Applied Energy 136 (2014) 186–196

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Modeling and forecasting of cooling and electricity load demand

A. Vaghefi [a,*], M.A. Jafari [a], Emmanuel Bisse [b], Y. Lu [b], J. Brouwer [c]

[a] Department of Industrial and System Engineering, Rutgers University, Piscataway, NJ 08904, USA
[b] Siemens Corporate Research, Princeton, NJ 08540, USA
[c] National Fuel Cell Research Center, University of California, Irvine, Irvine, CA 92697, USA

HIGHLIGHTS

- We propose a model for forecasting cooling and electricity load demand.
- The model takes the advantage of both time series and regression methods.
- The model is able to accurately forecast the load demands of the CCHP system.

ARTICLE INFO

Article history:
Received 25 January 2014
Received in revised form 14 August 2014
Accepted 2 September 2014

Keywords:
Load forecasting
Time series-regression model
Cochrane–Orcutt estimation
Thermal energy storage
Heat recovery steam generator

ABSTRACT

The objective of this paper is to extend a statistical approach to effectively provide look-ahead forecasts for cooling and electricity demand load. Our proposed model is a generalized form of a Cochrane–Orcutt estimation technique that combines a multiple linear regression model and a seasonal autoregressive moving average model. The proposed model is adaptive so that it updates forecast values every time that new information on cooling and electricity load is received. Therefore, the model can simultaneously take advantage of two statistical methods, time series, and linear regression in an adaptive way. The effectiveness of the proposed forecast model is shown through a use case. The example utilizes the proposed approach for economic dispatching of a combined cooling, heating and power (CCHP) plant at the University of California, Irvine. The results reveal the effectiveness of the proposed forecast model.

1. Introduction

U.S. households and commercial buildings consume approximately 40% of total energy use and account for 72% of total U.S. electricity consumption [1]. Commercial building energy demand, in particular, doubled between 1980 and 2000 and is predicted to increase 50% over the next 15 years [2]. As a result, energy demand management has emerged as a key policy for both public and private organizations. CCHP systems can significantly contribute to reducing buildings energy use, curtail pollutant and carbon emission, and help to decrease risks of blackouts and brownouts in the utility grid [3,4]. CCHP technology integrates processes of production and simultaneous use of cooling, heating, and power at a single site. However, since most commercial and industrial electrical loads are highly dynamic and typically not synchronized with local heating and cooling demands, advanced control strategies will be imperative to economic dispatch of CCHP resources.

A wide range of optimal control strategies has been proposed to improve the CCHP operation based on different objectives including power flow, capacity, operation, energy-use and environmental considerations [5–12]. A common element in almost all optimal control strategies is to have an accurate estimation of cooling, heating, and electricity load demands. Some researchers assume that load demands are known and available over a specific period [8,9]. However, cooling and electricity demands are typically stochastic and unknown mainly because of the complex interaction s between plant facilities and equipment, e.g. chillers and turbines yields. Liu et al. [8] point out that in practical applications, the exact future load profile does not exist; and forecasting methods should be taken into consideration by researchers. Therefore, a forecasting mechanism should be applied by researchers to find the future values of load demands.

A number of researchers employ building simulation platform to generate building load demand based on its physical characteristics and other dynamic input variables such as occupancy, weather, and time information. The cooling and electricity load demands are outputs of running the simulation and are then fed into the optimization model [10–12]. However, the quality of

* Corresponding author.
E-mail addresses: vaghefi@rutgers.edu (A. Vaghefi), jafari@rutgers.edu (M.A. Jafari), Emmanuel.Bisse@siemens.com (E. Bisse), yanlu@siemens.com (Y. Lu), jbrouwer@uci.edu (J. Brouwer).

http://dx.doi.org/10.1016/j.apenergy.2014.09.004
0306-2619/

Nomenclature

CCHP	combined cooling, heating and power
LSE	least square estimate
ARX	autoregressive with exogenous variable
ARMAX	autoregressive moving average with exogenous variable
ARMA	autoregressive moving average
AI	artificial intelligence
ANN	artificial neural network
R^2	coefficient of determination
R^2_{adj}	adjusted coefficient of determination
GT	gas turbine
ST	steam turbine
TES	thermal energy storage
HRSG	heat recovery steam generator
COP	coefficient of performance
W^k_{CHC}	cooling power generated by the kth chiller (kW)
W^k_{CHW}	power consumed by the kth chiller to cooling power (kW)
COP^k	coefficient of performance for the kth chiller
W_{CHW}	total power consumed by chillers to generate total cooling power of the campus (kW)
$Q_{cooling}$	cooling demand from the campus (kW)
T_{CHRw}	returned water temperature to chillers (K)
T_{CHSw}	supply water temperature from chillers (K)
$\dot{m}_{chw}$	chilled water mass flow rate (kg/s)
c_w	specific heat capacity of water (kJ/kg K)
$W_{electricity}$	electricity demand from the campus (kW)
W_{grid}	power purchased from grid (kW)
W_{GT}	power produced by gas turbine (kW)
W_{ST}	power produced by steam turbine (kW)

Symbols

W	electricity power
Q	cooling power
$\dot{m}$	mass flow
T	temperature
ε	random error term
y	dependent/output variable
x	independent/input variable
β	coefficients of input
Φ	autoregressive operator
Θ	moving average operator
B	backward operator

Subscripts

T	time (h)
J	index for input variables
CHC	cooling generated by chiller
CHW	power consumed by chiller
W	water
Chw	chilled water
$CHRw$	water returned to chiller
$CHSw$	water supplied by chiller
GT	gas turbine
ST	steam turbine
$grid$	power grid

Superscripts

k	chiller number

results highly depends on quality of the simulation models and their inputs. In addition, for any CCHP optimization, a detailed building simulation model needs to be accordingly built and run repeatedly. Another way to deal with this problem is to consider uncertainty in CCHP optimization model. Hu and Cho [12] for instance, propose an optimization model with some probabilistic constraints to guarantee that the model is reliable to satisfy the stochastic load demand. They assume load demands are independent and follow normal distributions in which 95% of the area is within the range of ±20% of the average load demands. Another approach to this problem is to develop a forecasting model and embed it into the optimization model. This is the main motivation of this work. In this paper, Cochrane–Orcutt estimation technique is used as an effective linear model to provide look-ahead forecasts for cooling and electricity demand load. It simultaneously fits a regression model and a time series to the data while maintaining least square estimate (LSE) conditions. In addition, the forecast values are modified when a new data is received from the real system. The proposed model is currently working as a part of an integrated optimal dispatch for CCHP plant at the University of California, Irvine and providing accurate forecasts for the entire campus cooling and electricity load demand.

2. Background study

In most real cases, cooling and electricity load demands are highly dynamic oscillating within a wide range of values during course of a day. This is mainly because several physically explicit or latent factors can instantaneously influence cooling and electricity demand patterns. These factors can be any one of the following types: (i) Static factors that are usually set at the design stage and only change due to aging wear and tear. Building characteristics, CCHP components, chiller types and generator nominal capacities are examples of such factors; (ii) Environmental variables extrinsic to the building, such as climate and weather data; (iii) operational variables, e.g. cooling/heating set point values, lighting, time schedule to operate various equipment and system components within plant or building; and (iv) uncontrollable dynamical variables, such as number of occupants at any time, noise due to structural variations etc. It is ideal to know all these factors and their impacts on energy dynamics in order to optimally forecast and control cooling and electricity demands for single building or a cluster of buildings. However, a complete forecast model is not practically attainable due to unknown significant dynamical variables, lack of tools to measure their effects, or that some of these variables are uncontrollable. Therefore, a wide range of different methods has been proposed to model and forecast load dynamics. In overall, these methods can be categorized into three general approaches.

In the first approach, a linear or nonlinear statistical model is used to explain the variability of response (load or energy dynamics) over time. The most popular example of such statistical models is Box and Jenkins time series paradigm where load demands are estimated based upon a linear combination of their past values [13,14]. There are a large family of different models in this category that can deal with many special cases including seasonality, non-stationary, and non-homogeneity of variances (see e.g. [15,16]). The major drawback of such models is that the future values are typically forecasted based upon the past and present values of cooling and electricity load demands without considering any *exogenous* factors in the model. Another example of statistical approach is using regression models (metamodel) where the variability within response is modeled via a number of exogenous factors [17–21]. The major problem of such models is that they often ignore the complex interactions between exogenous factors, which