Forecasting Wind & Solar Power Production

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Introduction

Global Energy Transition:

- Renewable energy → global strategy milestone.
- Decommissioning of nuclear plants.
- A 60% CO_2 reduction target.

Role of Wind and Solar Energy:

- Reducing reliance on fossil fuels.
- Transition to cleaner energy mix.
- Combat climate change.

Need for Advanced Forecasting

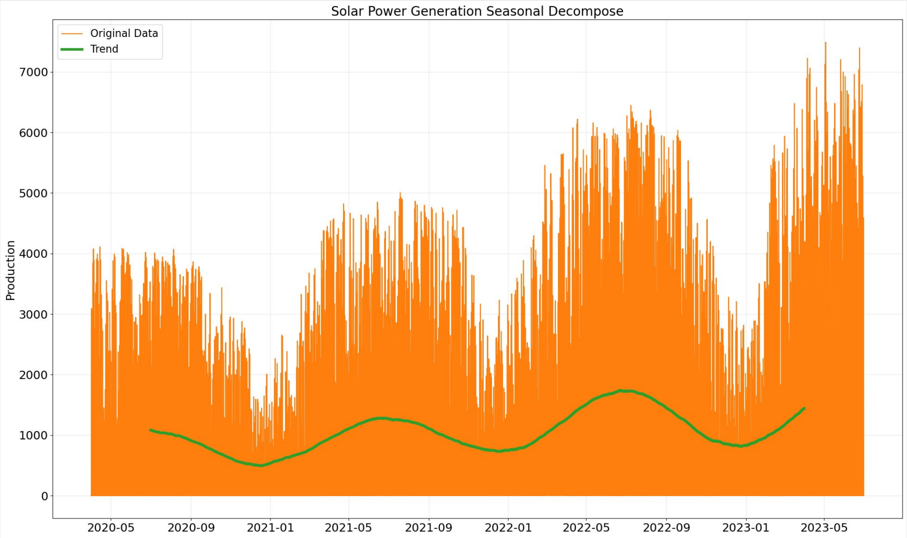
- Reliable energy production.
- Optimized energy distribution.
- Supporting decision-making.

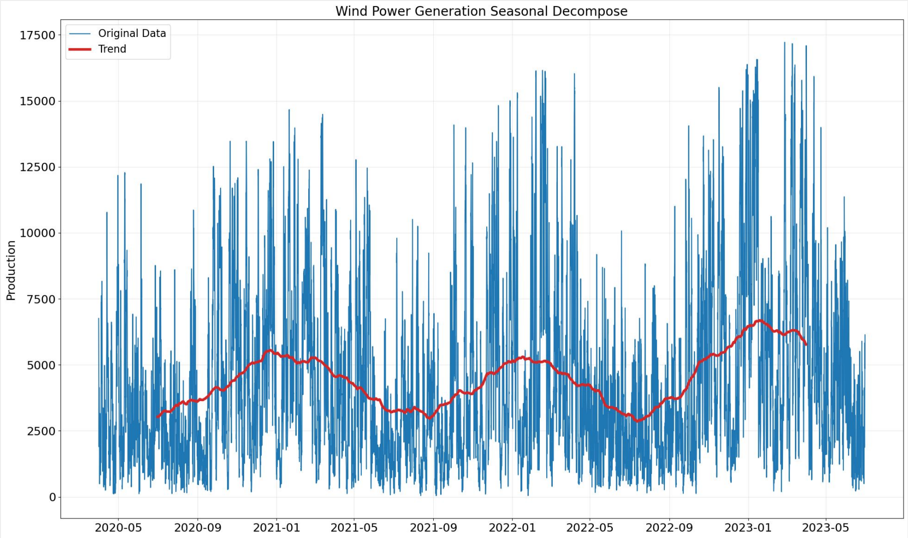
Objective

- Predicting wind & solar production energy.
- Time series and machine learning.

Time series Forecasting

- **Time series data** consists of data points recorded in chronological order.
- **Each data point** is associated with a specific time or time interval.





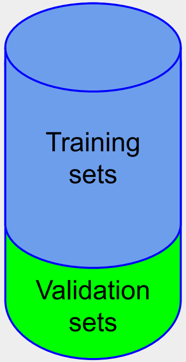
Exploratory Data Analysis:

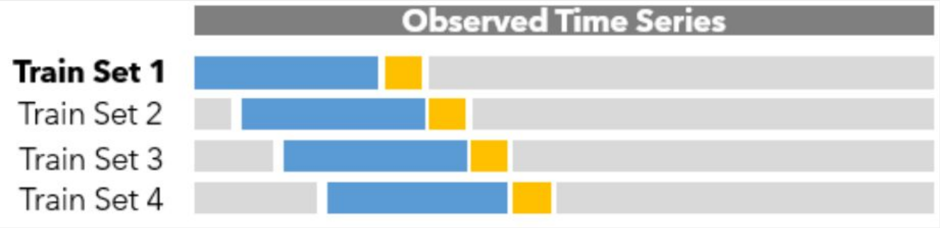
- **Trend:** Long-term increases in energy production.
- **Seasonality:** Recurring patterns due to daily or seasonal variations.

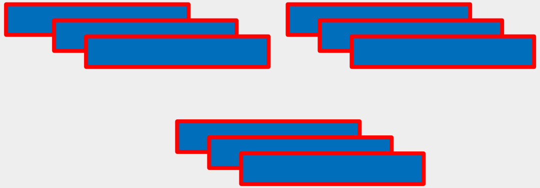
How Prediction Works in TensorFlow for Time Series Data

Data Preparation → Windowing and Slicing → Batching the Data → Building the Model

- Split data into training and validation sets.
- Create sliding windows of past observations to predict future values.
- Group multiple windows into batches for efficient training.



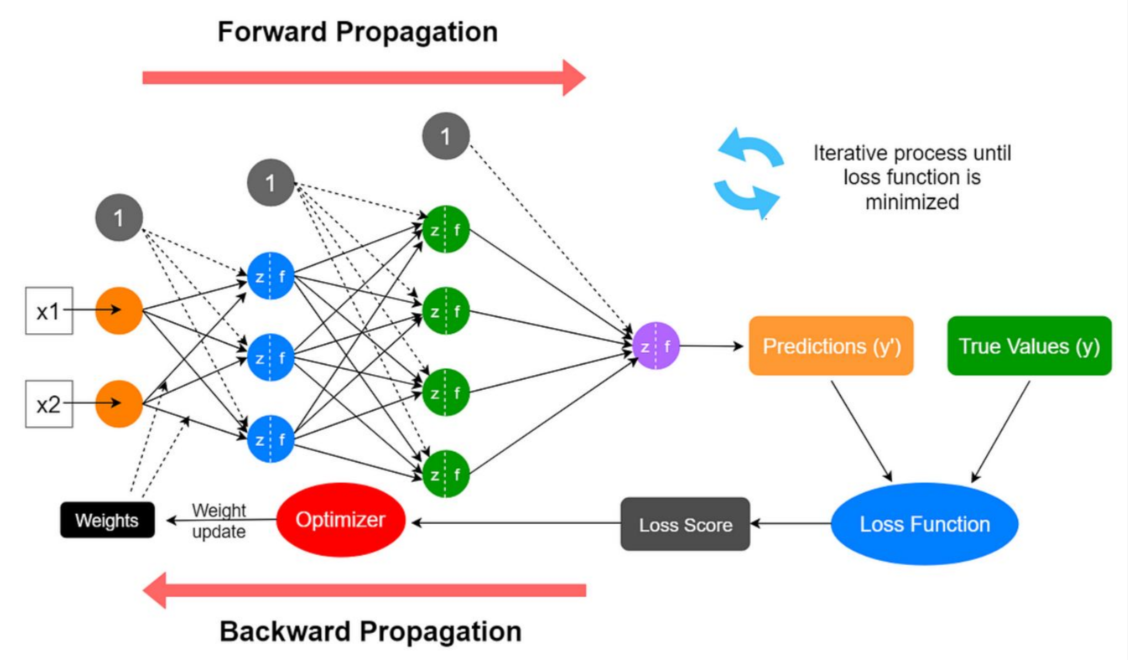




How Prediction Works in TensorFlow for Time Series Data

Building the Model → Training the Model → Making Predictions → Evaluating Performance

- Define a neural network architecture (e.g., LSTM, CNN, Transformer).
- Compile the model with a suitable loss function and optimizer.

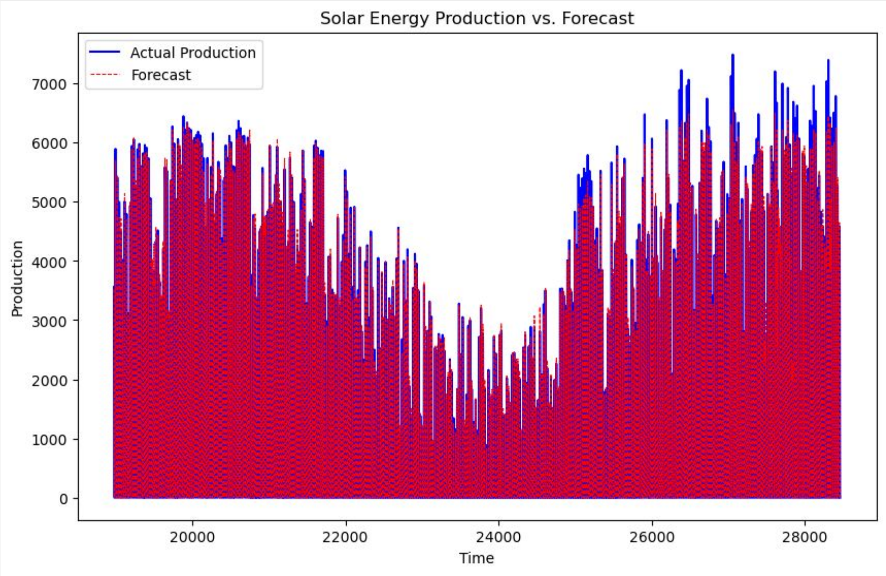


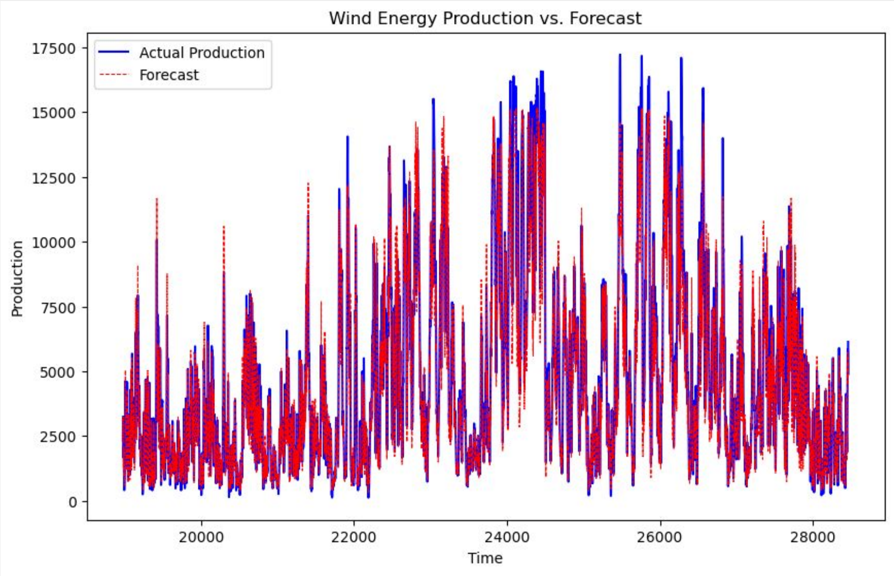
- Feed batched time series windows into the model.

- Pass unseen (test) data into the trained model.
- Generate predicted values based on learned patterns.

- Compare predictions with actual values using metrics like MAE or MAPE .

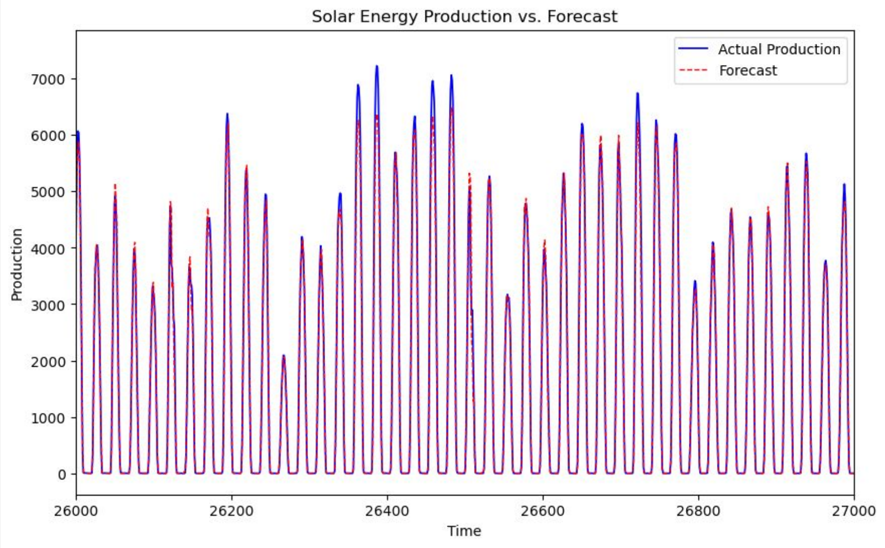
Comparison of training and validation dataset predictions

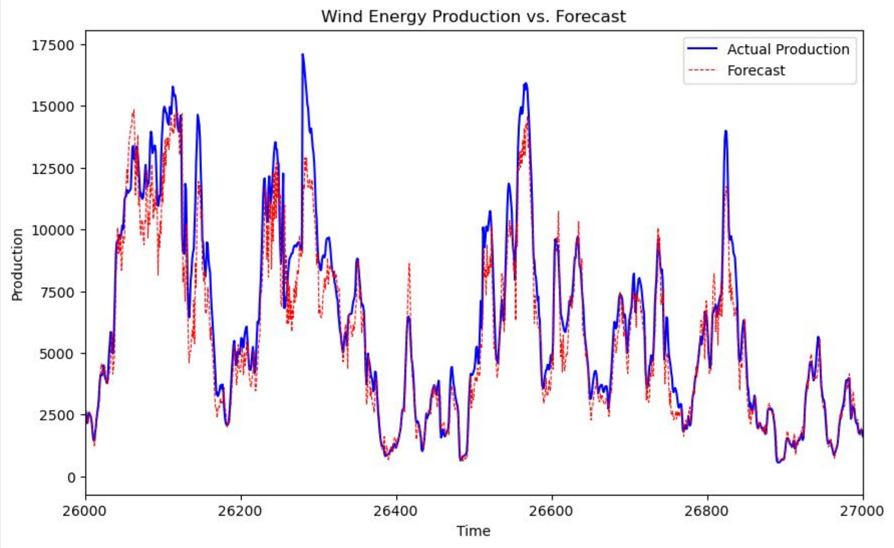




Mean Absolute Percentage Error (MAPE) = 12.9 %

Comparison of training and validation dataset predictions

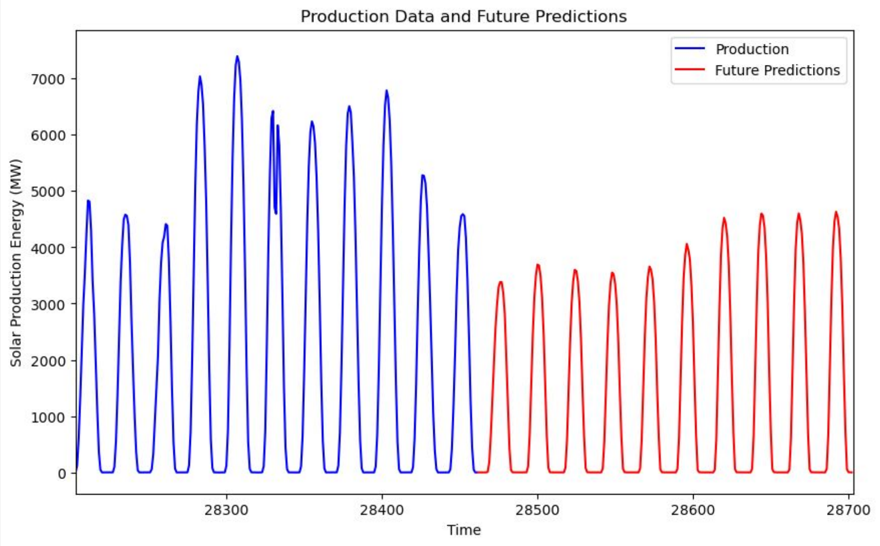


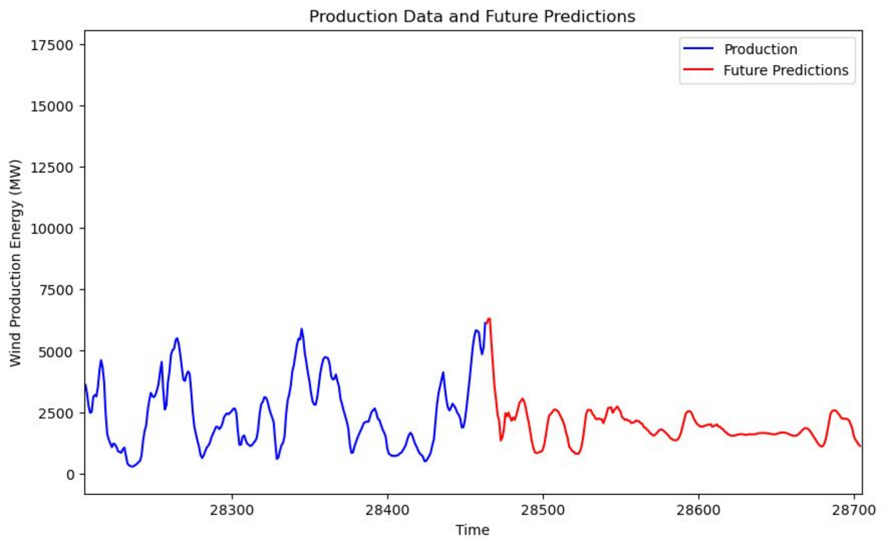


Mean Absolute Percentage Error (MAPE) = 12.9 %

Future data forecasting

Energy predictions for the next 10 days:





Streamlit app

Renewable Energy Production Forecast

Enter a date and hour to forecast energy production for wind and solar.

Select Date

2022/07/12

Select Time

12:45

Forecasting production for: 2022-07-12 12:45:00

Corresponding index in the series: 19980

Wind Energy Forecast

Predicted wind production: 698.90 MW

Solar Energy Forecast

Predicted solar production: 6153.07 MW

THANK YOU!

Backup slides

Analysis of hourly energy production data between 2020 and 2023 in France

Preprocessing Steps:

- Handled missing values using imputation techniques.
- Converted timestamps and aligned datasets for time series analysis.

	Date and Hour	Date	StartHour	EndHour	Source	Production	dayOfYear	dayName	monthName
0	2020-03-31 22:00:00+00:00	2020-04-01	1900-01-01 00:00:00	1900-01-01 01:00:00	Wind	6759.0	92	Wednesday	April
1	2020-03-31 23:00:00+00:00	2020-04-01	1900-01-01 01:00:00	1900-01-01 02:00:00	Wind	6293.0	92	Wednesday	April
2	2020-04-01 00:00:00+00:00	2020-04-01	1900-01-01 02:00:00	1900-01-01 03:00:00	Wind	5916.0	92	Wednesday	April
3	2020-04-01 01:00:00+00:00	2020-04-01	1900-01-01 03:00:00	1900-01-01 04:00:00	Wind	5679.0	92	Wednesday	April
4	2020-04-01 02:00:00+00:00	2020-04-01	1900-01-01 04:00:00	1900-01-01 05:00:00	Wind	5508.0	92	Wednesday	April

- **Recurrent Neural Networks** (RNNs) are deep learning models that can be utilized for time series analysis, with recurrent connections that allow them to retain information from previous time steps.
- RNN are distinguished by their “memory” as they take information from prior inputs to influence the current input and output.
- While traditional deep learning networks assume that inputs and outputs are independent of each other, the output of recurrent neural networks depend on the prior elements within the sequence.

Long Short-Term Memory (LSTM) can learn long-term dependencies:

Traditional RNNs struggle with the vanishing gradient problem, which makes it difficult for the network to identify long-term dependencies in sequential data. However, this challenge is elegantly addressed by LSTM, as it incorporates specialized memory cells and gating mechanisms that preserve and control the flow of gradients over extended sequences. This enables the network to capture long-term dependencies more effectively and significantly enhances its ability to learn from sequential data. **LSTM** has three gates (input, forget, and output) and excels at capturing long-term dependencies.

Exposure bias: refers to the train-test discrepancy that seemingly arises when an autoregressive generative model uses only ground-truth contexts at training time but generated ones at test time.

Multi-Variate Time Series Data in Recurrent Neural Networks (RNNs)