Robust Hourly Cooling Load Prediction Based On The Historical Weather and Load Data

Yin Guo[1] and Ehsan Nazarian[2]
[1]*Facilities Management & Planning*
[2]*Industrial & Management Systems Engineering*
University of Nebraska-Lincoln

Sponsors and Supporting Organizations

- Nebraska Center for Energy Science Research
- Nebraska Utility Corporation
- Lincoln Electric System (LES)

Participating UNL Units

- Industrial & Management Systems Engineering
- Construction Management
- Facility Management & Planning

Faculty Advisors

Jeonghan Ko
Industrial and Operations Engineering
The University of Michigan, Ann Arbor

Kamlakar Rajurkar
Mechanical & Materials Engineering
University of Nebraska-Lincoln

Abstract

This study presents a new prediction scheme for optimal control of cooling system with thermal energy storage and better energy management of a smart grid system. The proposed prediction scheme could provide up to 48 hours ahead accurate cooling load prediction. The proposed models are hourly indexed. Different sets of parameters are derived for cooling load prediction in each hour of day. The motivation for hourly indexing is based on the effect of different temperature trend and buildings utilization on the cooling load between each hour. The robust regression approach incorporates fast least trimmed squares algorithm for possible outlier detection and increased accuracy of the models. This study can enhance the prediction accuracy of cooling load for better scheduling and planning of the cooling facilities.

Motivation and Background

- An accurate cooling load prediction model is essential for
  - Optimal control of cooling system
  - Smart grid system integration
- Lack of generic models for both large building complexes and individual buildings

Objective

- To develop fast and accurate robust regression based prediction scheme
  - incorporating historical weather characteristics and buildings occupancy and usage patterns
  - with outlier detection capability

Approach

Modeling

- Autoregressive models with exogenous inputs models (ARX) that combine
  - Historical cooling load and weather data
  - Future weather prediction
- Hourly indexing of ARX models to incorporate the similarity of load profiles of the same hour from day to day (24 ARX models, one for each hour)
- Differentiation of weekend and weekday models to reflect building occupancy and usage patterns

Parameter Estimation

- Fast Least Trimmed Square algorithm for coefficients estimation and outlier detection
  - Recursive *h*-subset selection of *n* data points
  - Least Square estimation of coefficients
  - Arrangement of data points based on ascending residuals
  - Selection of *h*-subset of *n* data points with smallest residuals
  - Repetition until convergence
  - Global minimum sum of squared residuals for the converged model

Assumptions

- *t*-24 is defined by the day of week
  - Monday: 24-hour ahead refers to Friday
  - Tuesday to Friday: 24-hour ahead refers to the day before
  - Saturday: 24-hour ahead refers to the last Sunday
  - Sunday: 24-hour ahead refers to the day before

ARX Models

1-hour Ahead Prediction

$$CL_t = a_{t,0} + a_{t,1}T_{Max} + a_{t,2}T_{Min} + a_{t,3}T_t + a_{t,4}T_t^2 + a_{t,5}RH_t + a_{t,6}T_tRH_t + a_{t,7}CL_{t-1} + a_{t,8}T_{t-1} + a_{t,9}T_{t-1}^2 + a_{t,10}RH_{t-1} + a_{t,11}T_{t-1}RH_{t-1} + a_{t,12}T_tT_{t-1} + a_{t,13}RH_tRH_{t-1} + a_{t,14}CL_{t-2} + a_{t,15}T_{t-2} + a_{t,16}T_{t-2}^2 + a_{t,17}RH_{t-2} + a_{t,18}T_{t-2}RH_{t-2} + a_{t,19}T_tT_{t-2} + a_{t,20}RH_tRH_{t-2} + a_{t,21}CL_{t-24} + a_{t,22}T_{t-24} + a_{t,23}T_{t-24}^2 + a_{t,24}RH_{t-24} + a_{t,25}T_{t-24}RH_{t-24}$$

24-hour Ahead Prediction

$$CL_t = a_{t,0} + a_{t,1}T_{Max} + a_{t,2}T_{Min} + a_{t,3}T_t + a_{t,4}T_t^2 + a_{t,5}RH_t + a_{t,6}T_tRH_t + a_{t,7}CL_{t-24} + a_{t,8}T_{t-24} + a_{t,9}T_{t-24}^2 + a_{t,10}RH_{t-24} + a_{t,11}T_{t-24}RH_{t-24} + a_{t,12}CL_{t-168} + a_{t,13}T_{t-168} + a_{t,14}T_{t-168}^2 + a_{t,15}RH_{t-168} + a_{t,16}T_{t-168}RH_{t-168}$$

CL_t: Cooling load at time t T_{Max}: The maximum temperature of day
T_t: temperature at time t T_{Min}: The minimum temperature of day
RH_t: Relative humidity at time t

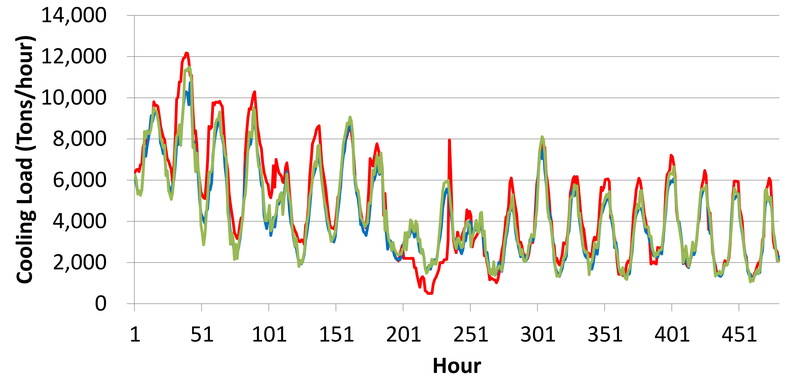
- 1-hour ahead prediction models are the same as up to 6-hour ahead prediction models

Numerical Studies

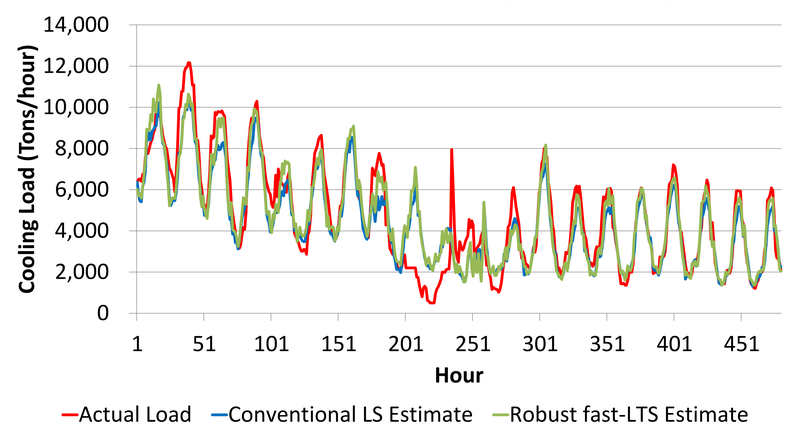
- UNL City campus hourly cooling load and weather data: 2010-2012
- Analysis period: April-October
- Learning data: 2010-2011
- Testing data: 2012

Results

1-hour Ahead Prediction for September 2012



24-hour Ahead Prediction for September 2012



Conclusions

- ARX model's integration of autoregressive and regression models enhanced the accuracy in prediction.
- Robust regression approaches could detect outliers and decrease the prediction error by 7%.