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SCIENCE DIRECT®
Applied Energy 83 (2006) 1033–1046
APPLIED ENERGY
www.elsevier.com/locate/apenergy

Cooling-load prediction by the combination of rough set theory and an artificial neural-network based on data-fusion technique

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Received 25 May 2005; received in revised form 28 July 2005; accepted 13 August 2005
Available online 22 December 2005

Abstract

A novel method integrating rough sets (RS) theory and an artificial neural network (ANN) based on data-fusion technique is presented to forecast an air-conditioning load. Data-fusion technique is the process of combining multiple sensors data or related information to estimate or predict entity states. In this paper, RS theory is applied to find relevant factors to the load, which are used as inputs of an artificial neural-network to predict the cooling load. To improve the accuracy and enhance the robustness of load forecasting results, a general load-prediction model, by synthesizing multi-RSAN (MRAN), is presented so as to make full use of redundant information. The optimum principle is employed to deduce the weights of each RSAN model. Actual prediction results from a real air-conditioning system show that, the MRAN forecasting model is better than the individual RSAN and moving average (AMIMA) ones, whose relative error is within 4%. In addition, individual RSAN forecasting results are better than that of ARIMA.

Keywords: Cooling-load forecasting; Rough sets; Artificial neural-networks; Data-fusion technique

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doi:10.1016/j.apenergy.2005.08.006

Nomenclature

CL	cooling load (kW)
H	relative humidity (kg/kg)
M	flow rate (kg/s)
P	pressure (Pa)
T	temperature (°C)

Subscripts and superscripts

f	fresh air
ra	return air
ro	room air
rw	return chilled water
sa	supply air
sw	supply chilled-water
1,2, . . ., I . . . 11	stand for AHU I
I	FHU 1
II	FHU 2

1. Introduction

Because of significant amounts of energy consumed in heating, ventilating and air-conditioning (HVAC) systems, there have been efforts to study energy use performance and promote good operational practice in buildings. In order to improve the operation of HVAC systems, it is necessary to have reliable optimization routines [1]. Accurate prediction of the dynamic air-conditioning load in a building is a key for the optimal control of a HVAC system. It is vital for adjusting the starting time of cooling to meet start-up loads, so minimizing or limiting the electric on-peak demand. Many techniques have been proposed in the last few decades for short-term load forecasting (STLF) [2]. The traditional techniques that have been used for the STLF include autoregressive integrated moving-average (ARIMA) model [3], linear regression (LR) technique [4], neural-network (ANN) model [5], and grey model [6]. However, no single one has performed well enough because each model can take a few or usually only one relevant factor into consideration. For the combined forecasting method [7], it cannot make use of the full capability of residual subspace. In addition, using all data would compromise the robustness of the prediction scheme. Recently, with the developments of artificial intelligence, alternative solutions to the STLF problem have been proposed. Expert systems have been successfully applied to STLF [2]. For an accurate forecasting model, it is important to understand which factors influence the load level most. Such knowledge is often acquired from experienced operators. However, manual selection of factors pertinent to prediction task would not guarantee an optimal solution: the inaccurate estimations result in inaccurate predictions. Hence, there is a need for a reliable model that can select relevant factors automatically from historical data. As a typical data-mining method, rough-set theory, which can be used for attribute reduction, provides a solvable method for this problem. By attribute reduction, irrelevant factors to the tasks can be identified and removed. ANN, on the