Conformalizing an LSTM to Optimize Revenue for a Renewable Energy Operator using Conditional Value at Risk

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We optimized the market trading of a renewable energy generation operator with conditional value at risk based on probabilistic forecasts made with a conformalized Long Short-term Memory (LSTM) recurrent neural network. This work demonstrates an end-to-end workflow of how field data can be ingested, analyzed, and exploited to reduce risk exposure for the operator. This is financially beneficial to the individual operator, but taken to a large scale this methodology increases the incentive for renewable generation participation which should drive cost and emissions down. This work used only eight features with favorable results, so it is expected that further studies and more advanced models with the same architecture would provide better yield.

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1 Introduction

The IEEE Hybrid Energy Forecasting and Trading Competition challenges participants to make day-ahead, half-hourly probabilistic forecasts of solar and wind energy production for a solar farm and Hornsea-1 Wind Farm in the east of England with a combined 3.6 GW capacity. The second task is to decide how much energy to commit to selling at the day-ahead price (DAP) to optimize revenues. Any difference between the committed energy and actual energy is rewarded or punished according to the single settlement price (SSP). As discussed later in the data, beyond their volatility, the DAP and SSP can also be negative indicating a surplus of energy on the market. In rare events, underproduction could be rewarded due to a negative SSP. The implied task is to also forecast the market prices so that the operator can reduce their risk exposure from both the energy production and market prices.

1.1 Motivation

This is an appropriate capstone project for this course as it applies many topics covered ranging from unit commitment and energy market trading to advanced predictive and prescriptive analytics for complex and uncertain events. It is an interesting and practical opportunity to wrestle with the available resources to make the best decisions for the operator. Lastly, we find it a compelling problem because reducing the risk for renewable energy generation operators will encourage more participation and be of a net benefit to investors, consumers, and the environment - a rare triple-win.

1.2 Objectives

We will show an end-to-end workflow where we process data to train a forecasting model and conformalize it so that its point forecasts can be transformed into probabilistic forecasts. These forecasts enable us to make market-trading decisions that consider the uncertainty in not only energy production but also in the market itself. Finally, we will demonstrate the financial benefit of leveraging the power of stochastic optimization to reduce the risk exposure of the operator.

1.3 Literature Review

What have other people done

Table 1: Data from RebaseAPI

	DateTime	Solar	Wind	TotalEnergy	DAP	SSP
	DateTime	Float32	Float32	Float32	Float32	Float32
1	2024-03-05T03:00:00	0.0	587.3	587.3	54.33	44.0
2	2024-03-05T03:30:00	0.0	601.86	601.86	54.33	55.94
3	2024-03-05T04:00:00	0.0	595.92	595.92	61.81	52.82
4	2024-03-05T04:30:00	0.0	575.42	575.42	61.81	52.63
5	2024-03-05T05:00:00	0.0	563.54	563.54	71.01	57.49

Table 2: Energy Data Summary

	variable	mean	min	median	max
	Symbol	Float32	Float32	Float64	Float32
1	Solar	277.007	0.0	8.42715	1853.73
2	Wind	546.151	0.0	703.09	826.254
3	TotalEnergy	823.159	0.0	778.34	2367.19
4	DAP	55.1001	-23.77	61.245	112.23
5	SSP	54.6884	-88.0	55.5	177.71

2 Data Analysis

We have obtained datasets from two sources: the competition itself which provides the energy production data through the Rebase API and the VisualCrossing API which provides the weather data. The energy data details the solar and wind energy production and the DAP and SSP in half-hourly increments. The weather data is treated as historic for the period preceding a given forecast and as a weather forecast for the forecast horizon. If deployed, the model would need to operate only using forecasted weather data. This approach is acceptable for this study as 24-hour-ahead weather forecasts are typically very accurate and we are only incorporating basic weather features.

2.1 Data Summary

The tables below provide a sample of what the data from each source look like for a few observation times and summary statistics.

2.2 Data Visualizations

The first thing to notice when looking at the DAP and SSP time-series plots below is the volatility of the prices. The DAP exhibits some seasonality but the trend and cycles are not as clear. The SSP is more volatile as it traverses from the daily minimum to the daily maximum

Table 3: Data from VisualCrossing

	DateTime	temp	windspeed	winddir	cloudcover	visibility
	DateTime	Float32	Float32	Float32	Float32	Float32
1	2024-03-05T03:00:00	6.9	14.8	132.0	100.0	10.0
2	2024-03-05T03:30:00	6.9	14.8	132.0	100.0	10.0
3	2024-03-05T04:00:00	6.3	13.9	140.0	94.0	8.0
4	2024-03-05T04:30:00	6.3	13.9	140.0	94.0	8.0
5	2024-03-05T05:00:00	6.2	12.5	150.0	100.0	6.0

Table 4: Weather Data Summary

	variable	mean	min	median	max
	Symbol	Union...	Any	Any	Any
1	DateTime		2024-02-29T23:00:00	2024-03-28T09:45:00	2024-04-23T21:30:00
2	temp	21.6039	-2.3	10.4	66.2
3	windspeed	14.6897	0.9	13.85	41.2
4	winddir	190.807	2.0	200.0	359.0
5	cloudcover	71.1433	0.0	91.6	100.0
6	visibility	12.2187	0.0	11.0	29.8

several times in a given day. This highlights how difficult it is for all participants to make accurate forecasts and fulfill their commitments.

The plots of the DAP and SSP for the third week of April below provide a closer look at the characteristics of these prices. While predicting the DAP appears feasible, the SSP is hardly distinguishable from noise.

Table @ref shows the energy generation over March 2024 while Table shows the first week of April 2024. We see solar energy production is, as expected, seasonal while wind energy production is very cyclical. It appears to go from nothing to its full capacity in a short amount of time and stay there for a random amount of time before dropping, usually back to nothing.

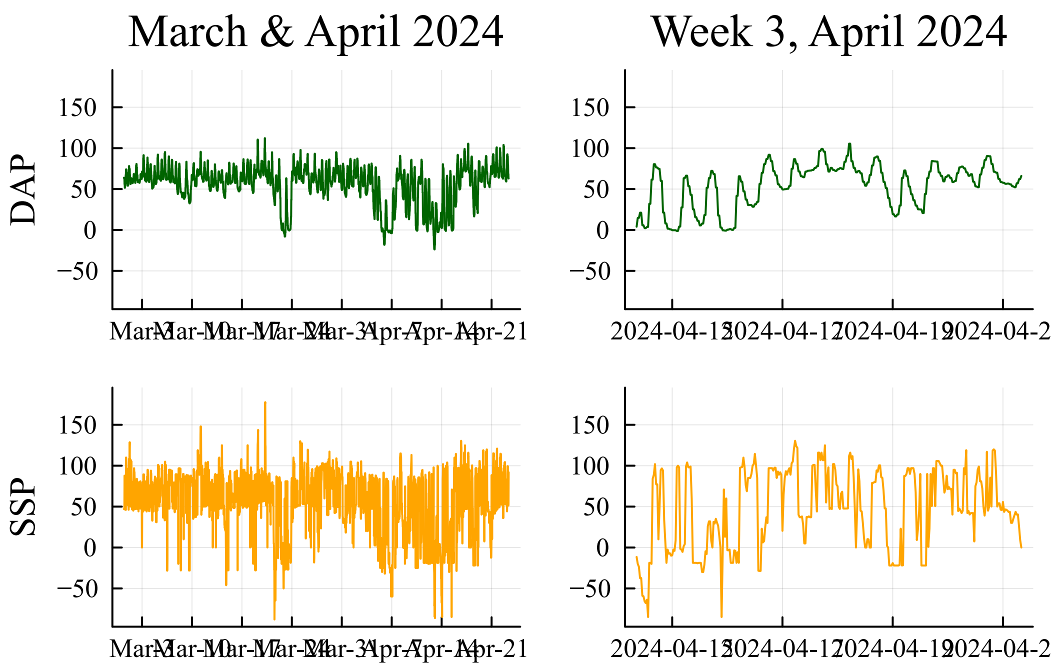


Figure 1: March & April 2024 Energy Prices

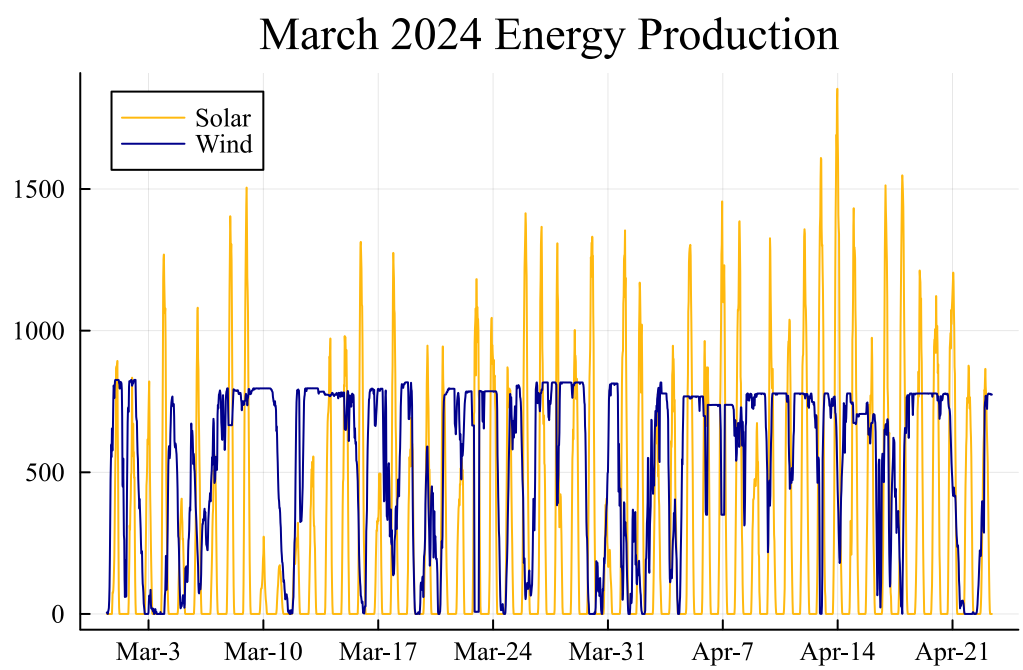


Figure 2: March 2024 Energy Production

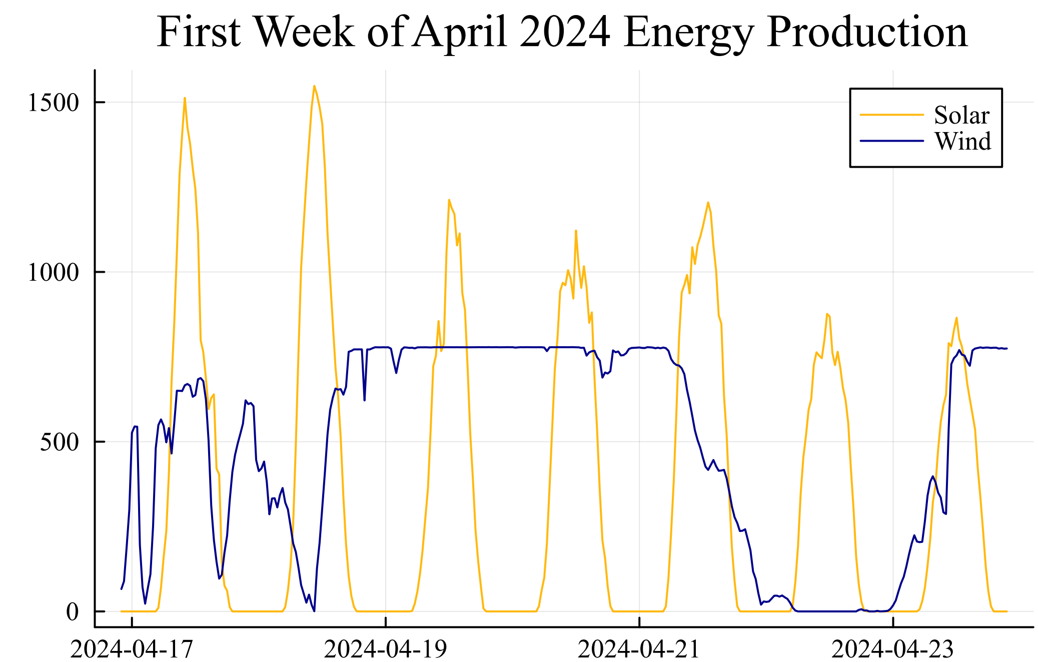


Figure 3: First Week of April 2024 Energy Prices

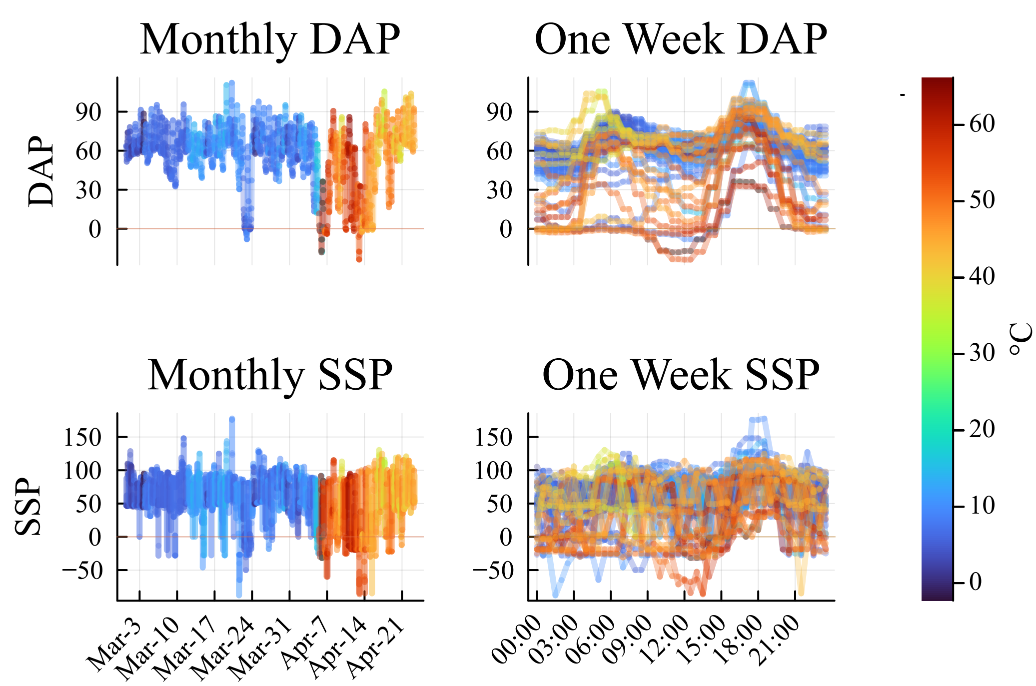


Figure 4: DAP, SSP vs Temperature

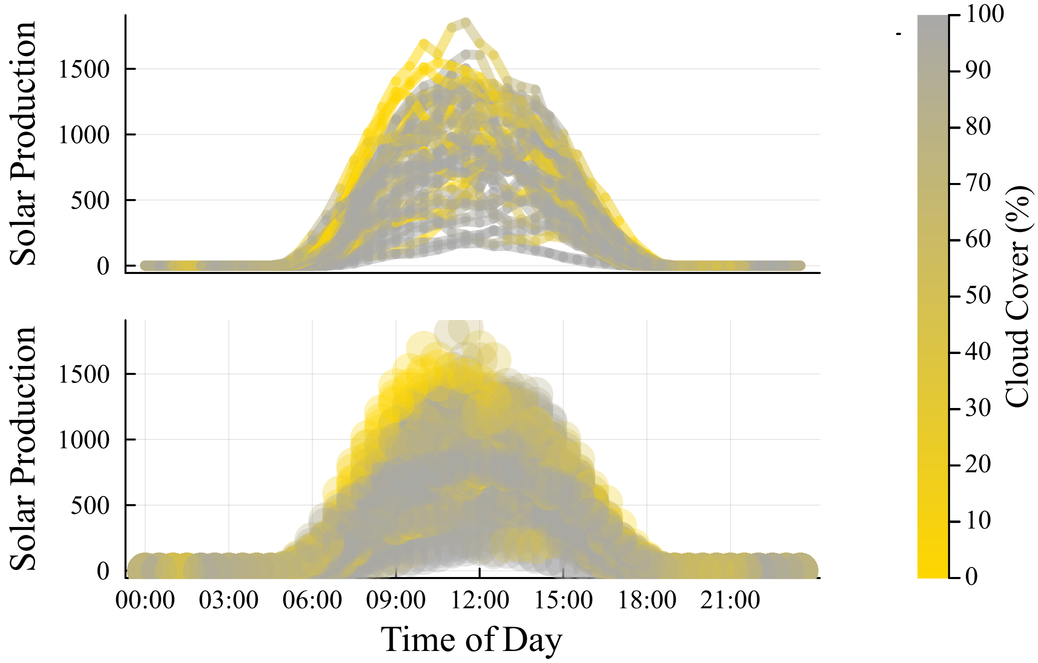


Figure 5: Daily Solar Production vs Cloud Cover

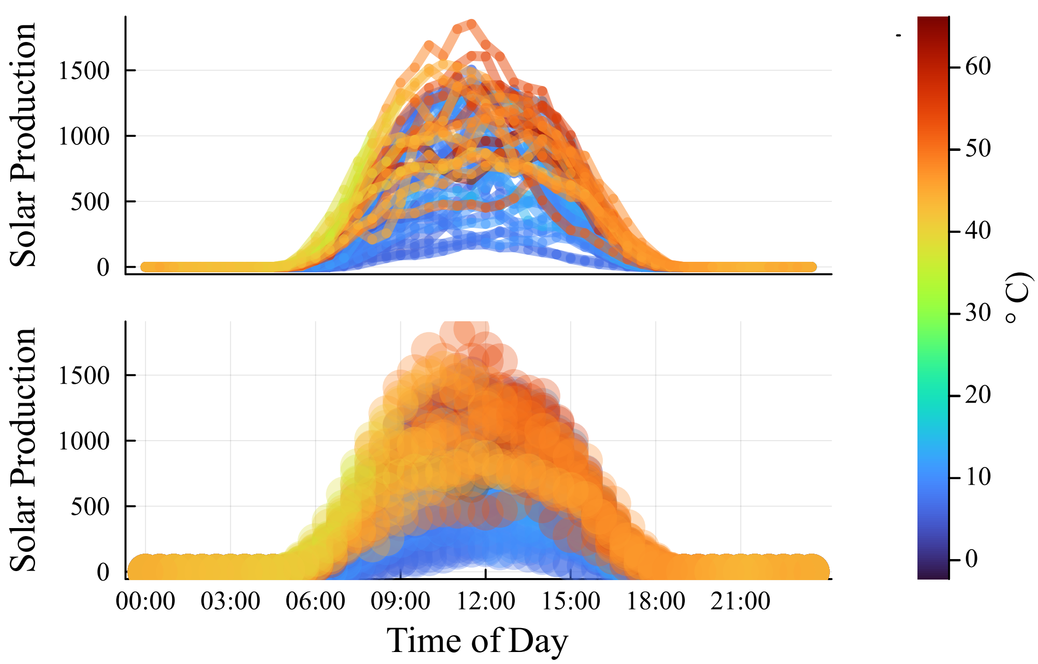
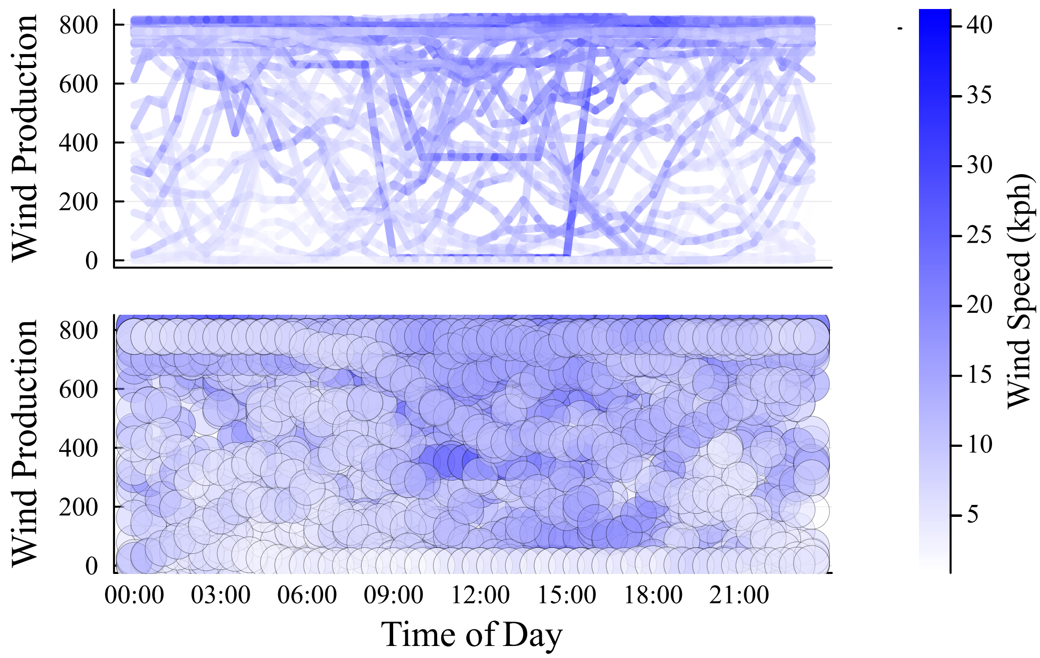
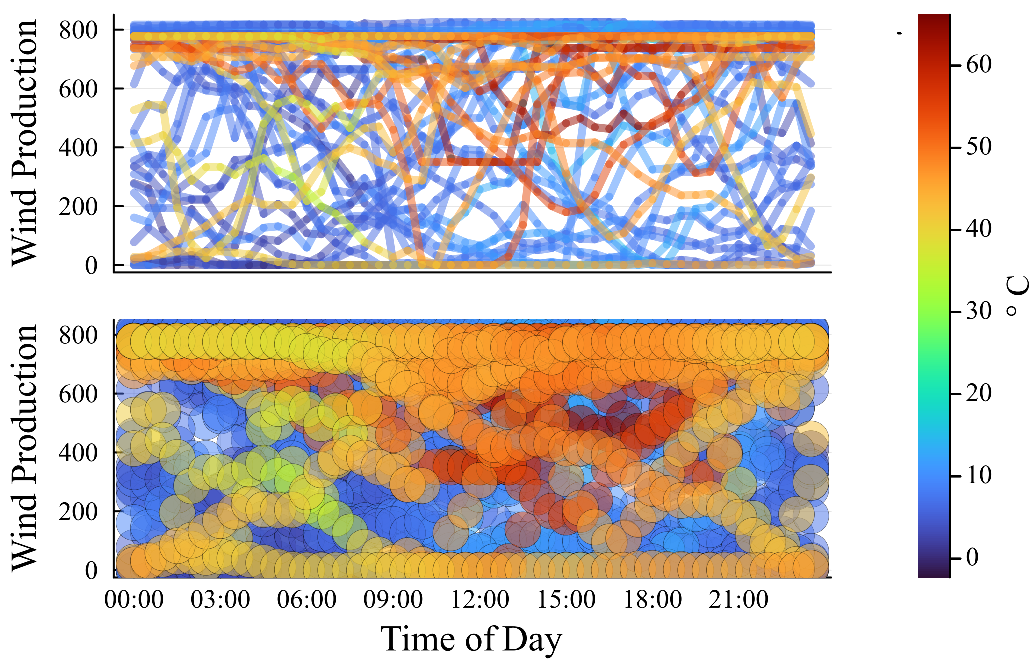


Figure 6: Daily Solar Production vs Temperature


Wind Production
Wind Production
Time of Day
Wind Speed (kph)


Wind Production
Wind Production
Time of Day
∘ C

3 Long Short-Term Memory Model

We used an LSTM Recurrent Neural Network (RNN) to predict the energy production and market prices for the following day. RNNs are designed to handle time-series data and LSTMs are a special type of RNN that can learn long-term dependencies in the data. Combined with a dense neural network, this model can remember (and forget) time-dependent relationships and approximate the complex dynamics among the variables.

3.1 Training

How did we make one?

3.2 Performance

Is it any good?

4 Conformalizing LSTM

What are conformal predictions? Why are they good

4.1 How to?

How did we conformalize the LSTM?

4.2 Performance

Is it any good?

5 Conditional Value at Risk

What is CVAR

Why do we do it?

5.1 Implementation

How did we do it?

5.2 Performance

Was it any good?

6 Conclusions

Was any of this worth while?

What did we learn?

What could others do?