Available online at www.sciencedirect.com
ScienceDirect
Energy and Buildings 40 (2008) 612–620
ENERGY and BUILDINGS
www.elsevier.com/locate/enbuild

# An applied artificial intelligence approach towards assessing building performance simulation tools

Abraham Yezioro [a,*], Bing Dong [b], Fernanda Leite [c]

[a] Faculty of Architecture and Town Planning, Technion IIT, Israel
[b] Center for Building Performance and Diagnostics, School of Architecture, Carnegie Mellon University, United States
[c] Department of Civil and Environmental Engineering, Carnegie Mellon University, United States

Received 7 February 2007; received in revised form 19 April 2007; accepted 21 April 2007

**Abstract**

With the development of modern computer technology, a large amount of building energy simulation tools is available in the market. When choosing which simulation tool to use in a project, the user must consider the tool's accuracy and reliability, considering the building information they have at hand, which will serve as input for the tool. This paper presents an approach towards assessing building performance simulation results to actual measurements, using artificial neural networks (ANN) for predicting building energy performance. Training and testing of the ANN were carried out with energy consumption data acquired for 1 week in the case building called the Solar House. The predicted results show a good fitness with the mathematical model with a mean absolute error of 0.9%. Moreover, four building simulation tools were selected in this study in order to compare their results with the ANN predicted energy consumption: Energy_10, Green Building Studio web tool, eQuest and EnergyPlus. The results showed that the more detailed simulation tools have the best simulation performance in terms of heating and cooling electricity consumption within 3% of mean absolute error.


*Keywords:* Simulation tools; Building energy performance; Artificial intelligence; Artificial neural networks; Inverse model

## 1. Introduction

Modeling has been a tradition in the architectural design process and that the increasing complexity of building technologies (architecture, engineering and construction as a whole) and growing building performance concerns has lead to a broader view of architectural modeling [1]. This view of building modeling covers aspects such as energy consumption and thermal, lighting and acoustic quality performance, as well as the traditionally modeled building aspects [2].

More specifically, building energy simulation is a powerful, analytical method for building energy research and evaluation of architectural design [3]. On the one hand, a better understanding of energy simulation tools, their advantages and their limitations, may encourage designers to have the confidence to use the simulation based design tools, according to their requirements. On the other hand, building simulation can consume a considerable amount of time before getting reliable results. Modeling the building, properly defining its properties, materials, internal loads and desired mechanical systems is a time consuming process that many times repeats itself for every building project. For each design solution studied, time is spent modeling the building's geometry into performance simulation applications.

Currently, a large amount of simulation tools are available for the designers. Some of them are intended to be used at the early design stages; others need the building to be well defined before the simulation can be performed [4].

In this sense, an approach towards identifying the reliability of such tools is needed. Previous research shows that artificial neural networks (ANN) can be used for the prediction of building energy consumption through a proper period of measurements [5]. Such approach uses sensor-acquired data on energy consumption for training and testing of the ANN. An ANN is an interconnected group of artificial neurons that uses a mathematical or computational model for information processing based on a connectionist approach to computation, simulating the way the human brain works. The results of

* Corresponding author. Tel.: +972 4 8294044; fax: +972 4 8294617.
*E-mail address:* ayez@tx.technion.ac.il (A. Yezioro).

0378-7788/$ – see front matter 
doi:10.1016/j.enbuild.2007.04.014

the ANN were used for comparison purposes of different building performance simulation tools: Energy_10, Green Building Studio, eQuest and EnergyPlus. Data acquired and simulations were developed for an existing building, the Solar House, presented in Section 3.

## 2. Simulation tools

The simulations were conducted using four different tools, according to the resolution and level of detail required for input of building-related information. Some of them require a very low building detail definition and others require a high one.

(A) *Energy_10* [6–8] is a user friendly tool intended to be used at the early design stages, where many design decisions has not been taken yet. The user needs to roughly define box volume, the size of the openings, material properties, the mechanical system to be used and basic schedules. The entire process may take just a few minutes. Results can give the designer an idea of the energy performance of the proposed building, yearly, monthly and/or hourly.

(B) *Green Building Studio* (*GBS*) [9] is a web-based energy analysis site. It links commercial architectural 3D CAD building models with energy analysis through gbXML language. The analysis could be performed at any step of the design process. The only requirement is to upload the three-dimensional (3D) model into the GBS website. The website is based on a database compiled for different cities in the United States of America. After the 3D model is uploaded, the website engine assigns, according to a predetermined location, function and the aforementioned database, the different characteristics of the building: materials, schedules, mechanical system, etc. The website uses DOE-2 as the simulation engine [10]. At this stage, all those assignments are not under the designers' control, so if he/she wants to check a different alternative, the interface does not enable such option. This limitation, leads to two possibilities. First, if the designer accepts the results presented by the GBS engine as valid, then these will be representative of the actual building. Second, if the designer wants different building characteristics, so, the obtained results can be very misleading and far from the real/intended building. However, the simulation takes just a few seconds to be performed, depending on the amount of zones simulated in the building. This simulation tool is fit for any of the design stages, early or later ones, since as the geometry of the building is better defined, results will be more accurate.

(C) *eQuest* [6,11] is a relatively easy to use energy analysis tool, where the designer can choose either to use the internal wizard or to import the building model from external applications. The level of definition required from the designer is high in order to get a more precise simulation. The definitions include materials and lighting properties, precise schedules, and a good definition of the mechanical system. As such, the level of expertise required to use the tool is rather high. Moreover, the tool suits for the late design stages, where the design is almost completed. At this level, it is relatively easy to change the properties of the building, but carrying out changes in the geometry is still rather cumbersome.

(D) *EnergyPlus* [6,12] is a comprehensive simulation engine for better temperature and comfort prediction. The level of expertise required to use the tool is rather high and any definition can result in a significant impact in the obtained results. Especially a high definition of the mechanical system is required. The tool is more suitable for the last design stages where a good level of detail is provided. The tool lacks a user friendly interface, making user input more difficult.

### *2.1. Evaluation of the accuracy of simulation tools*

Some research studies have been done in the evaluation of the accuracy of simulation tools. For example, HVAC BESTTEST project conducted by the International Energy Agency (IEA), the Solar Heating and Cooling (SHC) Program, subtask 22, developed practical procedures and data for an overall IEA validation methodology. The methodology combines empirical validation, analytical verification, and comparative analysis techniques [13–18]. In the present paper, a different approach was developed and applied to the simulation tools. An inverse data model was developed using artificial neural network method (ANN). This model was used as the base model for the validation and evaluation of heating and cooling electricity consumption for all simulation tools used in this study. The tools were evaluated using hourly, monthly and annual data.

#### *2.1.1. Developing an Inverse Model using ANN*

An ANN can be any model in which the output variables are computed from the input variables by compositions of basic functions or connections. However, one of the most commonly used ANN models is the multilayer perception. The detailed introduction of ANN can be refereed to Dong et al. [19]. The training algorithm for fully-connected, feed-forward have two stages [20].

*2.1.1.1. Forward activation flow.* During the first stage, the network is presented with a set of inputs and the desired output. The summed input, $I$, is determined by multiplying each input signal by the weight of its interconnection:

$$I = f\left(\sum w_i \times x_i\right) \qquad (1)$$

where $w_i$ is the weight of $x_i$, $i$ the number of neurons, and $f(x)$ is the activation function of the processing element (PE).

For a back-propagation network, this activation function should be sigmoid:

$$f(x) = \frac{1}{1 + \exp(-x)} \qquad (2)$$

By computing the summed input $I$, using the non-linear sigmoid function, the actual output of the PE is obtained. The output value of this function is 1.0 when the input is a large negative number and a value of 0.0 for large and positive input [5].