# Technical Indicators for Hourly Energy Market Trading

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# Biography

My background - Mathematics with Statistics (BSc); Risk Management & Financial Regulation (MSc); worked as Data Analyst for 5 years.

I’m currently a final year PhD researcher working in collaboration with Click Energy focusing on computational approaches to energy trading. I’m located at the Magee campus of Ulster University in Northern Ireland.

The aim of my project is to remain competitive in the **I**ntegrated **S**ingle **E**lectricity **M**arket (**ISEM**).
The goal is a robust working system that can analyse large datasets with the use of computational intelligence models to forecast future electricity prices.

# Overview

- Electricity Price Forecasting
- Technical Indicators
- Machine Learning Regression Algorithms
- Key Findings
- Summary

# Background

- Electricity Price Forecasting:
  - Volatile characteristics.
  - Imbalances between demand and supply.
  - A robust day-ahead prediction model is desirable to reduce trading costs.

- Time-series models:
  - Analyse patterns to follow past market trends.
  - Assists electricity suppliers in future planning to reduce purchasing costs.
  - This research develops eight new technical indicators specifically for the energy market to help control spending and reduce trading costs.

# Technical Indicators

- Technical analysis is an appropriate tool for finding information on upcoming share price, by building indicators from raw price data to capture trends over time.

- Technical indicators are widely used in the financial market for predicting stock market price, often combining machine learning.
  - Technical price indicators were set up in terms of energy trading derived from, but not identical to, the standard indicators applied to financial trading.
  - Energy data and financial data have similar features therefore deriving technical indicators specifically for electricity prices will help predict future prices and reduce trading costs.

# Price Technical Indicators

- The main price indicators can be split into three types:
    - Trend
    - Oscillator
    - Momentum

- The proposed technical indicators were derived from electricity price data, collected on an hourly basis (building on the idea of Demir et al. [2019]).

- This research examines 24-hour models first and then separate 1-hour models for each of the 24 hours to determine if technical indicators do follow hourly patterns and are therefore better at matching market trends when split by hour.

# Trend Technical Indicators

| Technical Indicator | Description | Calculation |
|---|---|---|
| **Percentage Price Change Moving Average (PPCMA)** | Used in time-series to include average values from previous i periods | $\sum_i PPC$ where $PPC = (\frac{Price_{Current} - Price_{Lag\,24}}{Price_{Lag24}}) * 100$ |
| **Moving Average Deviation (MAD)** | Deviation Rate of current price from moving average | $(\frac{Price_{Current} - PPCMA_i}{PPCMA_i})$ |
| **Average True Range (ATR)** | Price Volatility | $\sum_i MAX\,[A_i, B_i, C_i]$ where $A_i$ = (Highest $Price_i$ – Lowest $Price_i$), $B_i$ = \|Highest $Price_i$ – $Price_{Lag\,24}$\|, $C_i$ = \|Lowest $Price_i$ – $Price_{Lag\,24}$\| |
| **Average Directional Movement Index (ADX)** | Strength of trend | $(\frac{\Sigma_i\, DX\ Up[ai] - DX\ Down[bi]}{\Sigma_i\, DX\ Up[ai] + DX\ Down[bi]}) * 100$ where $a_i = (\frac{\Sigma_i\, Price\ Up[Price_{Current} - PriceLag_{\,i}]}{ATR_i})$, $b_i = (\frac{\Sigma_i\, Price\ Down[Price_{Current} - PriceLag_{\,i}]}{ATR_i})$ |

# Oscillator Technical Indicators

| Technical Indicator | Description | Calculation |
|---|---|---|
| Percentage Range (PR) | Relationship between current closing and high/low prices. Oscillates between 0 and 100. If value above 80 then oversold, if value below 20 then overbought. | $\left(\frac{\text{Highest Price}_i - \text{Price}_{\text{Current}}}{\text{Highest Price}_i - \text{Lowest Price}_i}\right) * 100$ |
| Relative Strength Index (RSI) | Compares recent gains to recent losses. Oscillates between 0 and 100. If value over 70 then overvalued, if value below 30 then undervalued | $100 - \left[\frac{100}{D_i}\right]$ <br> where $D_i = \left(1 - \frac{\sum_i \text{Price Up}[\text{Price}_{\text{Current}} - \text{PriceLag}_i]}{\sum_i \text{Price Down}[\text{Price}_{\text{Current}} - \text{PriceLag}_i]}\right)$ |
| Moving Average Convergence/Divergence (MACD) | Trend strength, trend direction, trend duration, and price momentum | $\sum_{7} \text{Price MALag}_7 - \sum_{14} \text{Price MALag}_{14}$ |

# Momentum Technical Indicators

| Technical Indicator | Description | Calculation |
| --- | --- | --- |
| **Price Momentum** | Power of the market | $Price_{Current} - Price_{Lag\ i}$ |

The individual calculations for each of the indicators are used in both the 24-hour models and separate hourly models.
For the 24-hour models, a rolling 24-hour window (i=24) was calculated.
For the hourly models, a pool (i) ranging from a rolling 1-hour window (i=1) to a 100-hour window (i=100) was calculated.

# Machine Learning Methodology

Trained three machine learning models, implemented using SkLearn:

- **Random Forest:** Implemented with 1000 trees and criterion measure of split was set to **M**ean **S**quared **E**rror (MSE) with minimum sample split set to 2 and minimum sample leaf node set to 1.

- **Gradient Boosting:** Implemented with 100 trees, minimum sample split set to 2, minimum sample leaf node set to 1, maximum depth of tree was set to 3, and learning rate of 0.1.

- **XG Boost:** Implemented with 1000 trees, the fraction of column to be a random tree sample was set to 0.6, the fraction of observations to be random tree subsample was set to 0.8, the maximum depth of tree was set to 4, with a learning rate of 0.05.

# 24-hour Models

- Data split by 85% train and 15% test.

  **Training period:** 04th February 2019 to 16th October 2019 (6121 records)

  **Testing period:** 17th October 2019 to 30th November 2019 (1081 records)

## Persistence Model:

- **Model Input:** System Marginal Price at time T

  **Model Output (y):** System Marginal Price at time T+24

## Technical Indicator Model:

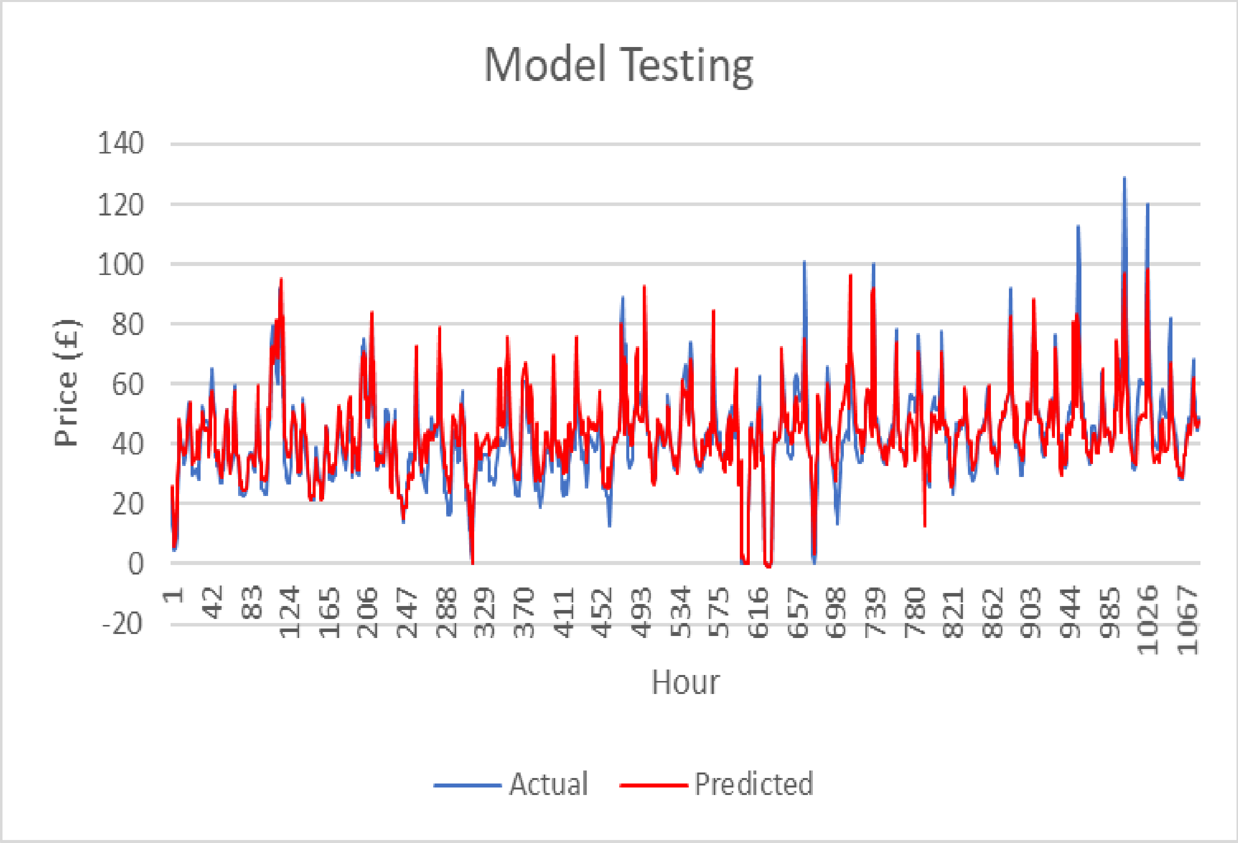
- **Model Inputs:** PPCMA, MAD, Percentage Range, ATR, RSI, ADX, MACD, Price Momentum (all indicator inputs at time T)

  **Model Output (y):** System Marginal Price at time T

# 24-hour Models Results

| Algorithm | Persistence Models | | Technical Indicators | |
|---|---|---|---|---|
| | Accuracy | RMSE | Accuracy | RMSE |
| Gradient Boosting | 75.44% | 13.18 | 86.90% | 6.66 |
| Random Forest | 73.21% | 16.30 | 91.57% | 6.77 |
| XG Boost | 75.02% | 14.39 | 89.70% | 5.34 |

# 24-hour Models Results




Random Forest 24-Hour Model Testing

# Hourly Optimal Models Methodology

- The hourly models contain different parameters depending on the hour (0-23).
- A pool of indicators ranging from 1 to 100 were created as the first step, selecting the optimal indicators for each hour.
- Hyperparameters n and s represent the lag factor and span respectively.
- In this research, n was utilized in the creation of five of our novel technical indicators (PR, ATR, RSI, ADX, and PMOM) and s was utilized in the creation of two of our novel technical indicators (PPCMA and MAD).
- To find the optimal n and s for each hour, the model which provided the lowest **R**oot **M**ean **S**quare **E**rror (RMSE) using the Random Forest algorithm was selected.
- Optimized through creating a list with all possible combinations for n and s and ranking the RMSE for each combination in order from lowest to highest RMSE.

# Hourly Optimal n and s

| Hour | Optimal n | Optimal s |
|---|---|---|
| 0 | 48 | 45 |
| 1 | 100 | 42 |
| 2 | 61 | 74 |
| 3 | 59 | 5 |
| 4 | 59 | 76 |
| 5 | 74 | 75 |
| 6 | 100 | 99 |
| 7 | 99 | 75 |
| 8 | 91 | 93 |
| 9 | 2 | 97 |
| 10 | 87 | 82 |
| 11 | 75 | 76 |

| Hour | Optimal n | Optimal s |
|---|---|---|
| 12 | 78 | 77 |
| 13 | 41 | 7 |
| 14 | 95 | 97 |
| 15 | 83 | 71 |
| 16 | 87 | 82 |
| 17 | 106 | 80 |
| 18 | 87 | 94 |
| 19 | 102 | 99 |
| 20 | 102 | 106 |
| 21 | 56 | 38 |
| 22 | 81 | 81 |
| 23 | 55 | 55 |

# Hourly Optimal Models

- Data split by 85% train and 15% test.

  **Training period:** 11th May 2019 to 31st October 2019 (174 records)

  **Testing period:** 01st November 2019 to 01st December 2019 (31 records)

- It was clear that no matter which machine learning algorithm was used, the use of technical indicators improved prediction performance. Therefore, we only create hourly models using the Random Forest algorithm.

**Technical Indicator Model:**

- **Model Inputs:** PPCMA, MAD, Percentage Range, ATR, RSI, ADX, MACD, Price Momentum (all indicator inputs at time T)

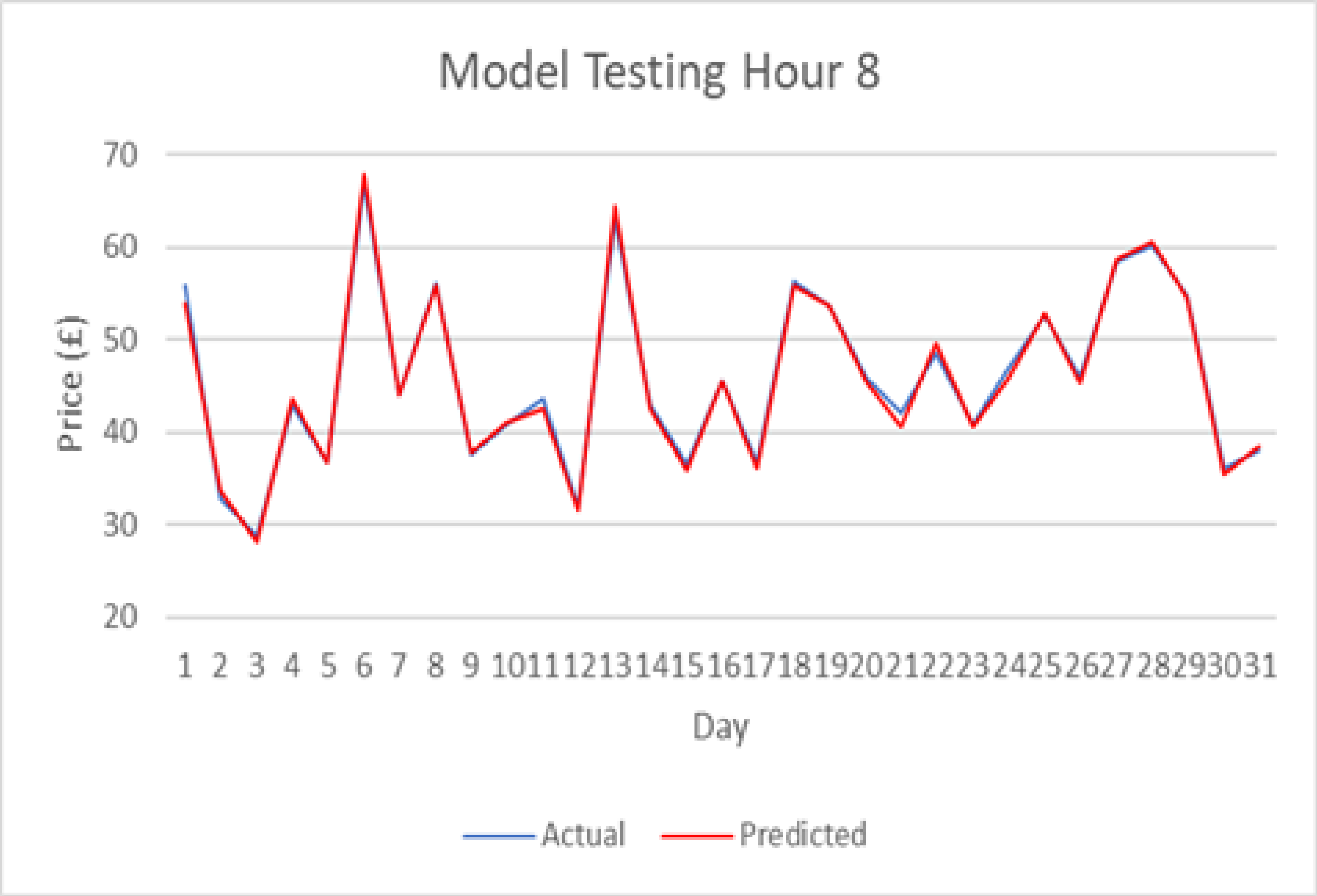
  **Model Output (y):** System Marginal Price at time T

# Hourly Optimal Models Results

| Hour | Accuracy | RMSE |
|---|---|---|
| 0 | 88.16% | 1.55 |
| 1 | 98.17% | 0.98 |
| 2 | 90.26% | 0.81 |
| 3 | 84.78% | 0.77 |
| 4 | 86.28% | 0.87 |
| 5 | 89.33% | 0.75 |
| 6 | 91.16% | 3.16 |
| 7 | 98.74% | 1.28 |
| 8 | 99.32% | 0.74 |
| 9 | 98.92% | 1.19 |
| 10 | 98.46% | 1.99 |
| 11 | 98.64% | 1.69 |

| Hour | Accuracy | RMSE |
|---|---|---|
| 12 | 98.82% | 1.47 |
| 13 | 98.02% | 2.38 |
| 14 | 97.89% | 2.42 |
| 15 | 98.50% | 1.74 |
| 16 | 98.04% | 3.24 |
| 17 | 94.62% | 11.86 |
| 18 | 97.65% | 4.6 |
| 19 | 98.58% | 1.79 |
| 20 | 98.70% | 1.44 |
| 21 | 98.32% | 1.95 |
| 22 | 98.32% | 1.59 |
| 23 | 86.87% | 1.75 |

# Hourly Optimal Models Results



# Conclusion

- Eight technical indicators were derived from raw data for energy trading and tested on three machine learning regression models to forecast electricity prices.

- The technical indicators were first calculated using a 24-hour approach and then re-calculated when split by hour.

- The accuracy ranged between 73% and 76% for the persistence models and ranged between 86% and 92% for the technical indicator 24-hour models.

- The testing accuracy ranged between 84% to over 99% for each of the optimal hour models and the majority had a RMSE value below 3. These promising results indicate that individual hour models are more homogeneous and beneficial for energy trading.

- To conclude, energy traders should consider technical indicators in price prediction models, especially individual models that have been optimised for each hour of the day, to capture market trends and enable accurate predictions, thus reducing purchasing costs.

# Questions?

Thank-you for listening

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