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Ensemble of various neural networks for prediction of heating energy consumption

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ABSTRACT

For prediction of heating energy consumption of a university campus, various artificial neural networks are used: feed forward backpropagation neural network (FFNN), radial basis function network (RBFN) and adaptive neuro-fuzzy interference system (ANFIS). Actual measured data are used for training and testing the models. For each neural networks type, three models (using different number of input parameters) are analyzed. In order to improve prediction accuracy, ensemble of neural networks is examined. Three different combinations of output are analyzed. It is shown that all proposed neural networks can predict heating consumption with great accuracy, and that using ensemble achieves even better results.

1. Introduction

The study of the building energy demand has become a topic of great importance, because of the significant increase of interest in energy sustainability, especially after the emanation of the EPB European Directive. In Europe, buildings account for 40% of total energy use and 36% of total CO_2 emission [1]. The estimation or prediction of building energy consumption has, therefore, played very important role in building energy management, since it can help to indicate above-normal energy use and/or diagnose the possible causes, if there has been enough historical data gathered. Scientists and engineers are lately moving from calculating energy consumption toward analyzing the real energy use of buildings. One of the reasons is that, due to the complexity of the building energy systems and behavior, non-calibrated models cannot predict well building energy consumption, so there is a need for real time image of energy use (using measured and analyzed data).

The classic approach to estimate the building energy use is based on the application of a model with known system structure and proprieties as well as forcing variables (forward approach). These engineering methods use physical principles to calculate thermal dynamics and energy behavior on the whole building level or for sub-level components [2]. A lot of different software tools have been developed for this purpose, such as DOE-2, EnergyPlus, TRNSYS, BLAST, ESP-r, HAP, APACHE. Using these tools requires detailed knowledge of the numerous building parameters (constructions, systems) and behavior, which are usually not available. Some simplified methods for building energy use prediction were developed. The steady-state method using degree-day was presented in [3]. A simple method of formulating load profile for UK domestic buildings has been introduced by Yao and Steemers in [4]. They used thermal dynamic model to predict daily breakdown energy demand load profile of appliance, domestic hot water and space heating.

A different approach for building energy analysis is based on the so-called inverse or data-driven models. In recent years, considerable attention has been given to data-driven based methods [5]. By a data-driven approach, building energy behavior is analyzed, while defining relationships with one or more different driving forces or parameters. It is required that the input and output variables are known and measured, and the development of the inverse model consists in determination of a mathematical description of the relationship between the independent variables and the dependent one. The data-driven approach is useful when the building (or a system) is already built, and actual consumption (or performance) data are measured and available. For this approach, different statistical methods can be used. Statistical regression models simply correlate the energy consumption with the influencing variables. Bauer and Scartezzini [6] introduced a regression model to predict heating and cooling load, dealing with internal and solar gains. Catalina et al. [7] developed the regression model for the prediction of the monthly heating need for the single-family residential sector. Katipamula et al. [8] found that a multilinear regression provides better accuracy than a single variable model for modeling energy

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consumption. Lam et al. [9] used Principal Component Analysis (PCA) of prevailing weather conditions in sub-tropical Hong Kong.

Artificial neural networks (ANN) are the most used artificial intelligence models for the building energy consumption prediction. In [10] detailed model simulation (in EnergyPlus) was compared with a simple model based on ANN. Regarding the ANN models, the results for the simpler (temperature-only input) and the more complex (temperature/relative humidity/solar radiation inputs) neural networks showed a fair agreement between energy consumption forecasts and actual values, when different networks for working days and weekends are implemented. Ekici et al. [11] used a backpropagation three-layered ANN for the prediction of the heating energy requirements of different building samples. The inputs of the network for training and testing were considered as building transparency ratio, orientation and insulation thickness and the output is building heating energy needs. Hourly heating energy consumption for a model house calculated by degree-hour method was used for training and testing the ANN model in [12]. In [13] actual recorded input and output data that influence long-term energy consumption were used in the training, validation and testing process. The produced ANN results were compared with the results produced by a linear regression method, a support vector machine method and with real energy consumption records showing much better prediction accuracy. In [14] authors tested several training algorithms, calibrated in real conditions and used ANN to predict the energy consumption and PMV value for an indoor swimming pool. Afterwards ANN is utilized as a cost function engine to develop an intelligent energy and thermal comfort management system for this pilot. Li et al. in [15] proposed the hybrid genetic algorithm-adaptive network-based fuzzy inference system which combined the fuzzy if-then rules into the neural network-like structure for the prediction of energy consumption in the library building. The calculated results indicated better performance compared with ANN in term of forecasting accuracy. In [16] Karatasou et al. discussed how neural networks, applied to predict energy consumption in buildings, can advantageously be improved guided by statistical procedures. They deal with the identification of all potential relevant input, the selection of hidden units for this preliminary set of inputs, through an additive phase and the remove of irrelevant inputs and useless hidden units through a subtractive phase. A review of the different neural network models used for building energy prediction can be found in [17]. In most papers, use of single neural network was analyzed, while some authors, as in [15], compared different network architectures. In this paper, idea was to analyze possible application of various network topologies on the same case study. At first stage, prediction results achieved with different networks (feedforward, radial basis and adaptive neuro-fuzzy inference system) are compared. In the second stage qualitative specific and innovative use of created networks by combining them into ensemble is proposed. All these analyses are done using different number of input variables. The ensemble of neural networks is a very successful technique where the outputs of a set of separately trained neural networks are combined to form one unified prediction [18]. Since an ensemble is often more accurate than its members, such a paradigm has become a hot topic in recent years and has already been successfully applied to time series prediction [19], weather forecasting [20], load prediction in a power system [21]. The novelty in this paper would be creating ensemble of neural networks for prediction of heating energy consumption.

2. Artificial neural networks models

The main advantage of an ANN model is its self-learning capability and the ability to approximate a nonlinear relationship between the input variables and the output of a complicated system. In this study, the three different architectures of ANN are used for prediction of the heating energy consumption.

2.1. Feedforward backpropagation neural network (FFNN)

The feedforward neural network architecture consists of an input layer, an output layer, and one or more hidden layers of neurons. Each layer has a number of neurons and each neuron is fully interconnected with adaptable weighted connections to neurons in the subsequent layer. The nonlinear activation functions in the hidden layer neurons enable the neural network to be a universal approximator. The process of training network is the adjustment of the weights, so that the network can produce the desired response to the given inputs. Different training algorithms could be applied to minimize the error function, but the most widely used are the backpropagation algorithm and the algorithms derived from it. They use a gradient descent technique to minimize the cost function which is the mean square difference between the desired and the actual network outputs. In this study, a multilayer feedforward network with single hidden layer and backpropagation learning algorithm is used.

2.2. Radial basis function networks (RBFN)

A RBF network, as a type of feedforward neural network, consists of three layers including an input layer, a single hidden layer and an output layer. The input nodes are directly connected to the hidden layer neurons. The hidden layer transforms the data from the input space to the hidden space using a nonlinear function. RBFN uses the radially symmetrical function as an activation function in the hidden layer, and the Gaussian function, the most commonly used activation function, is adopted in this study. For a RBFN with an n-dimensional input $x \in \mathcal{R}^n$ the output of the jth hidden neuron is given by

$$h_j(x) = \phi_j(||x - c_j||), \quad j = 1, 2, \ldots, m \tag{1}$$

where c_j is the center (vector) of the jth hidden neuron, m is the number of neurons in the hidden layer and $\phi(\cdot)$ is the radial basis function. The neurons of the output layer have a linear transfer function. The kth output of the network is obtained by the weighted summation of the outputs of all hidden neurons connected to that output neuron:

$$\hat{y}_k(x) = \sum_{j=1}^{m} w_{kj} h_j(x) + w_{k0} \tag{2}$$

where w_{kj} is the connecting weight between the jth hidden neuron and the kth output unit, w_{ko} is the bias and m is the number of the hidden layer neurons. The training RBFN is aimed at adjusting parameters of Gaussian functions (centers and widths) and the weights between the hidden and the output layers. The weights are optimized using least mean square algorithm, and the centers can be chosen randomly or using some clustering algorithms.

2.3. Adaptive neuro-fuzzy inference system (ANFIS)

The adaptive network-based fuzzy inference system (ANFIS) proposed by Jang [22] is one of the most commonly used fuzzy inference systems, and its architecture is obtained by embedding the fuzzy inference system (FIS) into the framework of adaptive networks. The architecture of the ANFIS used in this study is based