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Simplified dynamic neural network model to predict heating load of a building using Taguchi method

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ABSTRACT

Prediction of heating and cooling loads is necessary for building design and HVAC system operation, in order to reduce energy consumption. This study intended to develop a method for the prediction of the instantaneous building energy load, depending on various combinations of input parameters using a dynamic neural network model. The heating load was calculated for a typical apartment building in Seoul for a one-month period in winter using the Energy-Plus software. The data sets obtained were used to train neural network models. The input parameters included dry-bulb temperature, dew point temperature, direct normal radiation, diffuse horizontal radiation, and wind speed. The Taguchi method was applied to investigate the effect of the individual input parameters on the heating load. It was found that the outdoor temperature and wind speed are the most influential parameters, and that the dynamic model provides better results, as compared with the static model. Optimized system parameters, such as number of tapped delay lines and number of hidden neurons, were obtained for the present application. The results of this study show that Taguchi method can successfully reduce number of input parameters. Moreover dynamic neural network model can predict precisely instantaneous heating loads using a reduced number of inputs.

1. Introduction

Energy has been one of the most contentious issues for the past few decades around the world. The availability of energy has a big impact on the economic development and social growth of a country [1]. Current studies show that about 40% of global energy usage is taken up by the building sector [2]. Building energy consumption has rapidly increased in recent years owing to several factors, such as higher indoor air quality standards and improved building services [3]. In most of the residential buildings in Korea, the greatest amount of energy is consumed during winter for heating purposes. Energy for heating buildings should be able to be used in accordance with the demand. Hourly heating load estimations acquired ahead of time can help building management systems reduce the magnitude of peak energy demands, and can be used in determining operation strategies for heating systems. Heating loads can be calculated manually using a spreadsheet, or by using specialized software such as TRNSYS, Energy-Plus, DOE (design of experiments), and others. However, it is time-consuming to estimate hourly heating loads using the above-mentioned tools; hence, they are not suitable for real-time applications. Instead, machine learning tools that enable more rapid calculations can be effective alternatives for real-time operational purposes.

Machine learning tools have been frequently applied in many building energy applications for modeling and prediction purposes. Artificial neural network (ANN) models have been developed for various applications to estimate; total chiller power consumption based on several weather parameters [4]; electric demand for air conditioning systems and appliances in a bioclimatic building [5]; temperature to control the energy use of air conditioning systems [6]; energy performance of a photovoltaic-thermal evaporator [7]; and etc. Li et al. [8] used the support vector machines (SVM) method to predict hourly cooling loads. Chou et al. [9] examined various machine learning tools, including ANN and SVM, as well as classification and regression tree (CART), chi-squared automatic interaction detection (CHAID), and generalized likelihood ratio (GLR) in predicting building loads. A review of ANN models for predicting energy consumption based on cooling and heating loads is presented in Ref. [10].

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There are several sets of input parameters related to building energy prediction. Jovanović et al. [11] considered weather parameters in predicting heating energy consumption. Protić et al. [12] investigated several operational parameters of a heat exchanger in estimating heating load of district heating system. Catalina et al. [13] included the architectural parameters in forecasting monthly heating demand in residential buildings. Input predictors should be chosen among various input parameters according to research objectives. It is necessary to reduce the number of input parameters as much as possible to avoid complicated works in collecting data especially for real time objectives. Several methods have been developed to identify the most influential input parameters for training ANN models [14]. Efforts were made to select the best inputs for estimating hourly direct normal irradiances by Rodriguez et al. [15] by using the genetic algorithm. Principal component analysis (PCA) was applied to reduce the number of necessary input parameters for predicting building energy consumption [16]. The result reported that there was no accuracy loss between the 10 selected PCA inputs and the 22 previous inputs used for the training.

This paper describes the process of the development of simplified ANN models for the prediction of hourly heating load based on several weather parameters. Both static and dynamic ANN models were utilized for the prediction. Design of experiments (DOE) and analysis of variance (ANOVA) approaches were used to identify the significant inputs, in order to reduce the number of input parameters. The objective of this study is to create a simple architectural ANN model that can predict instantaneous heating loads using a reduced number of input parameters while maintaining high accuracy, and which can be generally implemented in other buildings.

2. Methodology

2.1. Building description

The subject building for this study is a typical 9-story apartment building in Seoul, which was constructed in 2004. A single unit located toward the middle of the building was chosen for the simulation [17]. The building is shown in Fig. 1. The floor area of the unit is 104.03 m^2, and the glazing area is 20.49 m^2, distributed along the north and south walls. The heat loss of the unit was assumed to occur only through the glazing and the exterior walls, which face north and south, since the unit shares interior walls in the other directions with other units. The layout plan of the unit is also shown in Fig. 1. Details of the window and wall structure, and wall material properties, are found in Table 1 and Table 2, respectively. An indoor design temperature of 20 °C was chosen for the heating load simulation. The leakage area for infiltration was taken to be 63.5 cm^2, which is equivalent to the value given by ASHRAE for a medium tightness condition [18]. Standard weather data for Seoul was used for this simulation. Additionally, the heat sources from the occupants, lighting, and electrical equipment were ignored. The heating load calculation was therefore based on the outdoor conditions only.

2.2. Artificial neural networks

An ANN is a machine learning tool that can be used to correlate input and output values. The structure of an ANN is composed of inputs, hidden neurons, and outputs. The inputs are multiplied by weights, added with the bias number, and then computed using a mathematical function that determines the specific activation function of the neurons in order to produce an output response. The greatest advantage of using an ANN is that it can manage the correlation of complex and expansive data [19]. In this study, feed-forward back propagation model with a Bayesian regulation algorithm and a tan-sigmoid transfer function were used for training. Fig. 2 shows the structure of the time delay neural network (TDNN) model. In the illustration, x represents an input variable, n is the number of input variables, and k is the number of tapped delay lines. If the network model does not have any tapped delay lines for the inputs, the model is considered to be a static ANN model. Generally, TDNN models can also be referred to as dynamic neural network models. During the training phase, selection of the input parameters and the number of neurons is important for acquiring reliable and precise estimations. For complex problems, the number of hidden layers can be greater than one.

The accuracy of the training is determined by the root mean square error (RMSE), the mean absolute percentage error (MAPE), and the absolute fraction of variation (R^2). These are defined as follows [20]:

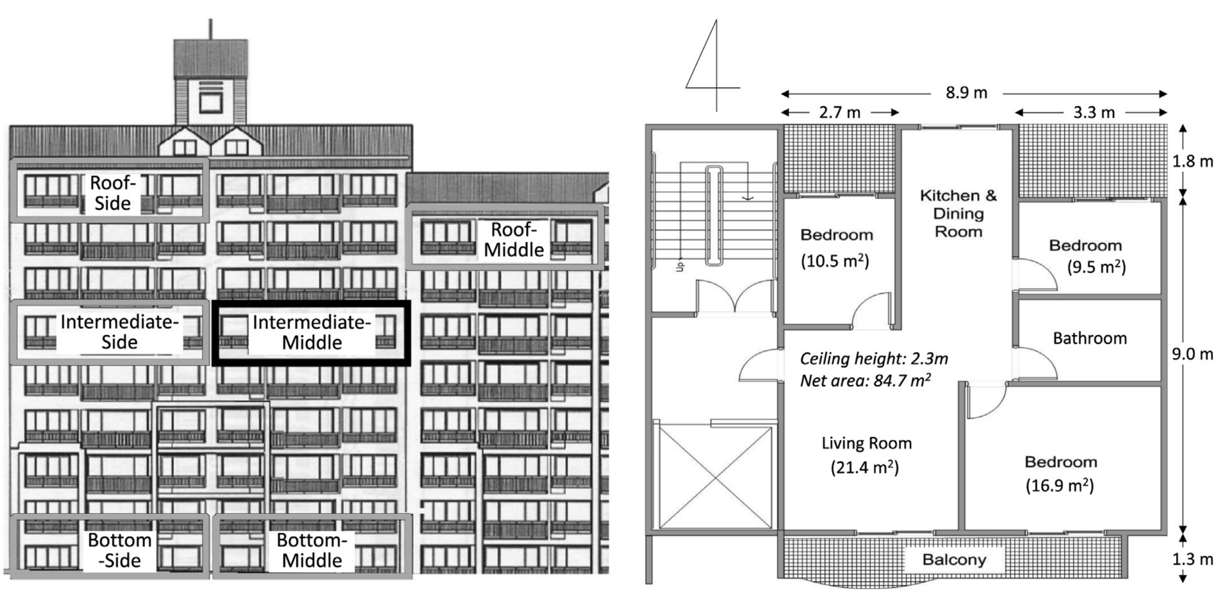

Fig. 1. Building elevation and apartment floor plan used for simulation.