Power Prediction and Energy Arbitrage Modeling for Wind Farms Using ML

Presented:

Karan Soni

Madhvesh Gorakhiya

Date : 06.01.2026
Place: Flensburg

Overview

1 Introduction

2 Problem Statement

3 Data & Preprocessing

4 Flowchart

5 ML Models

6 Hydrogen Storage Concept

7 Economic Analysis

8 Results

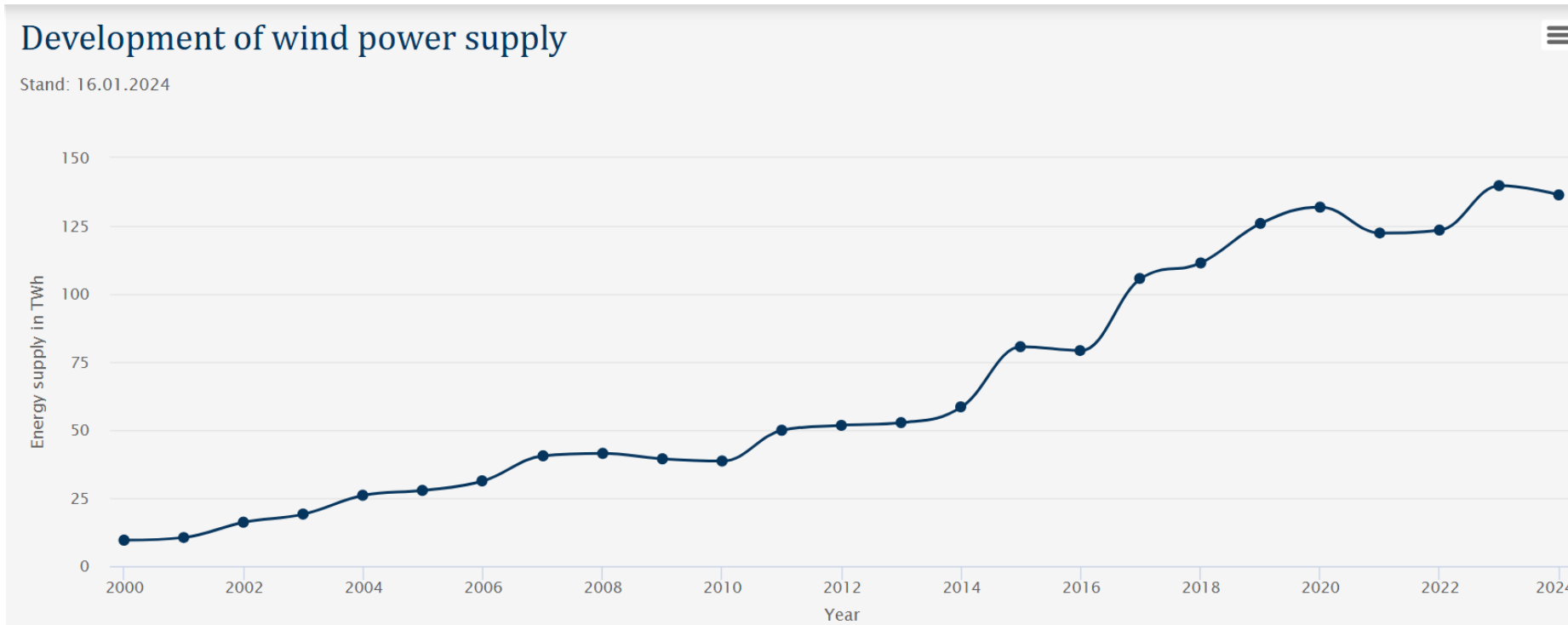**9** Conclusion

10 Future Tasks

➢ **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

Reference: Statistics Germany | BWE e.V.

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

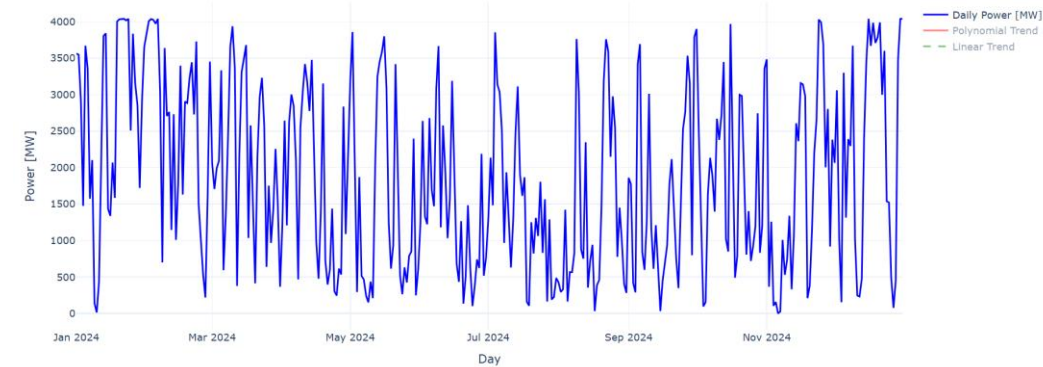➢ A **data-driven ML model** is needed to support STORE vs SELL decisions

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?

1. Wind Data (ERA5):

➢ Used ERA5 reanalysis dataset for wind components (**u100**, **v100**) **(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)**

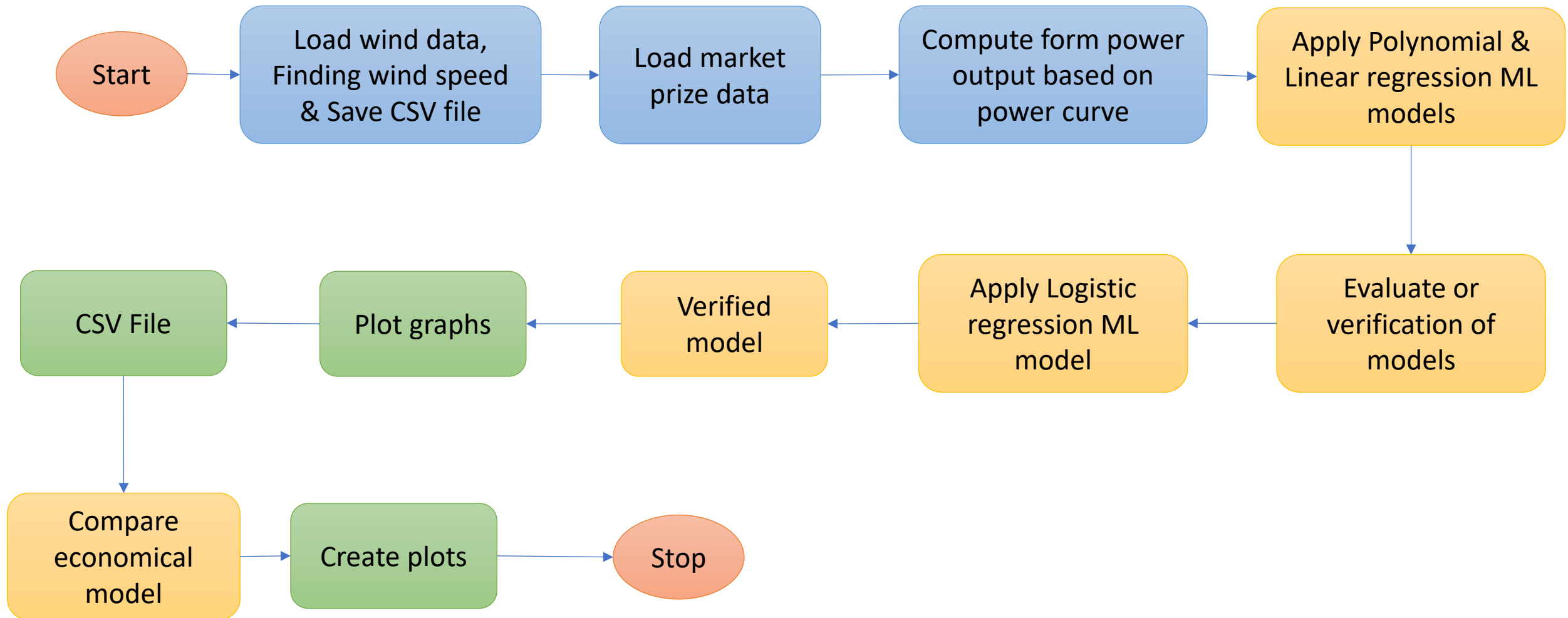➢ Cleaned timestamps and extracted **hour** and **month**

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

Power Prediction and Energy Arbitrage Modeling for Wind Farms Using ML

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

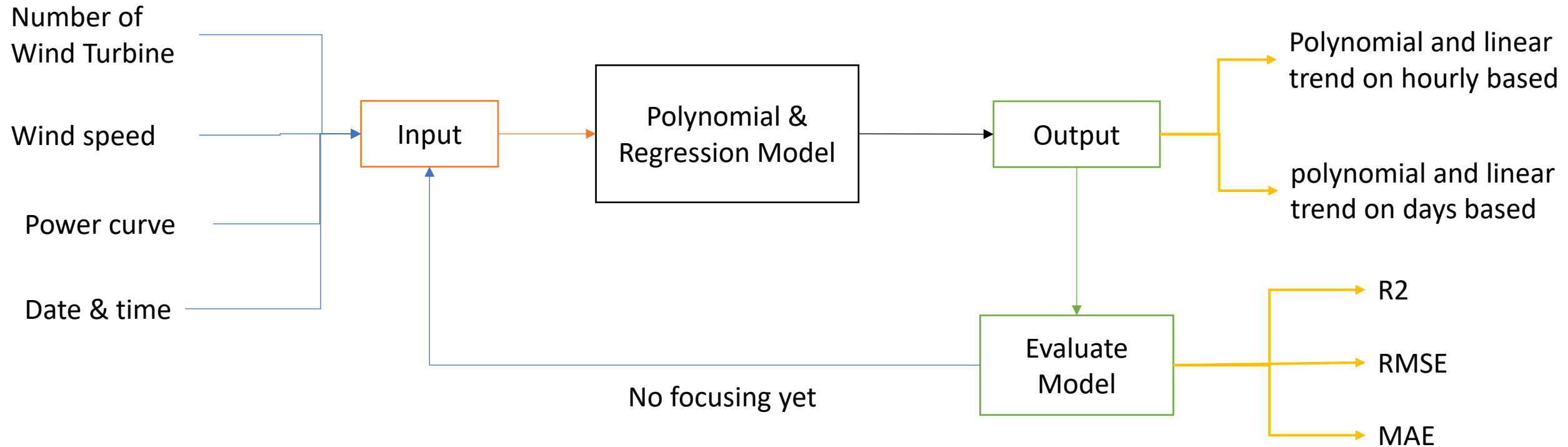(4) Patterns are **non-linear** and difficult to capture manually

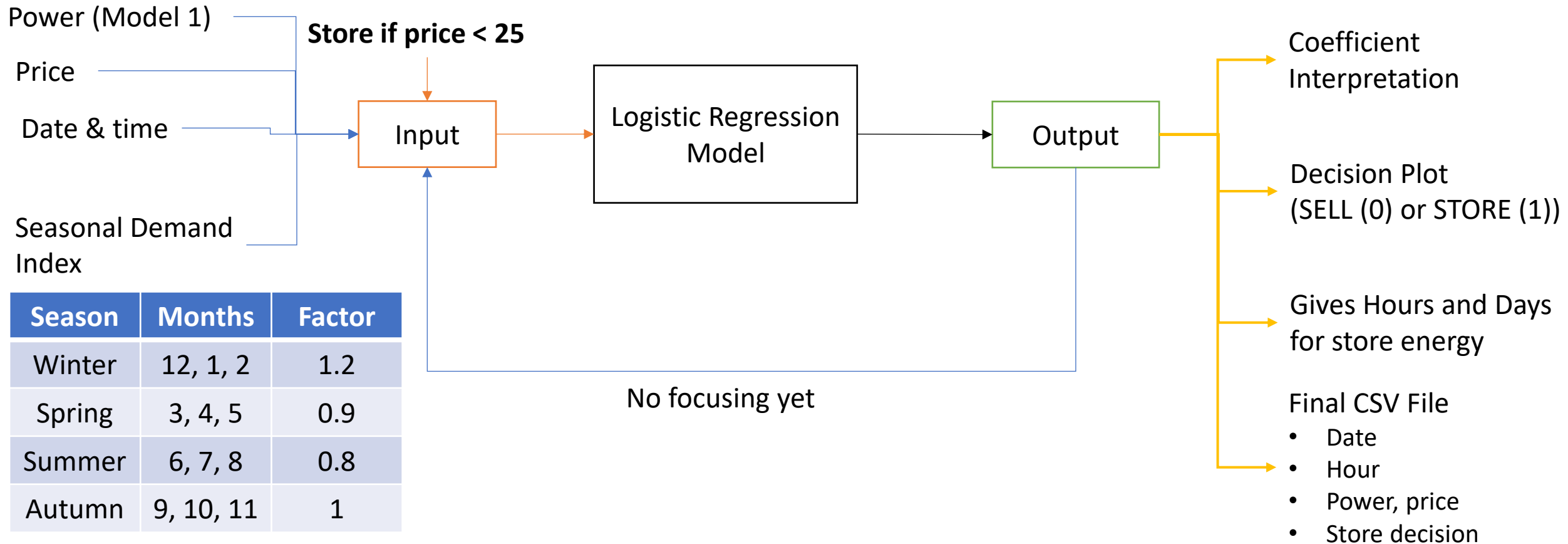(5) ML learns from historical data and improves decision accuracy

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

Block Diagram of Wind Farm Model:

Power Prediction and Energy Arbitrage Modeling for Wind Farms Using ML

Decision Arbitrage Model:

Power (Model 1)

Price

Date & time

Seasonal Demand Index

Store if price < 25

Input → Logistic Regression Model → Output

No focusing yet

Coefficient Interpretation

Decision Plot (SELL (0) or STORE (1))

Gives Hours and Days for store energy

Final CSV File
- Date
- Hour
- Power, price
- Store decision

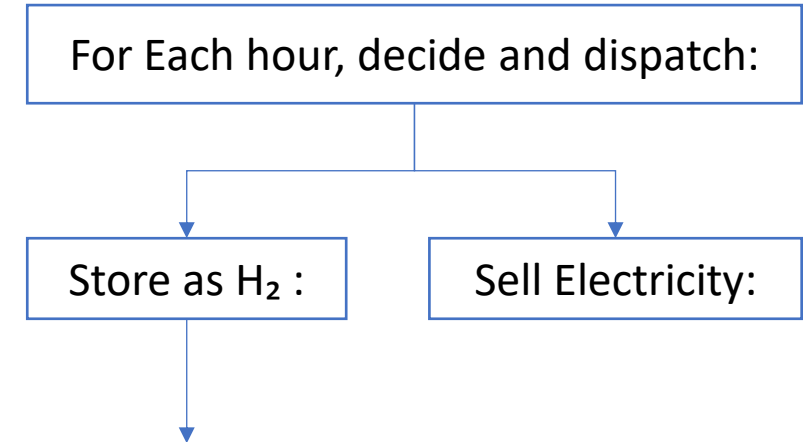| Season	Months	Factor
Winter	12, 1, 2	1.2
Spring	3, 4, 5	0.9
Summer	6, 7, 8	0.8
Autumn	9, 10, 11	1

6. Hydrogen Storage Concept

Set Economical and Technical Parameters:

- H_2 price = **4 (€/kg)**

- variable O&M = **20% (€/kg)**

- Electricity Required to produce 1 kg H_2 = **52.2 (kWh/kg)**

- Maximum power capacity of the electrolyze = **50 (MW)**

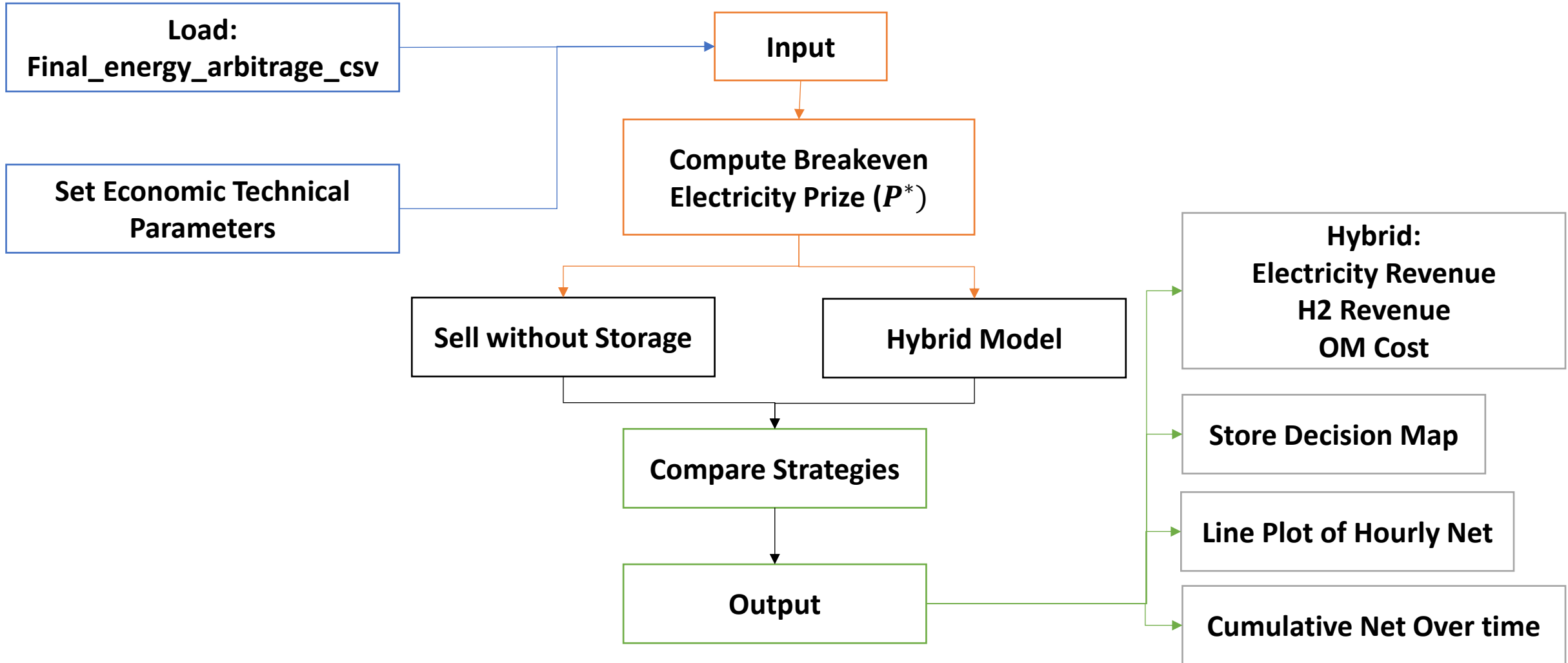- Min load fraction = **10%**

Compute Breakeven Electricity Prize:

$$P^*\left(\frac{€}{MWh}\right) = \frac{(H_2 \text{ price -variable O\&M}) * 1000}{\text{Electricity Required to produce 1 kg } H_2}$$

For Each hour, decide and dispatch:

Store as H_2 :   Sell Electricity:

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

- Run electrolyzer at min(wind, 50 MW) if ≥ 5 MW; else off
- H_2 produced = (MW × 1000) / 52.2 kg/h
- Electricity sold = wind – electrolyzer_MW
- Hybrid net = elec revenue + H_2 revenue – var O&M

Model 1: Polynomial and Regression Model

Microsoft Edge
HTML Document

Daily Wind Farm Power Production with ML Trends
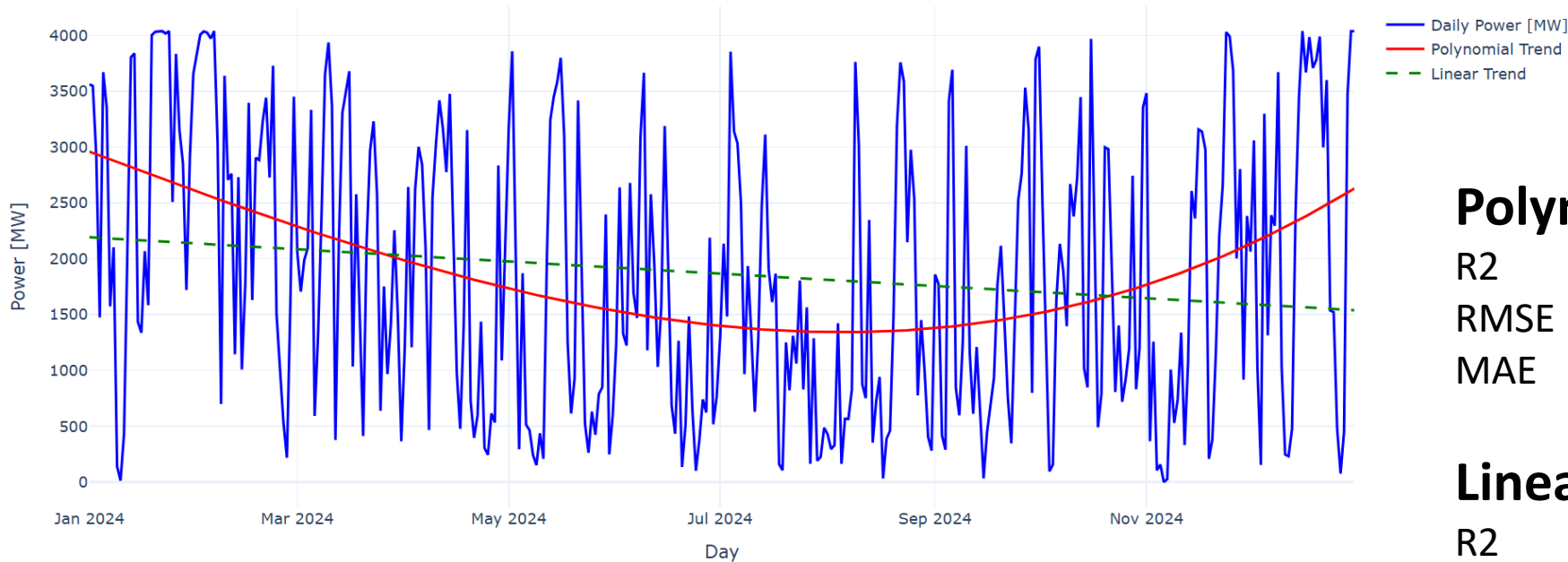
Fig 8.1: Day Vs Power

Polynomial Regression Model:

R2   : 0.14

RMSE   : 1155

MAE   : 993

Linear Regression Model:

R2   : 0.02

RMSE   : 1230

Mae   : 1079

Model 1: Polynomial and Regression Model

Fig 8.2: Hours Vs Power

Microsoft Edge
HTML Document

Polynomial Regression Model:

R2   : 0.94
RMSE   : 3347
MAE   : 2723

Linear Regression Model:

R2   : 0.16
RMSE   : 12308
Mae   : 10524

Model 2: Logistic Regression Model

Microsoft Edge
HTML Document

Fig 8.2: Hours Vs Power

Polynomial Regression Model:

R2   : 0.94
RMSE   : 3347
MAE   : 2723

Linear Regression Model:

R2   : 0.16
RMSE   : 12308
Mae   : 10524

9. Conclusion

Power Prediction and Energy Arbitrage Modeling for Wind Farms Using ML

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

1. https://www.nsenergybusiness.com/projects/reusenkoge-wind-farm-expansion/?cf-view
2. https://en.wind-turbine-models.com/turbines/693-vestas-v112-3.3
3. ECMWF. (2024). ERA5 Reanalysis Data. Copernicus Climate Change Service.
4. Siemens Energy. (2023). Silyzer 300 PEM Electrolyzer Datasheet.
5. Day-Ahead Auction prices (DE-LU Zone, 2024)