AEP Electricity Forecast: Phase 3

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Overview

Deregulation in the energy industry allows consumers to choose suppliers, increasing market competition. Accurate demand forecasts help suppliers like AEP meet consumer needs and plan expenses. Our team forecasted AEP's hourly energy load for the Appalachian Power transmission zone from October 27, 2023, to November 2, 2023.

We combined a linear regression with ARIMA, prophet and neural network methods to create an ensemble forecast of energy load. The ensemble model achieved a mean absolute percent error (MAPE) of 2.74% on validation data. However, because the validation forecast was developed using actual temperature data, we anticipate that MAPE will rise for future forecasts.

Methodology & Analysis

Data Used

We received hourly metered energy data from the AEP Appalachian Power transmission zone. Our model underwent training using data from January 1, 2021, to October 18, 2023, and was validated using data spanning October 19, 2023, to October 25, 2023. Because of daylight savings, the data included duplicate and missing observations in some hours, which we addressed by mean-imputing energy values for those observations.

In addition, we pulled hourly temperature data for three cities across the AEP transmission area: Blacksburg, Virginia; Columbus, Ohio; and Benton Lake, Michigan. The data was provided by the Iowa State University Mesonet and covered January 1, 2021, to October 25, 2023.

Model Development

Online weather forecasts suggest that there will be rapid cooling in the AEP region for the forecast week, moving from highs of near 70 degrees on October 27 to highs in the mid-40's by November 1. Therefore, we determined that an energy forecast for the coming week should incorporate expected temperature.

All time series models were fit to the residuals of a linear regression of metered load on temperature. The linear model included variables for hourly temperature, lagging hourly temperature, day of the week, month, and various higher-order and interaction effects. The best linear model had an adjusted R-squared of 0.95, and had about 2.70% MAPE on hold-out data.

We used an ensemble approach to model the linear regression residuals. Our ensemble gave equal weight to an ARIMA model, a prophet model, and an auto-regressive neural network.

The ARIMA model was selected by examining correlation plots of the differenced residual series. The final ARIMA model included two autoregressive lags, five seasonal autoregressive lags, and one seasonal moving average term on the differenced series. The prophet model used two fourier seasonal terms, a piecewise linear trend, and holiday effects. The neural network was fit on differenced data with 2 autoregressive lags and 3 seasonal autoregressive lags.

Results & Recommendations

Model Evaluation

The table below displays the MAPE and MAE of each model on the validation data.

Table 1: Model Validation Metrics

Model	MAPE	MAE (mw)
Neural Network	2.57%	99.21
Ensemble Model	2.74%	105.50
ARIMA	2.90%	111.91
Prophet Model	2.94%	113.45

The lowest-error forecast was performed by the neural network, followed by the ensemble model, the ARIMA model, and the prophet model. Even though the ensemble was not the best-performing model, we selected the ensemble model for future forecasting in order to reduce prediction variance.

Figure 1 below displays the forecasted metered load for the validation week.

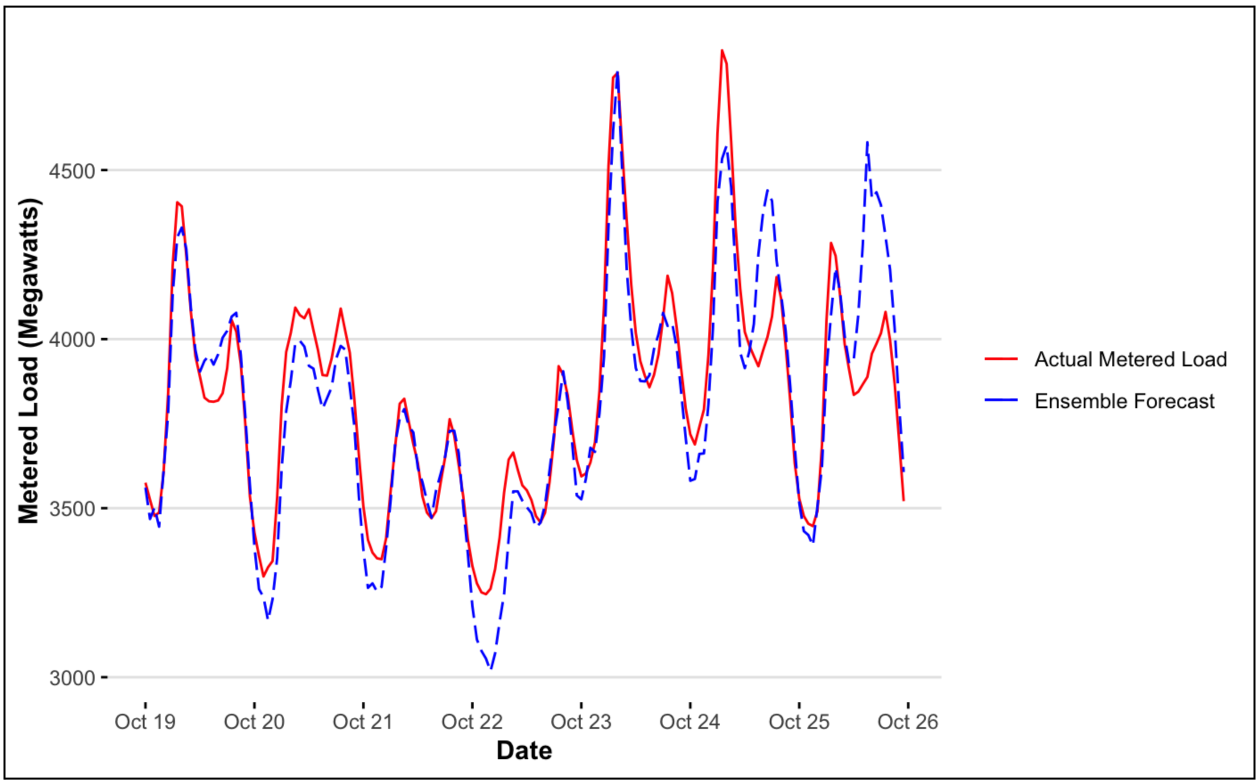

Figure 1: Hourly Metered Load Forecast

While the MAPE of the ensemble model is below 3% for the validation data, this is not necessarily indicative of future performance. Our model was validated using actual temperature data, whereas all future forecasts were made using predicted temperature. If weather forecasts are inaccurate, then our energy forecast will be inaccurate as well.

Recommendations

We recommend using our ensemble model to forecast future energy load. However, because our model uses temperature forecast data, disparities between actual and forecasted temperatures will adversely affect model performance. Therefore, we recommend that the model only be used for forecasting short-term energy usage. PJM should likely turn to other methods for long-term forecasting.

Conclusion

To forecast future metered energy load, we developed an ensemble model and fit it to the residuals of a linear regression of metered load on temperature and other variables. Using actual temperature data, the model achieved 2.74% MAPE on the validation set. However, because forward-looking forecasts will have to incorporate temperature forecasts, error is likely to be higher in the future.

Future short-term forecasting models may be improved by incorporating information related to holidays and other unusual events, along with weather data such as humidity and precipitation.