our strategy, the margin parameter has been set to 1, meaning that for every trade, we will, at the time of trade, pay the net payment amount. Due to the short-term nature of the trade, the clearing house states that all standard products and markets are set to a margin parameter of 1 for buying and selling.

EPEX Spot is a highly liquid market that is in operation 24/7 with 176TWh traded in 2023 alone, 346TWh if you consider double-sided volumes (EPEX SPOT SE, 2024). This translates to 482,192 MWh per day without considering double-sided volumes. The volume tick size for a transaction is c. 0.1 MWh, meaning that the exchange processes thousands of trades per day. The UK market alone (the focus of our analysis) accounts for c. 10-12% of total traded volume, meaning the daily traded volume is c. 50,000 MWh. The practical implementation of our strategy, despite trading several thousand times per day, should therefore still be feasible from a volume perspective.

Results of the strategy

We considered two scenarios for the strategy: the first one where the transaction costs were nil and the second one where each MWh traded had a cost of £0.07. The trading test dataset consisted of 44 trading days. The nil transaction cost trading strategy yielded a return of 79.16% over the trading period. Corresponding to an annualized return of 12,513% with an annualized volatility of 52.7%. The second scenario, however, only yielded a return of 1.14% during the trading period, equivalent to an annualized return of 9.82% with an annualized volatility of 62.98%.

The vast difference between the two scenarios is explained by the high-frequency nature of the trading strategy. The algorithm conducts approximately 2,200 trades per day across the 12 settlement periods included. In essence, the marginal gain of each transaction is heavily diminished by the transaction costs. Despite the trading simulation taking into account that a theoretical gain should exceed transaction costs, the mere existence of transaction costs continues to severely punish the strategy due to its imperfect predictions.

When assessing our strategy we applied two measures:

1. Maximum Drawdown (“MDD”): the largest percentage loss in the value of an investment portfolio over a period of time.
2. Calmar Ratio: the ratio between the difference of the return of the strategy and the risk-free rate, and the maximum drawdown.

In the following table the performance of the strategy on the two metrics is shown:

Metric	Strategy without costs	Strategy with transaction costs
MDD	-8.43%	-28.62%
Calmar Ratio	1,484.66	0.21

Table 2: Assessment of the strategy.

As mentioned previously, the difference in assuming no transaction costs has a major impact on the performance of the strategy. Our strategy performs poorly both in terms of MDD and Calmar ratio when factoring in transaction costs. The only positive highlight of the strategy is that it continues to display a positive annualized return, however, when considering the volatility of this return, the strategy is less favorable.

Based on our assessment of the strategy in its current form, using it to achieve excess returns would not be advised.

Further developments of the strategy

The fundamental hypothesis of our strategy, that hourly changes in expected wind speeds would have a statistically significant effect on intraday settlement period prices, proved to not display meaningful results within our model setup. However, as has been shown by Xiao and Mu (2024), this should not be the case. Further developments of our model should therefore be focused on adjusting the parameters by which we ascertain the wind speed production factor. A more granular approach, also taking into account individual wind farm's optimal wind speed level, could yield a higher predictive power. On a more practical basis, we found that the transaction costs of the strategy had a significant impact on returns achieved. Adjusting the model's certainty threshold, i.e., requiring the deviations between the predicted current- and last intraday price to be higher, thereby reducing the number of trades (and hopefully the accuracy of each trade), could yield positive results for the strategy.

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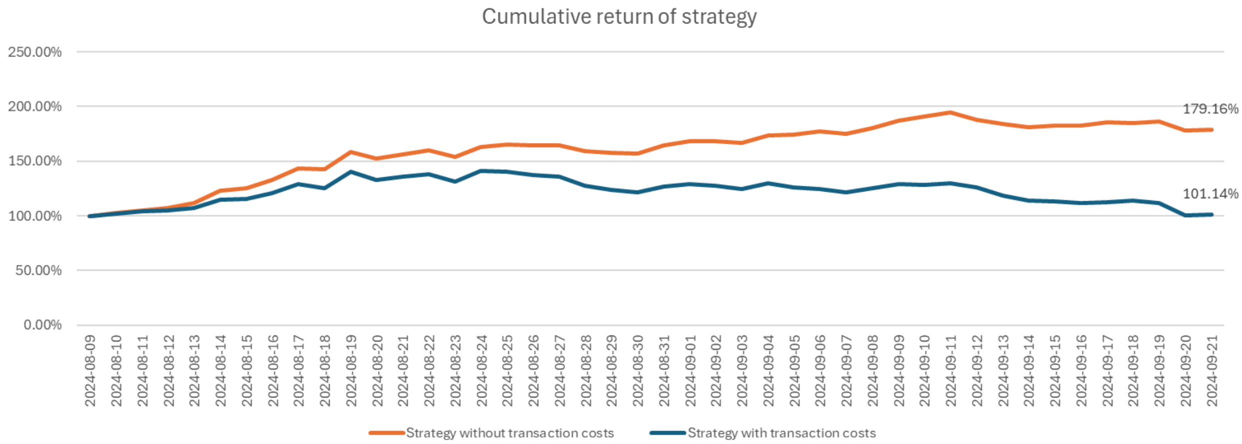
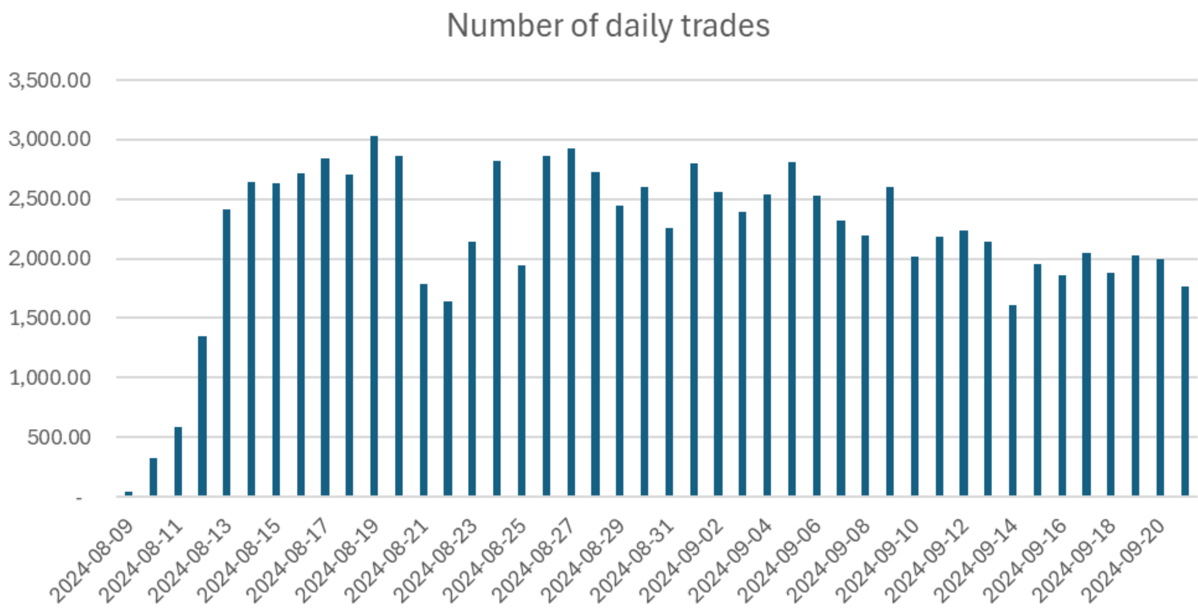
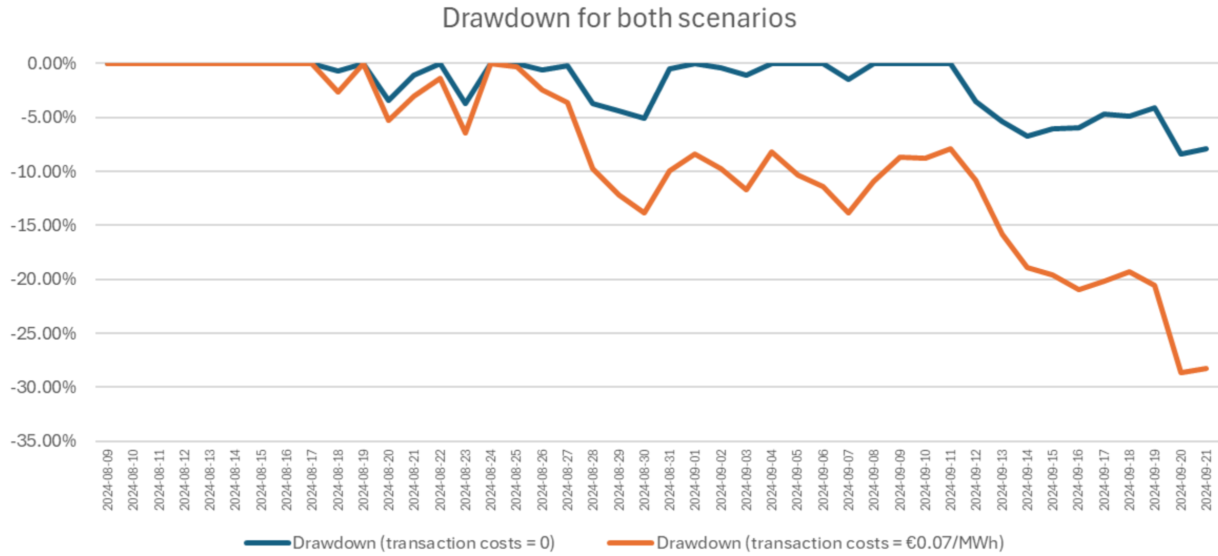
Appendix



Graph 1: Cumulative return of strategy.



Graph 2: Number of trades executed daily by date.



Graph 3: Drawdown for both scenarios.