

Team 5: Power Prediction and Energy Arbitrage Modeling for Wind Farms Using ML

Market Integration and Commercial Optimization, WiSe 2025/26

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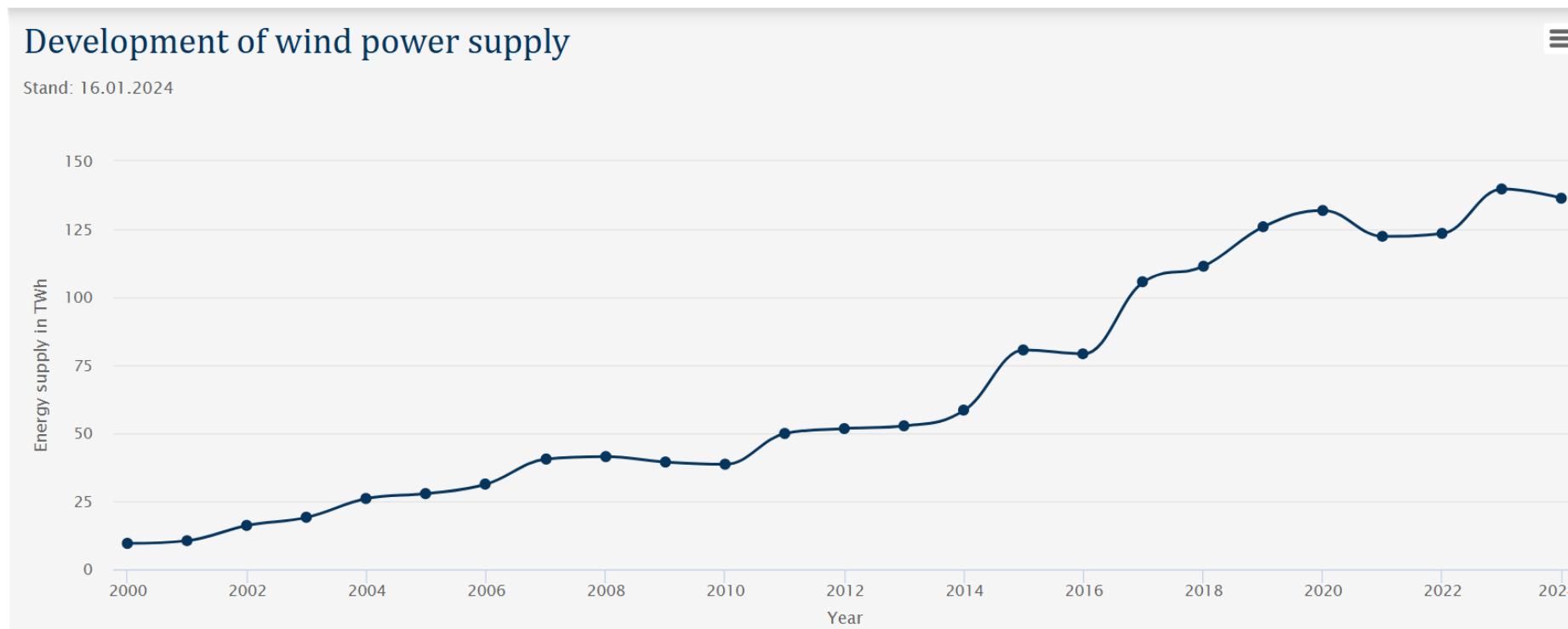
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1. Introduction

- **Wind Energy:** One of the fastest-growing (Germany)
- Wind power (variable) → wind speeds (change)
- Electricity markets (fluctuate) → Wind production (high)
- Modern energy systems increasingly use **data** and **machine learning**:
 - improve forecasting
 - operational decisions



2. Problem Statements

- Wind power output changes every hour → difficult to predict
- Electricity prices fluctuate strongly → revenue is uncertain
- Selling at the wrong time reduces profit for wind-farm operators
- Hard to know when storing energy will be more profitable than selling
- A **data-driven ML model** is needed to support STORE vs SELL decisions

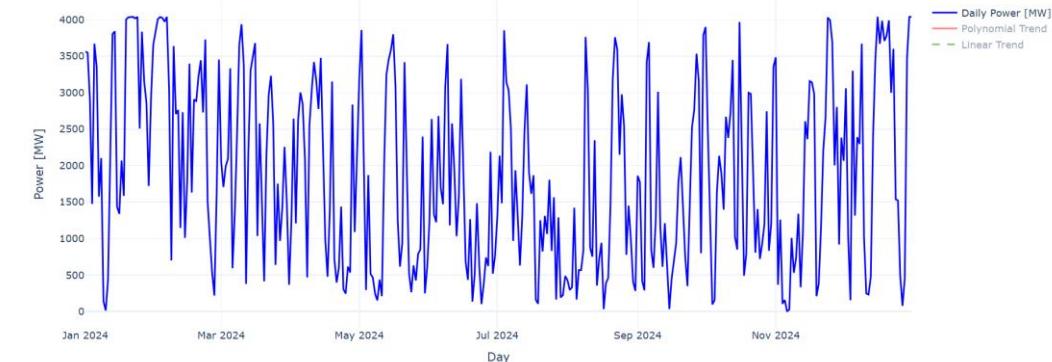


Fig 2.1: Day Vs Power generation (MW) ([Own](#)).

Research Question:

1. Can machine-learning models accurately predict wind-farm power output and identify the optimal hours to STORE or SELL energy?
2. If low-price energy is stored as hydrogen, can the hybrid system remain economically profitable without subsidies?

3. Data and Preprocessing

1. Wind Data (ERA5):

- Used ERA5 reanalysis dataset for wind components (u_{100}, v_{100}) (3)
- Calculated wind speed at 100m
- Converted to a clean CSV file (wind_speed.csv)

2. Electricity Price Data:

- Imported sport market prices (EUR/MW) (5)
- Cleaned timestamps and extracted hour and month

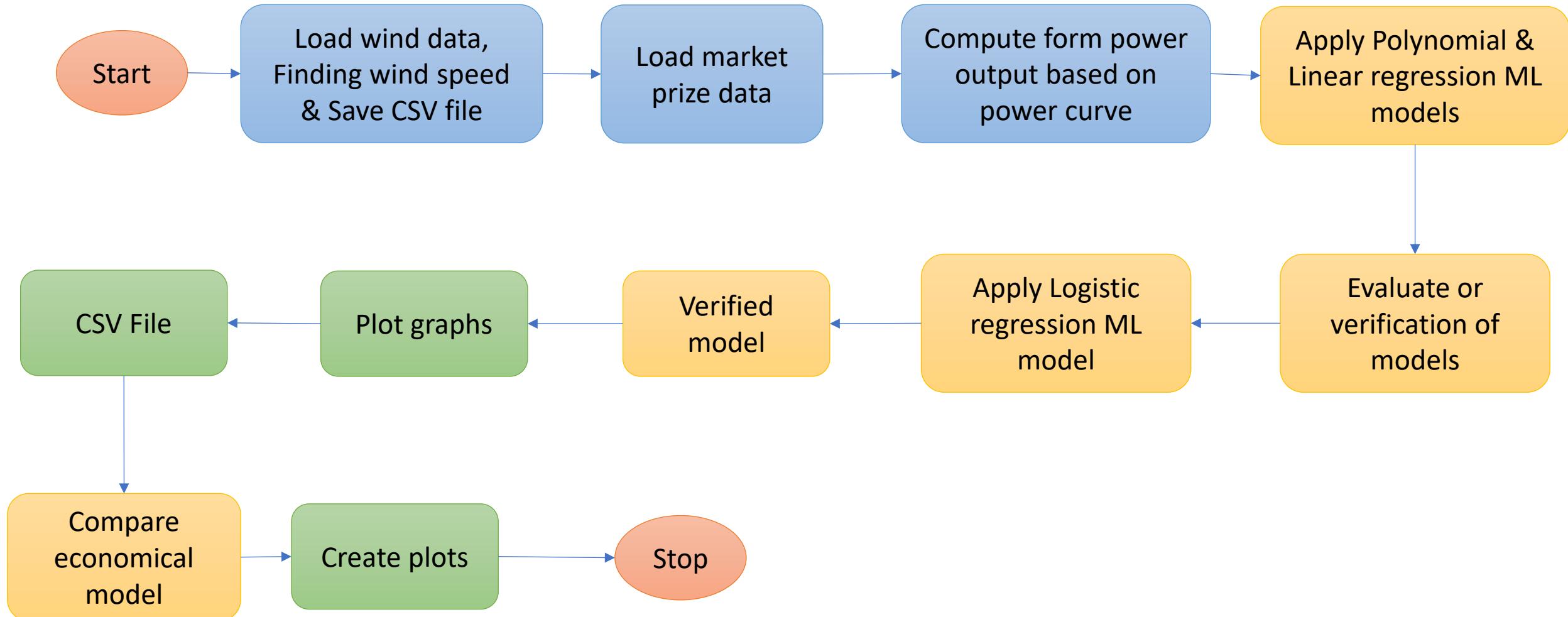
3. Power Curve Processing:

- Location: Reusenkoog, Germany
- Scaled for 51 turbines (total farm capacity) (1)
- Used Vestas V112-3.3 MW turbine power curve (2)
- Converted wind speed → power output

4. Electricity Price Data:

- Model: 50 MW PEM System (4)
- Efficiency: 52.2 kWh /kg H₂ Nominal
- Min Load: 10% (5MW)

4. Flowchart



5. Machine Learning Models

Why ML?

1

Fast growing and widely used field

2

ML helps automate STORE vs SELL decisions

3

Gives a more mathematical and accurate solution

4

Patterns are **non-linear** and difficult to capture manually

5

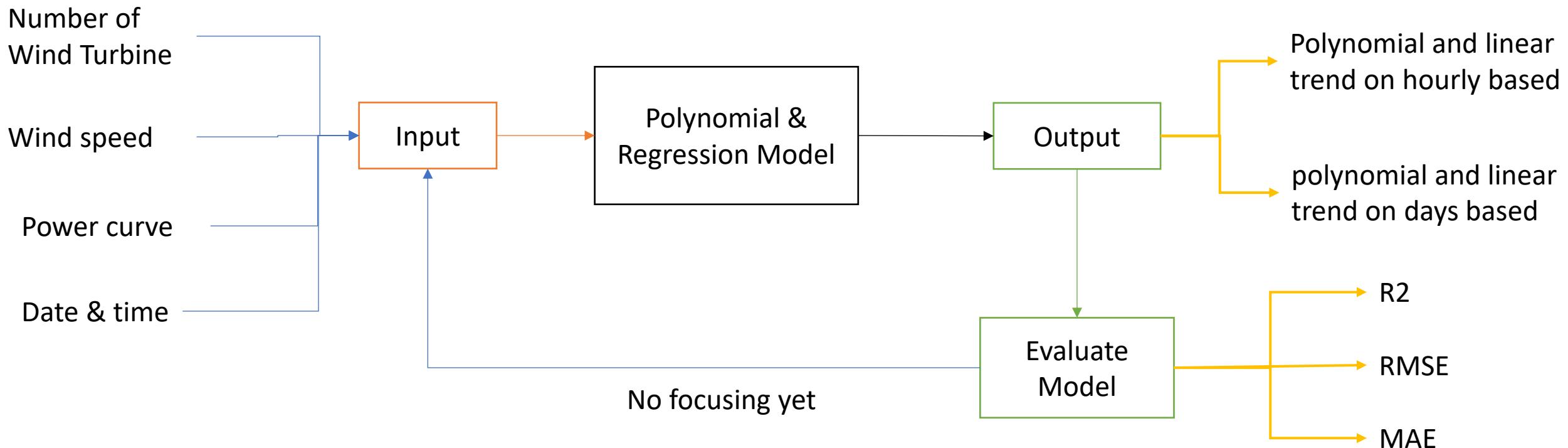
ML learns from historical data and improves decision accuracy



Reference: <https://www.vecteezy.com/free-photos/machine-learning>

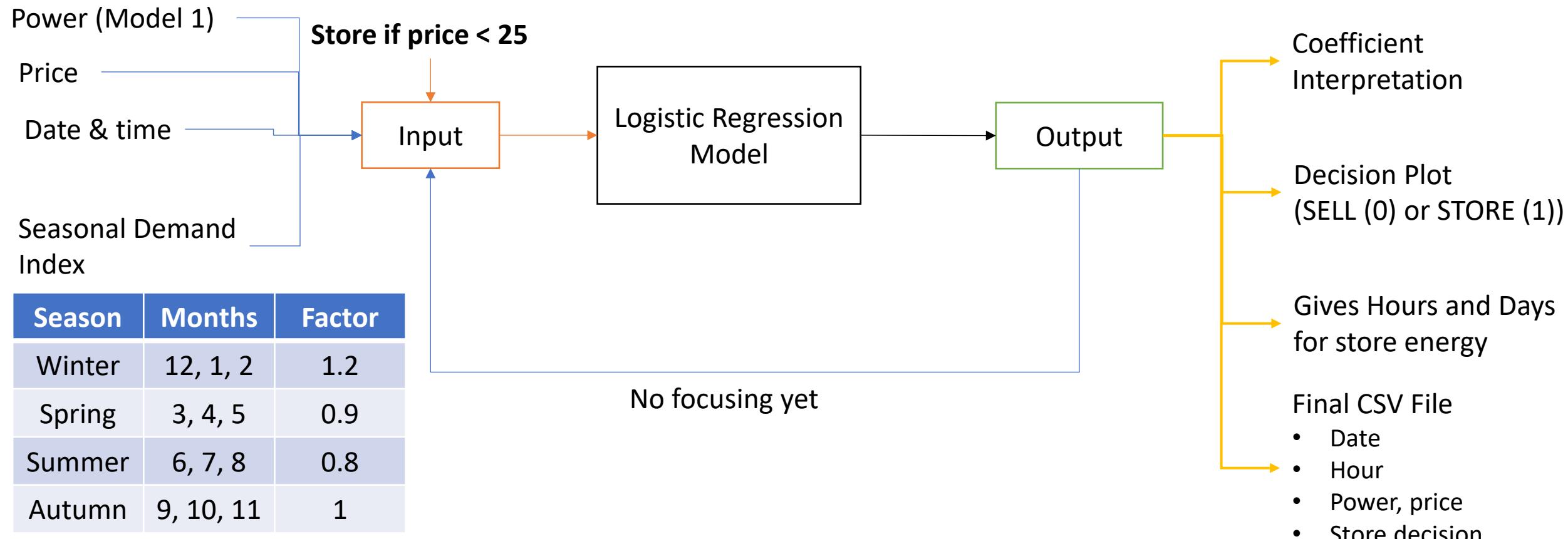
5. Machine Learning Models

Block Diagram of Wind Farm Model:



5. Machine Learning Models

Decision Arbitrage Model:



6. Hydrogen Storage Concept

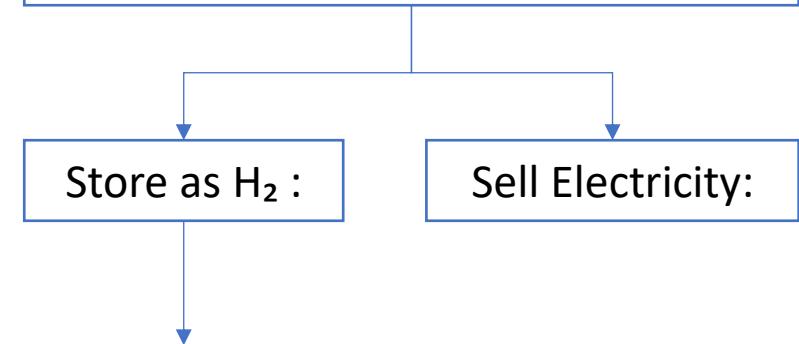
Set Economical and Technical Parameters:

- H₂ price = 4 (€/kg)
- variable O&M = 20% (€/kg)
- Electricity Required to produce 1 kg H₂= 52.2 (kWh/kg)
- Maximum power capacity of the electrolyze = 50 (MW)
- Min load fraction = 10%

Compute Breakeven Electricity Prize:

$$P^* \left(\frac{\text{€}}{\text{MWh}} \right) = \frac{(\text{H}_2 \text{ price} - \text{variable O&M}) * 1000}{\text{Electricity Required to produce 1 kg H}_2}$$

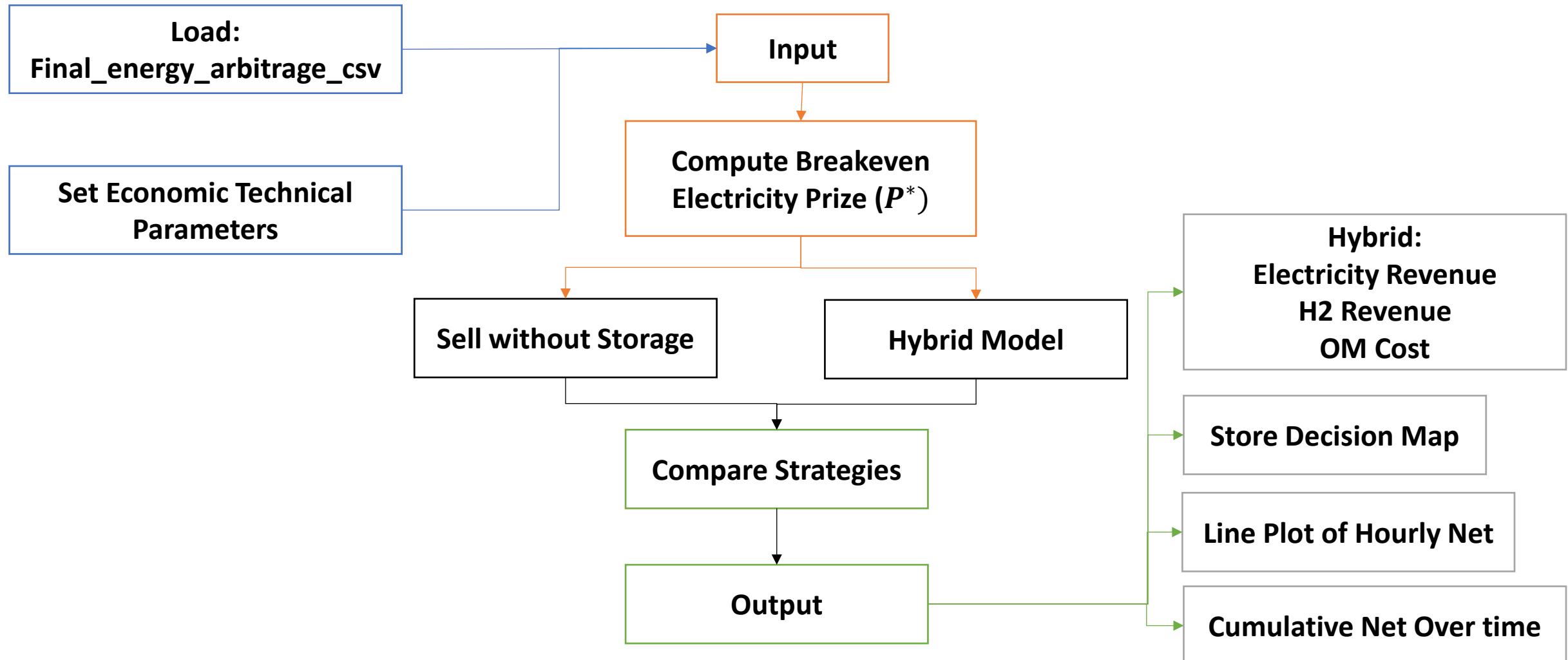
For Each hour, decide and dispatch:



If store_decision = 1 and (optionally) price ≤ p*:

- Run electrolyzer at min(wind, 50 MW) if ≥ 5 MW; else off
- H₂ produced = (MW × 1000) / 52.2 kg/h
- Electricity sold = wind – electrolyzer_MW
- Hybrid net = elec revenue + H₂ revenue – var O&M

7. Economic Analysis Modelling



8. Results

Model 1: Polynomial and Regression Model

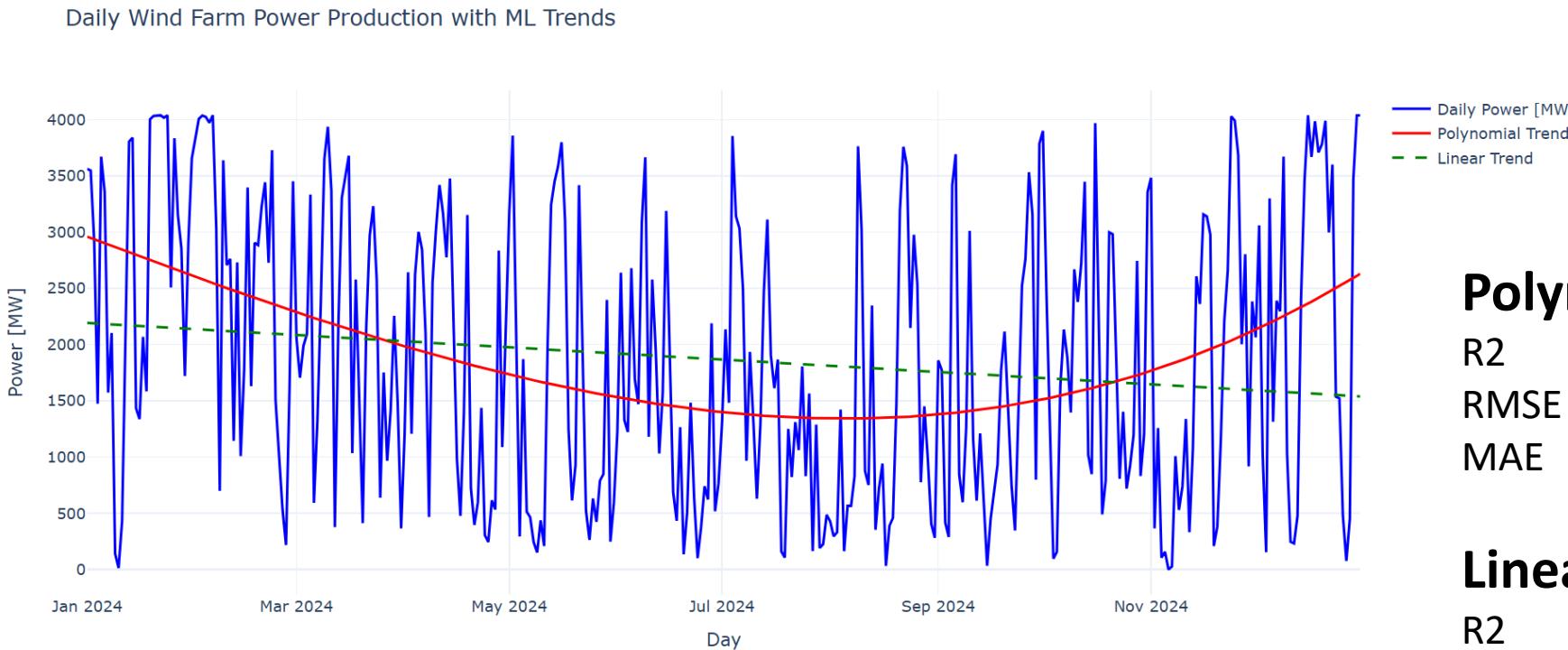


Fig 8.1: Day Vs Power



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Polynomial Regression Model:

R2 : 0.14
RMSE : 1155
MAE : 993

Linear Regression Model:

R2 : 0.02
RMSE : 1230
Mae : 1079

8. Results

Model 1: Polynomial and Regression Model

Hourly Wind Farm Power Production with ML

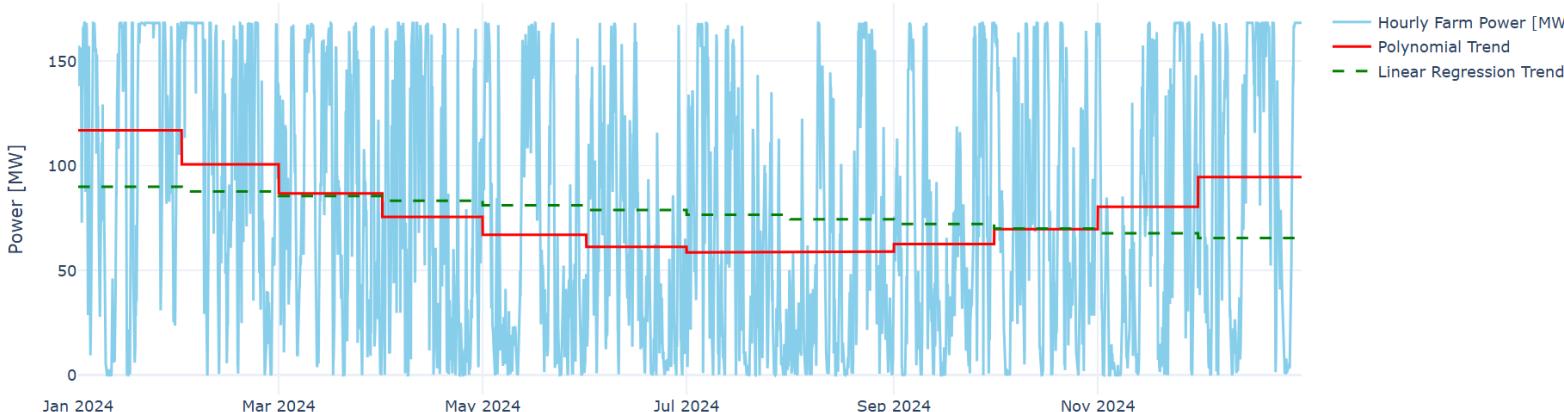


Fig 8.2: Hours Vs Power



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Polynomial Regression Model:

R2 : 0.94
RMSE : 3347
MAE : 2723

Linear Regression Model:

R2 : 0.16
RMSE : 12308
Mae : 10524

8. Results

Model 2: Logistic Regression Model

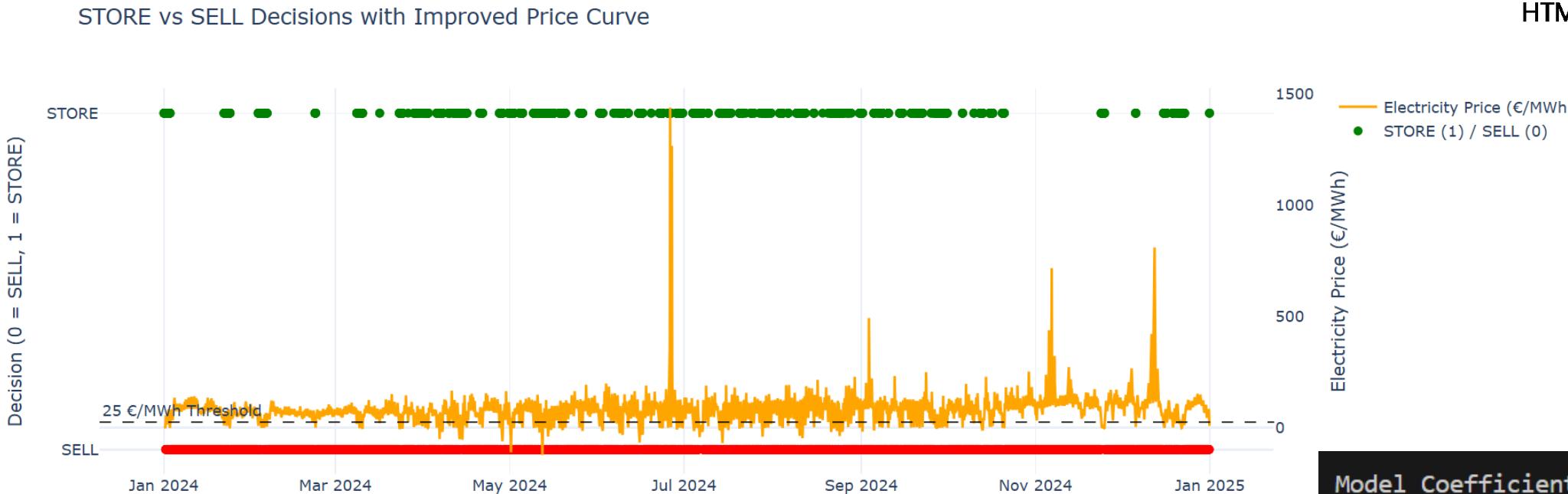


Fig 8.3: Hours Vs Store or Sell Vs Electricity Price

Model Coefficients:

Power	:	-0.01
Price	:	-2.82
Seasonal Demand	:	-0.09

8. Results

Model 3: Hydrogen Storage Concepts

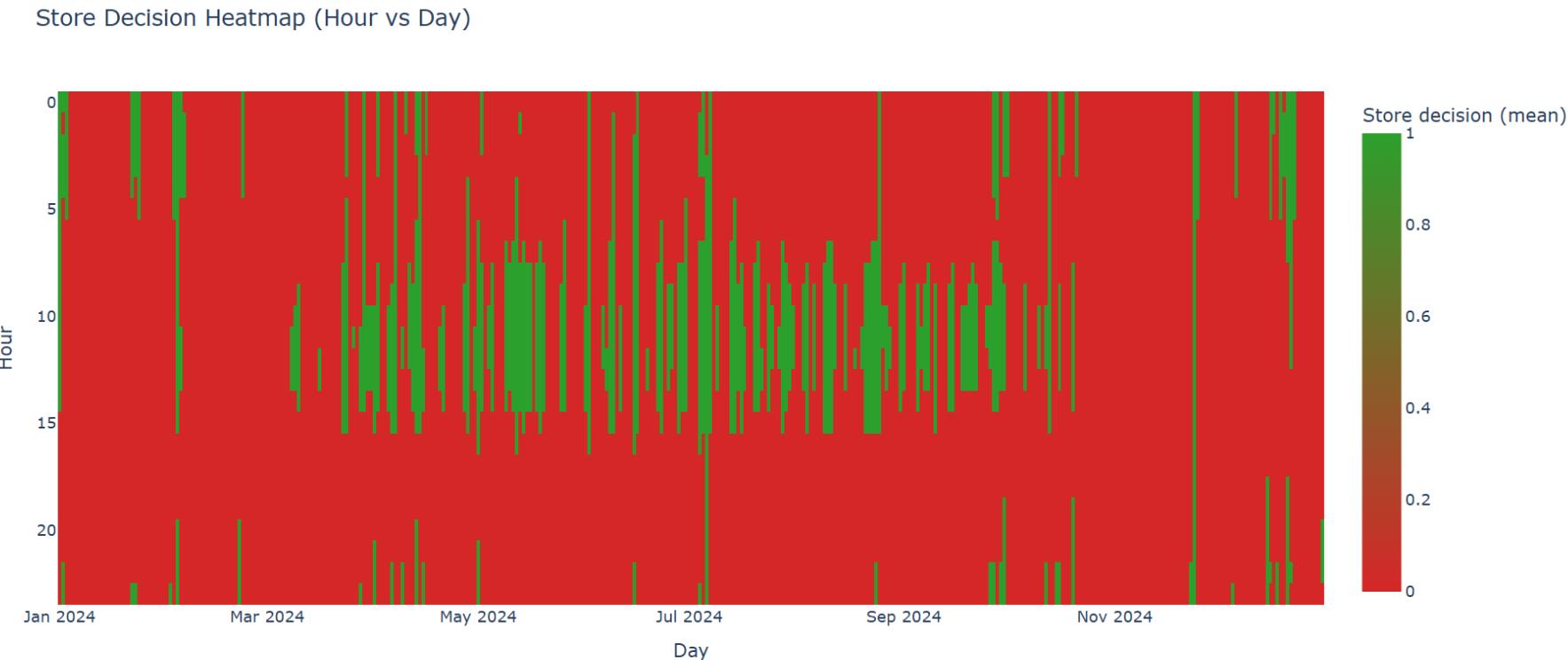


Fig 8.4: Store Decision Map



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8. Results

Model 3: Hydrogen Storage Concepts

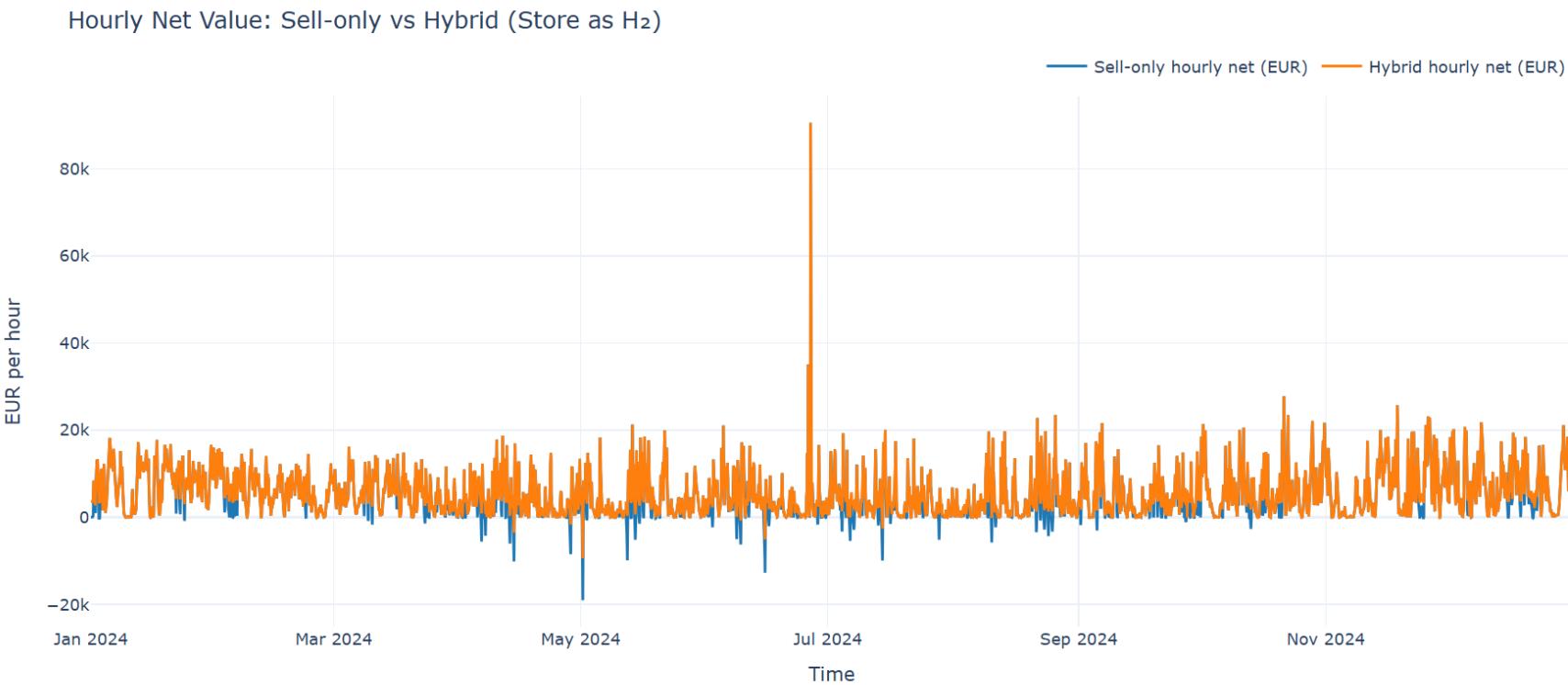


Fig 8.5: Hourly Net Value : Without Storage and With Storage



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8. Results

Model 3: Hydrogen Storage Concepts

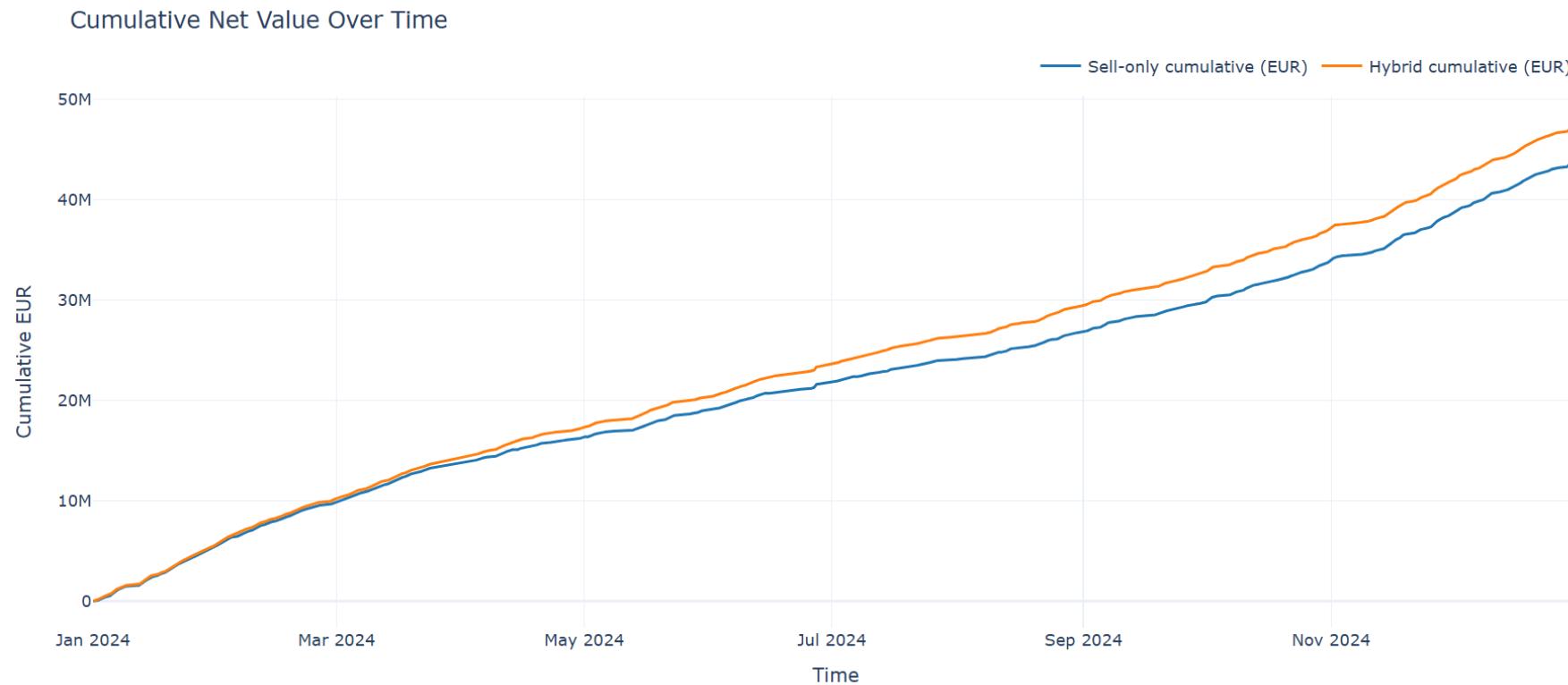


Fig 8.6: Cumulative Net Value Over Time



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9. Conclusion

- Improves predicting of wind power output
- Optimizing when to sell electricity or store as hydrogen

the current ML model is not fully accurate:

- It ignores some additional input variables
- Uses only one year of data (2024)
- Profitability depends on hydrogen price and system efficiency

10. Future Tasks

- Add more feature of wind (air density, wind direction, turbulence)
- Improve power curve for better outputs
- Try higher order polynomial regression
- Use some other ML models
- Improve data cleaning
- Possible to use more years of data
- Add more economic features (forecasted prices, market demand, so on)
- Optimize the decision threshold
- Use real seasonal power demands data



Reference: [Wind Farm Layout Design at NAYXA || We're Wind Energy Experts](#)

References

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