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Reconstruction of multidecadal historical hourly demand data

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Motivation: Why is the use of hourly demand data?

Solar and wind power are intermittent, can they be used to serve demand at all hours?

Necessary for assessing hourly residual capacity requirements, i.e. unmet demand. Reliability is defined as serving demand for all hours of the year.

Temperature has drastically changed from 1980 and has altered electricity demand requirements. But by how much?

Problem Statement

Aggregated data neglects any subtle information about hourly requirements - coarse vs. granular.

Summer electricity demand have different peaks as compared to winter electricity demand.

Climate dataset has large spatial and temporal resolution

Available hourly electricity demand records for each BA** start from 2015.

**BA or Balancing Authority: An entity that is responsible for regulating the supply and distribution of electricity in the US. There are 66 BAs in the US governing different regions.

What is & why reconstruction (back-forecasting)? Why not forecasting for future?

$$t \rightarrow t_1 \rightarrow t_2 \ldots . t_n$$

Forecasting

$$t_{-n} \ldots . t_{-2} \leftarrow t_{-1} \leftarrow t$$

Back-Forecasting

1. To reduce dependency on coarse climate change data.
2. Analyze the real observed phenomenon, rather than using estimated future temperature from climate data to derive future demand forecasts – added *uncertainty*

AIM: Develop back-forecasting based regression models that can be generalized to any BA with minimal final tuning and assess contribution of solar and wind power

Define Problem Statement → Define hypothesis/propose experiments → Collect and understand data → Prepare Data → Train/Tune Models → Validate and Evaluate

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Data: Sources

1. Available hourly demand data: Balancing Authority database (2015-2019) = ***43,800 records***

2. Hourly Temperature data: NASA MERRA Reanalysis
    - Training set: records from 2019 – 2016 (reversed dataset as we back-forecast)
    - Validation set: hourly records from 2015
    - Prediction/test set time frame: 2014-1980

    - Other predictors are feature engineered
        1. Hour of the day
        2. Day of the week
        3. Month
        4. Quarter

What is reanalysis dataset?

NASA reanalysis data is a consistent collection of observed data. It is consistent because Numerical Weather Prediction methods have been used to impute/correct missing/erroneous data. Available in grid size of 50km x 60 km

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Model

1. Piecewise Linear Regression
2. Categorical Boosting
3. Stacked Long Short Term Model

MAPE: Mean Absolute Percentage Error – very commonly used in time series analysis

RMSE: Root Mean Squared Error

R^2 : Coefficient of Determination

Inputs
(Batch size, time steps = 24**, number of predictors)

LSTM layer 1 with dropout = 0.2

LSTM layer 2

Learning Rate = 0.009, number of epochs = 1700, Adam optimizer

**Fixed sequence length/time steps = 24.Back-forecasted hourly demand value depends on temperature records in the past 24 hours. Experimented with other values (6-48)

Model Training and Tuning:

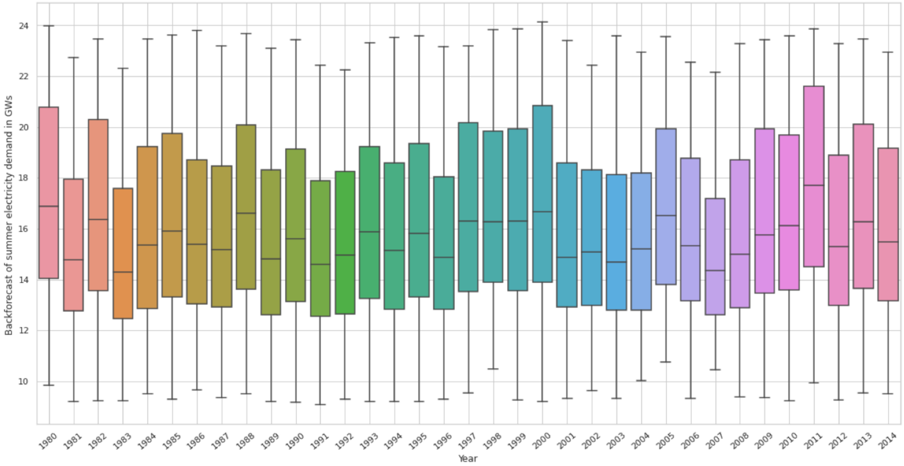
Model type	Piecewise Linear Regression	Cat Boost	LSTM
RMSE	1693	1501	1485
MAPE	0.113	0.09	0.07
R^2	0.73	0.81	0.87

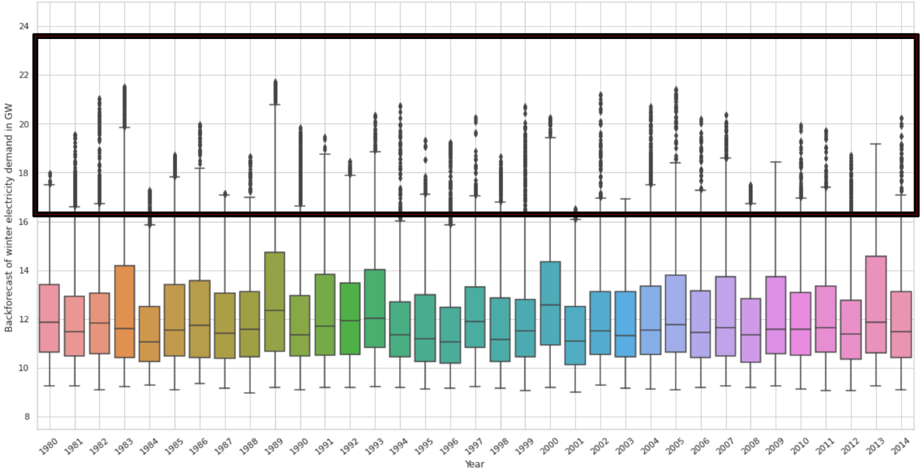
**RMSE is scale dependent

Results: Test set hourly demand distribution

Single model fitted to predict all demand values

Large outliers





Further analysis on validation set shows
Summer Back-forecast distribution, R^2 : 83%
Winter Back-forecast distribution, R^2 48.1% ***(only 48.1% of the variance in winter hourly demand data could be explained by the model)***

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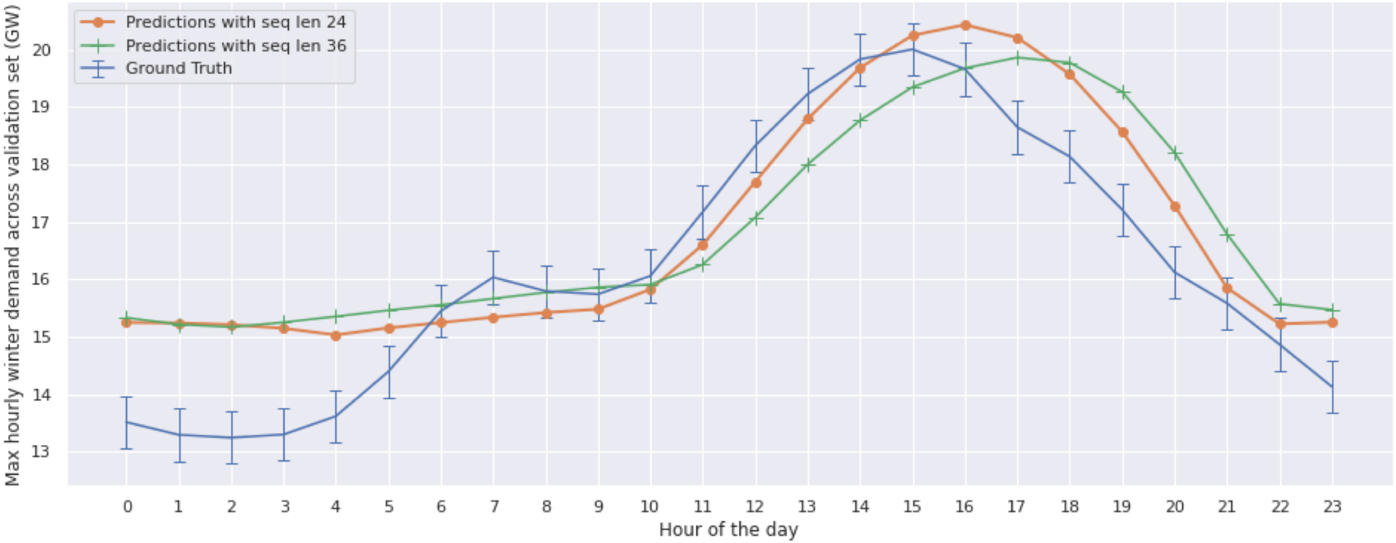
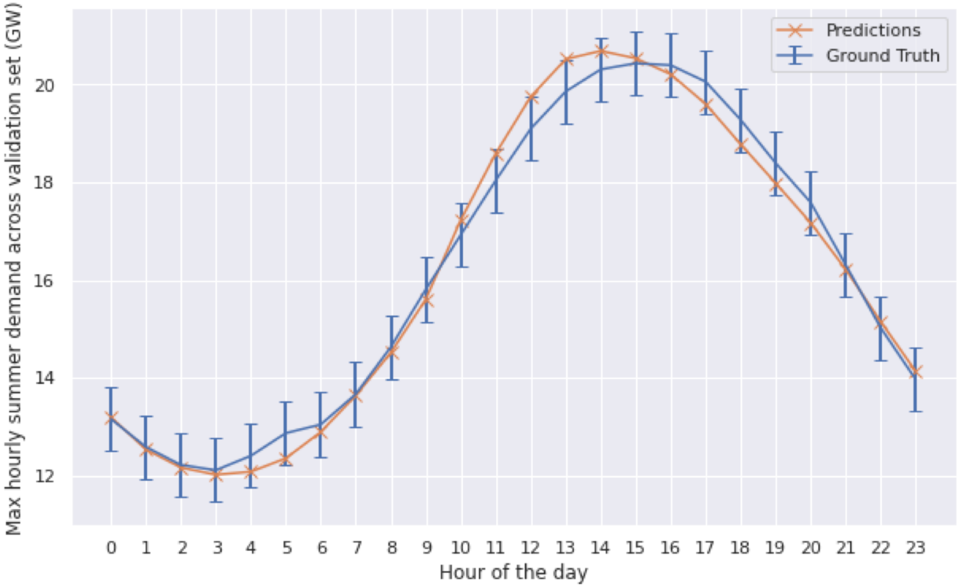
Modified Model: Winter Predictions (back-forecasts)

- Winter months: December, January, February predictions
- R^2 value: 67.3%
- Improvement over predictions in winter months from single fitted model (R^2 value 48.1%)

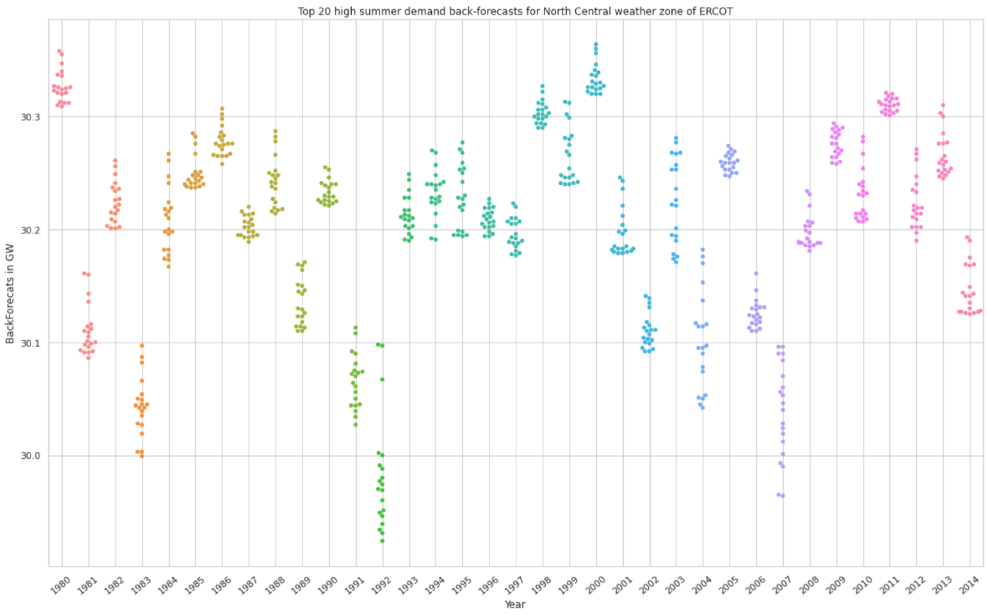


Modified model: Summer Predictions (back-forecasts)

- Summer months: June, July, August predictions
- R^2 value: 95.2% (initial model 83%)
- Predictions fall under error-bars (within one standard deviation of mean of ground truth)



Results: Top 20 back-forecasted summer demand hours per year



Hourly back-forecasted demand shows large variability in-between years.

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Conclusions:

- LSTM model outperforms all other machine learning models in terms of RMSE, MAPE, and R^2
- 'One model fits all' approach to back-forecasting demand is not appropriate as the relationship between winter temperature and demand is more complex than summer.
- It is imperative to use separate models for summer and winter.

Future Work:

1. Experiment with Attention based architecture to check if accuracy improves. Understand if any extreme-event based weather events affected the winter predictions.
2. Identify additional weather dependent variables to be included – Humidity.

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THANK YOU!