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On-line building energy prediction using adaptive artificial neural networks

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Abstract

While most of the existing artificial neural networks (ANN) models for building energy prediction are static in nature, this paper evaluates the performance of adaptive ANN models that are capable of adapting themselves to unexpected pattern changes in the incoming data, and therefore can be used for the real-time on-line building energy prediction. Two adaptive ANN models are proposed and tested: accumulative training and sliding window training. The computational experiments presented in the paper use both simulated (synthetic) data and measured data. In the case of synthetic data, the accumulative training technique appears to have an almost equal performance with the sliding window training approach, in terms of training time and accuracy. In the case of real measurements, the sliding window technique gives better results, compared with the accumulative training, if the coefficient of variance is used as an indicator.

Keywords: On-line prediction; Electric demand; Energy demand prediction; Building cooling; Artificial neural networks; Adaptive models

1. Introduction

The prediction of building energy consumption can play an important role in building management since it can help optimize the building daily operation and select better control strategies [1]. An automated energy prediction system is often built on top of a mathematical prediction model consisting of several parameters. The model parameters are estimated using existing data that typically include energy demand or consumption and temperature measurements recorded in the past. A variety of prediction models have been proposed in the literature that include time-series models, Fourier series models, regression models, artificial neural network (ANN) models and fuzzy logic models. Each model type has its own features, advantages and disadvantages, and in addition, its performance varies from one application to another.

With the exception of a few ANN models, most of the surveyed literature focus on static prediction, a prediction scheme that involves a single prediction model that does not evolve over time: when the estimation of the model parameters is completed, the model is fixed; the most recently collected data is not used to update the model parameters. To obtain an accurate static model, a large volume of historical data is required to estimate the model parameters. The alternative approach is the use of a dynamic (adaptive) model that constantly updates model parameters based on newly available data. As the energy data collection process is automated, the entire process of retrieving new measurements, updating the model and making short-term energy prediction can be performed in 'real time' on-line.

The objective of this paper is to evaluate the performance of several adaptive neural network models for the on-line prediction of building energy demand using both simulated (synthetic) and measured data.

2. Literature survey

Regression models have been demonstrated to be effective for building energy predictions in a number of

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experiments (e.g., [2–4]). Relatively few parameters must be identified, thus reducing the time required for the model development. The regression models do not, however, accurately reflect the hourly or sub-hourly energy demand. They are best suited for predicting the average consumption over longer periods such as days or months. For different buildings with different environment and weather conditions, much effort and time must be spent on selecting time scales and regressors to find a best fit model. Also, autocorrelation or multicollinearity problems must be considered when evaluating the performance of prediction because they tend to lead to model uncertainty.

The use of time-series analysis techniques to forecast energy use is logical because the history of energy use can be represented by a time series. Kimbara et al. [5] experimented with the autoregressive integrated moving average (ARIMA) model and found the performance of ARIMA to be better than a two-dimensional autoregressive (AR) model. Several models and applications have been implemented based on the autoregressive moving average with exogenous input model (ARMAX) model (e.g., [6]). On one hand, time-series models can capture the relationship between the hourly energy use and time variation given a set of time-series data. On the other hand, both ARMA and AR models work under the assumption that the present value is a linear combination of the previous ones. In most cases, this assumption is invalid. The ARIMA and ARMAX models can handle the changes in an unstationary process, but require the estimation of many parameters. Also, the autocorrelation between variables must be considered because it strongly impacts the accuracy of the prediction. Dhar et al. [7] used a Fourier series model to predict the energy demand in an institutional building. Fourier series models provide better performance compared to the above time-series models; however, they are based on the assumption that energy use in most buildings is periodic. If dramatic changes happen, high-frequency Fourier components must be included in the model, thus dramatically increasing the computational cost.

Artificial neural networks (ANN) is a type of artificial intelligence technique that mimics the behavior of the human brain. It can approximate a nonlinear relationship between the input variables and the output of a complicated system. The main advantage of an ANN model is its self-learning capability. The use of ANN in building energy prediction has been investigated by many researchers (e.g., [8,9]). Their models share some similarities, but each differs significantly in implementation details because each is tailored toward a specific type of energy prediction under a specific building environment. On one hand, ANN models estimate parameters faster by learning from examples automatically. On the other hand, because it is hard to distinguish structure from noise in the data, an ANN tends to memorize noise. Also, an ANN might not be able to adapt to dramatic changes such as unstable behavior in the power load–temperature relationship.

Most of the literature focuses primarily on static prediction. In a static prediction, the prediction model is set up in advance using historical data and does not change afterward, when new information become available. It is highly possible that such a model becomes invalid when new patterns emerge and more recent data becomes available. In this case, a dynamic prediction model that can adapt itself to such changes in the energy consumption pattern is desirable. This is especially true for short-term energy prediction. Only a few dynamic prediction systems were found in the literature and all in the field of electric load forecasting for power system. They all used a sliding window approach in which the size of data set used for training is kept constant; however, the data set is periodically updated as the window moves forward in time. Djukanovic et al. [10] used an adaptive system for short-term load forecasting with a moving window consisting of data associated with the 4 previous weeks as well as with 8 weeks at the same time in the previous year. Khotanzad et al. [11] used a combination of three separate models (i.e., weekly, daily and hourly models) for short-term load forecasts. Each model is updated at the end of each period with the data associated with that period (e.g., at the end of each week, the weekly model is updated using the last week data). Mohammed et al. [12] used three ANN adaptive models and a two-stage training algorithm. The first training stage produces a set of initial ANN weights that capture the general, day by day trend of the electric load. During the second-stage training, the ANN is refined and enhanced to capture special features of that particular day for which the forecast is made by using a subset of data consisting of those that share similar temperature conditions with the day being forecasted as well as data from the previous 5 days. Charytoniuk and Chen [13] used an ANN model with an adaptive scheme that involves a moving window, which consists of training data from the 3 last weeks as well as 2 weeks around the same day in the previous year. These approaches have potentials in the area of on-line building energy prediction.

The regression and time-series models are based on classical mathematical theory. Thus, the behavior of these models is well understood and the model parameters are straightforward to estimate. However, these models tend to work well only for energy systems that are well behaved. The ANN model generally works better for buildings that exhibit highly nonlinear energy consumption patterns. However, the success of using ANN depends on a number of design issues such as the choice of input and output data, the number of hidden layers, the number of neurons used in each layer and the training algorithms used. A few studies have compared these forecasting methods. Kawashima et al. [14] found that ANN models provide the best performance. Dhar et al. [7] compared Fourier series models, ANN models and the winners of the Great Energy Prediction Shootout [15]. The performance of Fourier series was found to be comparable to the performance of ANN models and that of the winners of the shootout competition. Fourier series