Ensembling Approaches to Hierarchical Electric Load Forecasting

James Barrios, Simon Gleeson, Charlie Natoli
Department of Management Science & Engineering, Stanford University

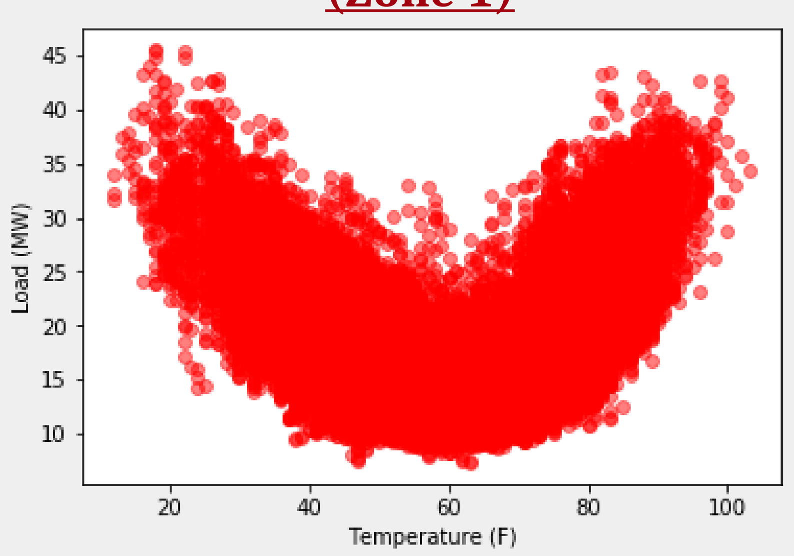
Motivation

- Electrical load forecasting needs to be accurate to prevent power surges and blackouts.
- Deep Neural Networks have recently become popular with energy forecasting.
- Typically Independent System Operators, (ISOs), who monitor energy supply, forecast demand by breaking load into 'zones', which aggregate to total demand.
- We compare and implement ensembling approaches with deep learning with hierarchical load forecasting.

Dataset

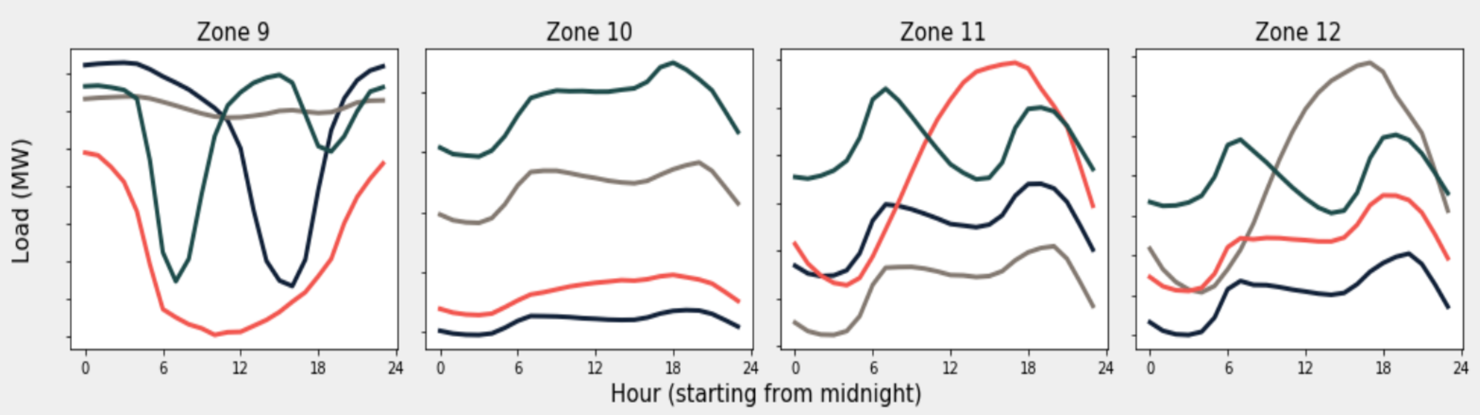
- The dataset contains hourly load profiles from 20 separate geographic sub areas (load zones) from Jan-2004 to June-2008.
- It was used for a Kaggle load 'backcasting competition', we compare our results with the winning teams.
- It contains weather readings from 11 stations, but there is no information on which weather station maps to which load zone.

Load Weather Relationship (Zone 1)



- We observe a quadratic relationship between temperature and load, which reflects heating and cooling loads.
- Most but not all zones follow this pattern.

Typical Day Load Profiles, Zones 9 - 12

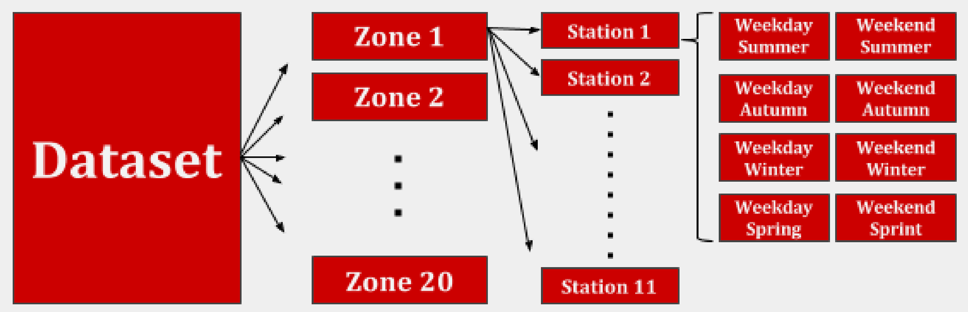


- Most load zones have similar daily profiles, but some such as zone 9 have different daily usage (industrial zone)
- This leads us to consider each load zone's forecast separately

Models

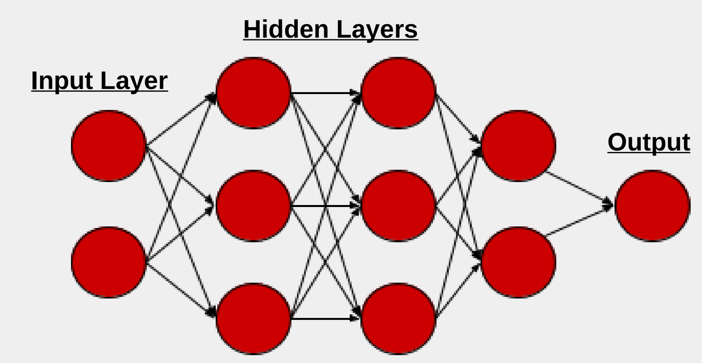
Parametric Regression:

- The dataset is disaggregated by load zone, weather, season and hour.
- The weather that minimizes mean squared error is chosen per hour, zone and season.
- We fit a parametric regression for each disaggregated dataset.



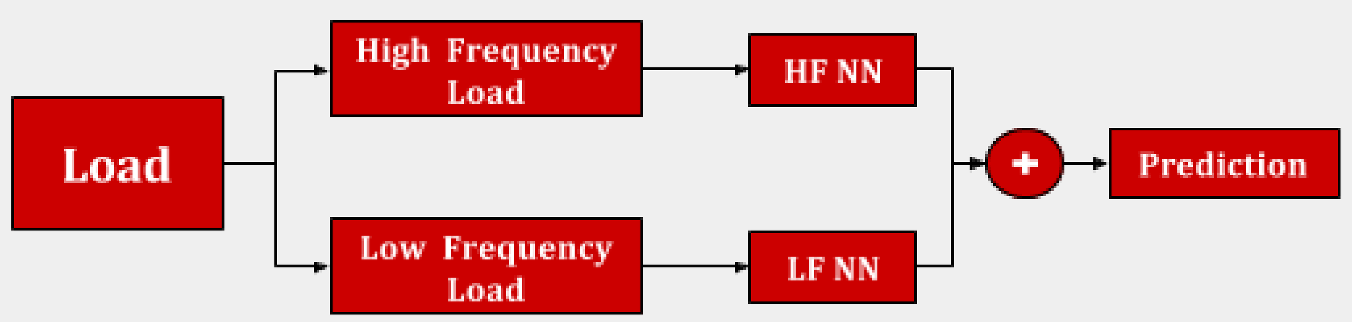
Neural Network:

- Trained a 3 layer Neural Network.
- The load of a day with similar weather and the same daytype (weekend, weekday) was used as input, as well as temperature and calendar effects.



Wavelet Decomposition:

- Load decomposed into low and high frequency patterns with Daubechies transform.
- A network is trained for each component, with the month and year variables masked from the high frequency network.



Ensembling:

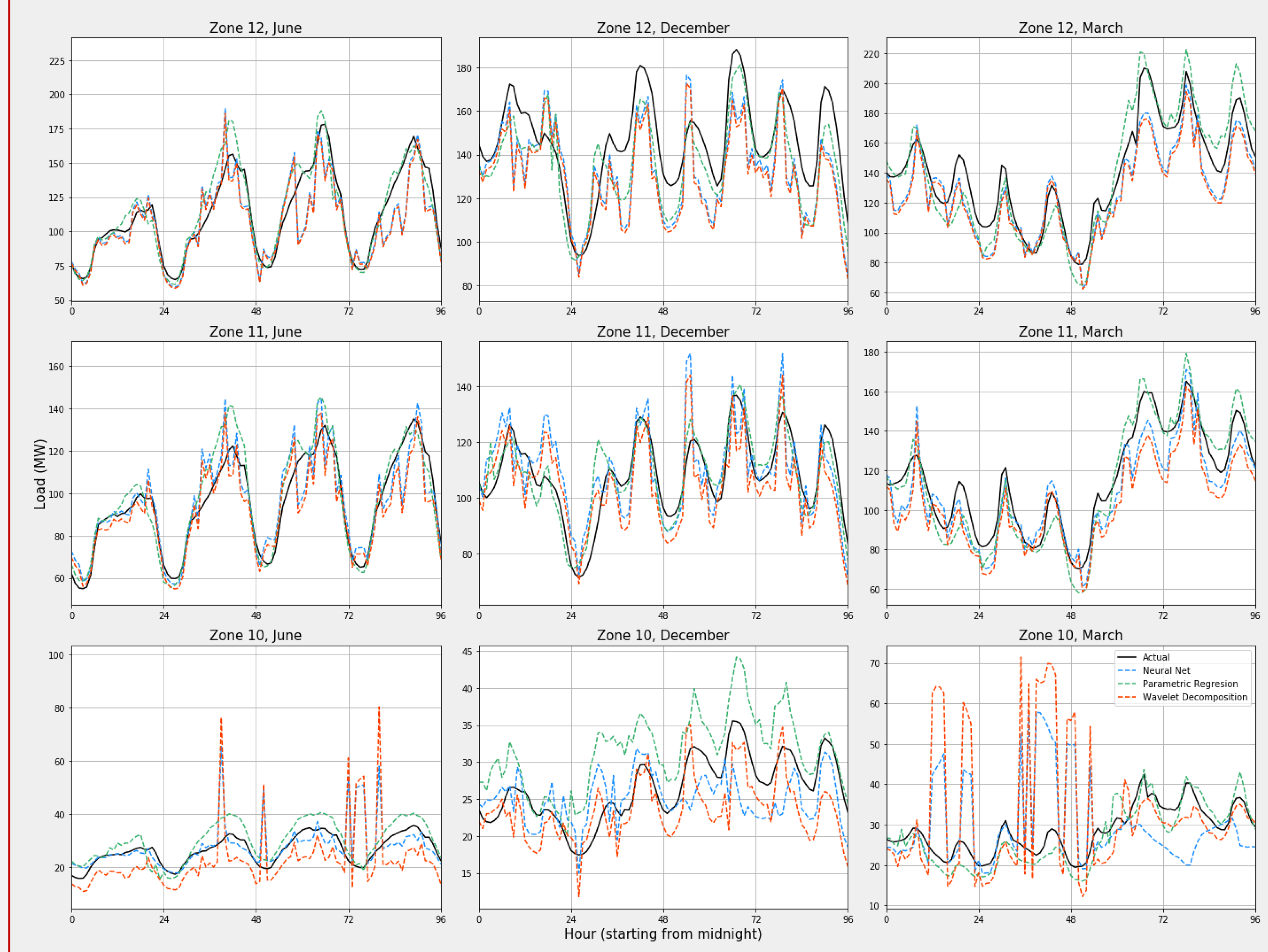
- We then take linear combinations of these models to ensemble the prediction to optimize weighted root mean squared error (WRMSE).
- Each zone is forecasted, with the weights for each zone as 1 for the WRMSE. The total load is also forecasted, with weight 20.

References

[1] Nathaniel Charlton and Colin Singleton. A refined parametric model for short term load forecasting. International Journal of Forecasting, 30(2):364 – 368, 2014.
[2] Chen et. al, Short-term load forecasting: Similar day-based wavelet neural networks. World Congress on Intelligent Control and Automation, June 2008.
[3] De Felice et. al, Short-term load forecasting with neural network ensembles: A comparative study. IEEE Computational Intelligence Magazine, 2011.
[4] Hong et. al, Global energy forecasting competition 2012. International Journal of Forecasting, 2014.

Results

Select Prediction Results

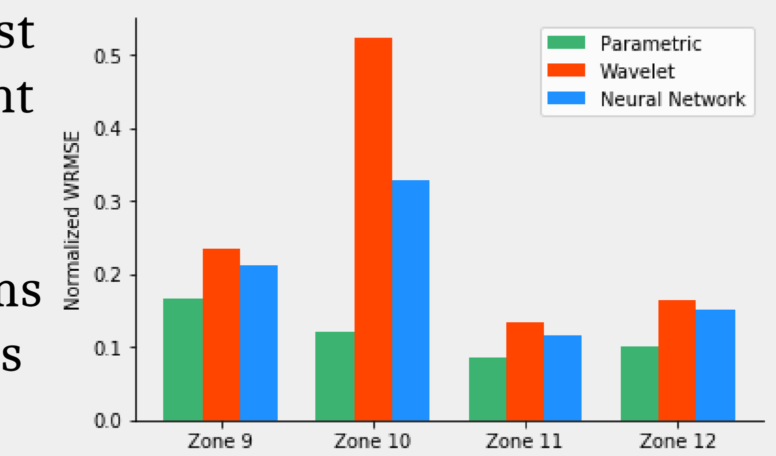


- The Parametric model performed best out of the individual models.
- Ensembling produced the best results:
  - ◯ 0.125 weight on Neural Network
  - ◯ 0.625 weight on Parametric
  - ◯ 0.25 weight on Wavelet model
- The models tend to fit well on most zones, but fail to capture important behaviors for atypical zones such as zone 10.
- While Neural Network outperforms Wavelet model, wavelet ensembles better with Parametric model.

Model Performance, WRMSE

Model	WRMSE
Parametric Regression	71,744
Neural Network	100,803
Wavelet Decomposition	107,023
Best Ensemble	64,138

Normalized WRMSE, Zones 9 -12



Next Steps

- Handcraft special features for atypical zones.
- Experiment with different numbers of layers & neurons.
- Evaluate performance on test set.

{jbarrio5, sgleeson, cnatoli} @stanford.edu