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Using Machine Learning to Forecast NIH Campus Cooling Load

Introduction

Today, machine learning is widely used to provide valuable information by identifying patterns within large volumes of data. At NIH, the Division of Technical Resources (DTR) uses machine learning to optimize the operation of the Central Utility Plant (CUP), which continuously supplies the campus with electricity, chilled water, and steam. One of the machine learning engines that DTR developed is the "Campus Cooling Load Forecaster," which forecasts the campus' chilled water demand for the next four days. With this information, CUP management can plan and optimize the chiller plant's operation and maintenance.

Overview

We start by assuming that the future campus load nonlinearly depends on past campus load and local weather, which can be described by a nonlinear autoregressive exogenous (NARX) model that is written as:

$$\hat{y}(t+1) = F[y(t), y(t-1), \dots, y(t-n_y),$$
$$X(t), X(t-1), \dots, X(t-n_x)] \qquad (1)$$

where *y(t)* and *X(t)* represent campus load and weather variables at time *t* and *F* represents a nonlinear function that predicts future campus load $\hat{y}(t+1)$. The differences between the NARX model and linear autoregressive model are the nonlinear function *F* and the exogenous terms *X* in addition to autoregressive terms y. Ending terms n_y and n_x in equation (1) represent the autoregressive order and exogenous order, respectively.

The nonlinear function *F* is modeled by a feed-forward artificial neural network (ANN). The ANN was trained on campus cooling load data and weather data (dry bulb and wet bulb temperature) collected over four years (2018 to 2021). The training process determined optimal ANN hyperparameters, such as the number of network layers and neurons at each layer, and neuron weights that minimize forecast errors.

After function *F* is determined, it is recursively applied to forecasting campus load for future hours. For example, once the campus load for the first hour $\hat{y}(t+1)$ is predicted with equation (1), it is fed into function F to forecast the campus load at the second hour as shown in equation (2).

$$\hat{y}(t+2) = F[\hat{y}(t+1), y(t), \dots, y(t-n_y-1),$$
$$X(t+1), X(t), \dots, X(t-n_x-1)] \qquad (2)$$

This procedure is repeated until all 96 hours of campus load are forecasted.

Model Improvement

A major issue with the standard NARX model is error accumulation. As the forecasted value ŷ is fed into the function, the forecast error is added into the ANN and passed to the next prediction. This error accumulation will negatively impact the result as the forecast horizon expands. One way to stop this error propagation is to train a single model for each hour of campus load forecast and employ 96 distinct models to forecast campus load for the next four days.

Results

DTR tested the campus cooling load forecaster of 96 ANN models using recently collected data. Figure 1 shows a comparison of true campus load with five forecast results that were forecasted one hour and one through four days in advance. While the forecast of the next one-hour campus load achieved the most accurate result, all forecasts captured the trend of the true campus load. The forecast for the past 10 months shows that the overall average forecast error is under 2000 tons, which is less than the capacity of one standard 5000-ton chiller. This forecaster can therefore assist in operation planning for the 10 chillers at the NIH CUP.

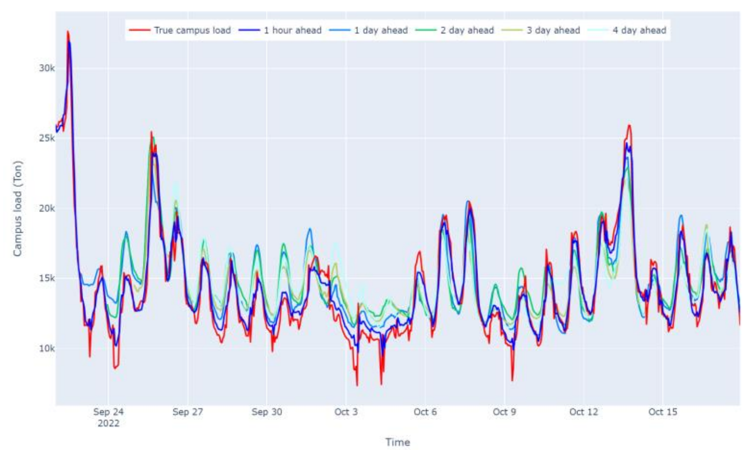

Figure 1: Campus load and forecasting results

Conclusion

The machine learning model developed here can be used to forecast campus cooling load with a reasonable confidence interval to allow accurate, efficient operation planning for the NIH chiller plant without impacting campus reliability.