Technical Report 2: Holt-Winters Exponential Smoothing for DA Market Price Forecasting

February 2025

1 Introduction

Forecasting electricity market prices is a crucial task in energy trading, as accurate predictions enable better decision-making and risk management. Time series forecasting methods provide a way to model historical patterns and predict future price fluctuations. Among these, the Holt-Winters Exponential Smoothing method is particularly useful for data with trend and seasonality, making it well-suited for Day-Ahead Market (DAM) price forecasting.

The Holt-Winters method, also known as Triple Exponential Smoothing, is an extension of simple exponential smoothing that accounts for level, trend, and seasonal effects. This technique is especially relevant for ISEM price forecasting, where electricity prices exhibit daily and weekly cyclic patterns influenced by demand fluctuations, wind generation, and fuel prices.

This report explores how Holt-Winters Exponential Smoothing can be applied to ISEM DAM price forecasting and outlines its implementation in Python.

2 Why Use Holt-Winters?

Electricity prices exhibit both trends and seasonal patterns, making accurate forecasting challenging. The Holt-Winters method is particularly useful because:

- It smooths out fluctuations and detects long-term trends.
- It effectively captures daily and weekly price cycles.
- It predicts future prices by combining three key components: level, trend, and seasonality.

3 Holt-Winters Model

The Holt-Winters Exponential Smoothing method is a time series forecasting technique designed to handle data that exhibits both trend and seasonality. This method is an extension of simple exponential smoothing, incorporating two additional components to account for trends and seasonal cycles.

The Holt-Winters Exponential Smoothing model consists of three components:

- **Level** (a_t) – The overall average price at time t. **ISEM DA Price**
- **Trend** (b_t) – The rate of change over time. **ISEM_DA_Price over time**
- **Seasonality** (c_t) – Recurring patterns in price fluctuations. **Weekday, Season, StartHR**

3.1 Forecasting Equations

The forecast for h steps ahead is given by:

- Multiplicative Model (used when seasonal variations are proportional to trend):

$$\hat{x}_{t+h} = (a_t + hb_t) \cdot c_{t+h-L}$$

- Additive Model (used when seasonal variations are independent of trend):

$$\hat{x}_{t+h} = a_t + hb_t + c_{t+h-L}$$

where:

- $\hat{x}_{t+h}$ = Forecasted price at time $t + h$.
- h = Forecast horizon (how many steps into the future we predict e.g 48 steps for a 24hr forecast with 30min intervals.).
- L = Seasonal period (e.g., 48 for 30 min data with daily seasonality).
- c_{t+h-L} = Seasonal adjustment factor.

The choice between the multiplicative and additive model depends on whether seasonal effects are proportional to the trend (multiplicative) or remain constant over time (additive).

3.2 Updating Model Components

At each new time step t, the model updates its components as follows:

- Level Update:

$$a_t = \alpha \frac{x_t}{c_{t-L}} + (1 - \alpha)(a_{t-1} + b_{t-1})$$

- Trend Update:

$$b_t = \beta(a_t - a_{t-1}) + (1 - \beta)b_{t-1}$$

- Seasonality Update:

$$c_t = \gamma \frac{x_t}{a_t} + (1 - \gamma)c_{t-L}$$

where α, β, γ are smoothing parameters optimised to minimise forecasting errors.

4 Performance Evaluation

To measure model accuracy, we compute:

1. Mean Absolute Error

$$MAE = \frac{1}{n} \sum |x_t - \hat{x}_t|$$

2. Root Mean Squared Error

$$RMSE = \sqrt{\frac{1}{n} \sum (x_t - \hat{x}_t)^2}$$

3. Mean Absolute Percentage Error

$$MAPE = \frac{100}{n} \sum \left| \frac{x_t - \hat{x}_t}{x_t} \right|$$

Component	Description	Formula/Implementation	Dataset Variables
Level (a_t)	Expected price at time t.	$a_t = \alpha \frac{x_t}{c_{t-L}} + (1-\alpha)(a_{t-1} + b_{t-1})$	ISEM_DA_Price
Trend (b_t)	Rate of price change over time.	$b_t = \beta(a_t - a_{t-1}) + (1-\beta)b_{t-1}$	ISEM_DA_Price over time
Seasonality (c_t)	Recurring patterns in electricity prices.	$c_t = \gamma \frac{x_t}{a_t} + (1-\gamma)c_{t-L}$	StartHr, WeekdayGroup, Season
Smoothing (α)	Weight of recent data on level.	Auto-optimised in Python.	Computed
Smoothing (β)	Weight of trend component.	Auto-optimised in Python.	Computed
Smoothing (γ)	Weight of seasonality.	Auto-optimised in Python.	Computed

Table 1: Holt-Winters Model Components and Relevant Variables

5 How Does the Model Work?

At each time step, the model:

1. Estimates a baseline price (Level).
2. Tracks how price changes over time (Trend).
3. Adjusts for repeating daily/weekly cycles (Seasonality).

These components allow for dynamic adaptation, ensuring that price forecasts reflect both long-term trends and short-term variations.

6 How Do We Implement It?

The implementation of the Holt-Winters model follows these key steps:

- **Step 1:** Load the ISEM DA Price dataset for historical electricity prices.
- **Step 2:** Fit the Holt-Winters model using Python's statsmodels library.
- **Step 3:** Generate forecast for the next 24 hours in increments of 30 minutes.
- **Step 4:** Evaluate forecast accuracy using error metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE).