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# ARTIFICIAL NEURAL NETWORK MODELS FOR BUILDING ENERGY PREDICTION

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## ABSTRACT

There is a national need for a quick and easy building energy performance assessment system of existing buildings, without resorting to dynamic building energy simulation tools which usually require significant cost, time and expertise. In this study, the authors report the development of a building energy profiling system which is based on Artificial Neural Network (ANN) models. The ANN models were made by a series of EnergyPlus pre-simulations sampled by a Monte Carlo technique. The MBE and CVRMSE between EnergyPlus and ANN models are 1.53% and 7.82%, respectively. It is concluded that the profiling system requires minimalistic inputs and provides accurate energy performance assessment of a given building.

## 1 INTRODUCTION

The building sector accounts for about 40% of primary energy consumption in the world (IEA and UNDP 2013). In South Korea, 75% of existing buildings are older than 15 years (MOLIT 2013). Globally, governments have promoted building energy retrofit with financial support. Korean government has operated energy retrofit program for existing buildings, and the number of retrofit implementations has increased eightfold for last two years (MOLIT 2016). There is a widespread awareness of achieving energy savings by improving the energy performance of existing buildings (Ahn et al. 2016a; Ahn et al. 2016b).

Building energy simulation programs have played a role for energy performance assessment and decision making (Ahn et al. 2016a). Building simulation is a discipline that combines the knowledge of relevant sciences, engineering and mathematics to predict the thermal behavior of buildings in their interaction with external and internal driving forces such as outside climate, internal heat gains (people, lights, and equipment), mechanical and electrical systems and controls(CIBSE 2015). However, for the development of an accurate dynamic building energy simulation model for a given single building, in-depth expertise, and significant cost and time are indispensable (Ahn and Park 2017).

Alternatively, a large set of packaged pre-simulations performed by experts can be used for quick building energy performance assessments (Roth et al. 2012). Although this pre-simulation approach comes with limitations, such as the use of prototypes to represent actual buildings which may not match the actual geometry of the buildings, it provides an immediate and reliable energy assessment (Lee et al. 2015).

In this study, the profiling system was developed based on a set of Artificial Neural Network (ANN) models, which are trained by a series of EnergyPlus pre-simulation cases generated by a Monte Carlo technique. Latin Hypercube Sampling (LHS), one of the Monte Carlo sampling methods, was used to reduce the number of pre-simulation cases. This paper describes the development of the building energy profiling system.

## 2 SIMULATION APPROACHES

The dynamic energy simulation tools are capable of capturing thermal dynamics of a building and its mechanical systems. DOE-2, EnergyPlus and TRNSYS are popular dynamic simulation tools. The application of building energy simulation tools to existing buildings need in-depth knowledge and expertise for data collection, and modeling of building geometry, envelope, and mechanical systems. In addition, the modeling process usually takes several weeks or months depending upon the complexity of a given building (Lee et al. 2015).

To overcome the aforementioned limitations, the pre-simulation approach, which uses a pre-performed simulation database, has been introduced (Roth et al. 2012). The advantages of this pre-simulation approach are reduced modeling and computation time . EnCompass (2017) and DEER (2017) are such examples.

However, the existing pre-simulation tools , e.g. EnCompass (2017) and DEER (2017), are limited by the number of inputs. For example, if there are 20 inputs and each input is divided into three discrete levels (e.g. U-value of wall: high/medium/low), $3^{20}$(=95,367,431,640,625) simulation models have to be pre-simulated (Ahn et al. 2016b). To overcome this issue, the authors used a Monte Carlo sampling in this study. Then, the authors developed the ANN models based on the set of pre-simulation cases, which will be described in the following sections.

## 3 DEVELOPMENT PROCESS OF PROFILING SYSTEM

### 3.1 Overview

The development process of the profiling system is shown in Figure 1. To represent existing buildings in South Korea, stochastic characteristics of inputs were obtained from Geographic Information System (GIS) data of Seoul, national building energy standards of South Korea and literature (Ahn et al. 2016a; Ahn et al. 2016b; Ahn and Park 2017). In this study, a total of 34,400 EnergyPlus simulation models were generated by a Latin Hypercube Sampling.

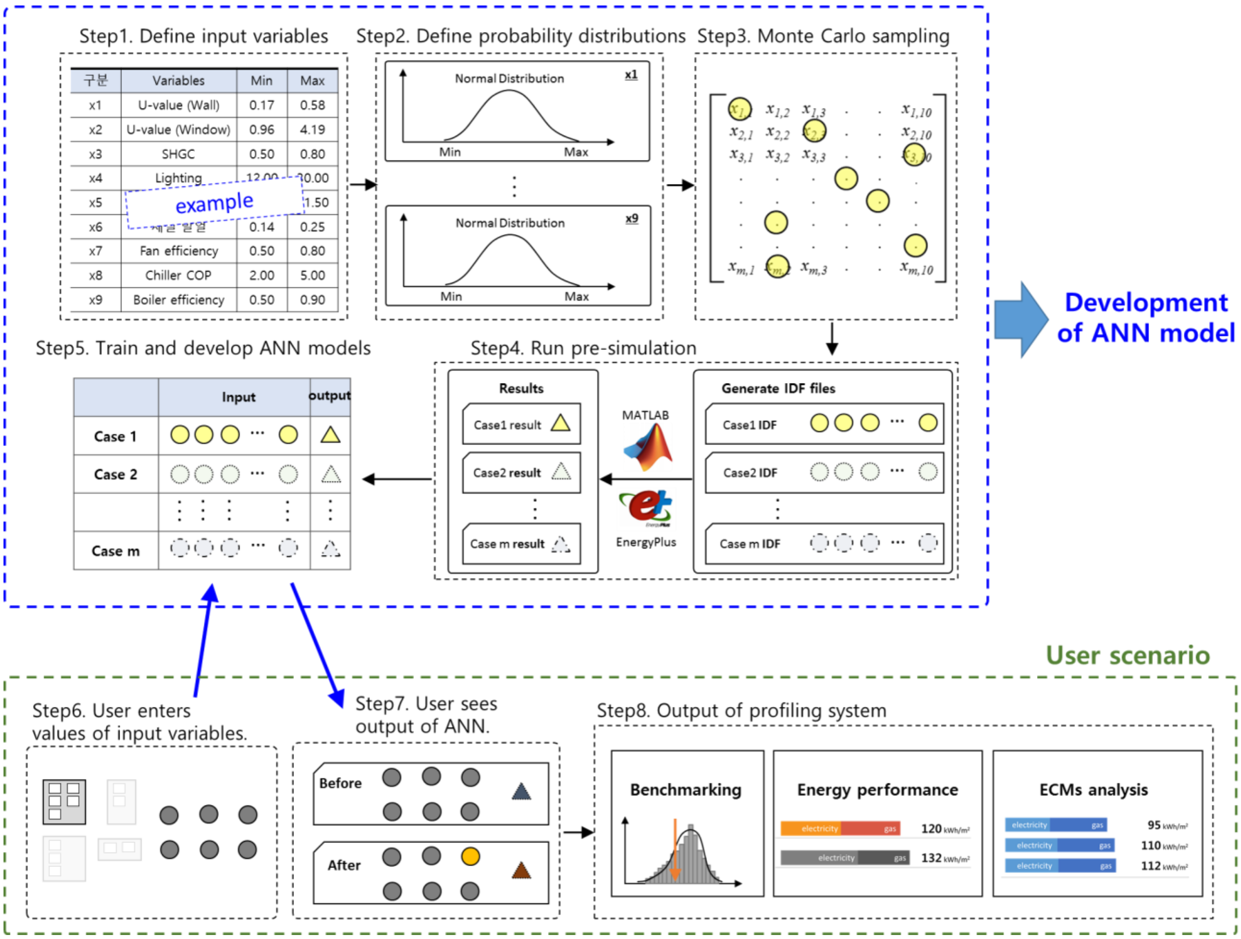



Figure 1: Development process of building energy profiling system (Ahn et al. 2016a; Ahn et al. 2016b; Ahn and Park 2017).

## 3.2 Inputs

The inputs in the profiling system are as follows:

- Geometry: total floor area, the number of floor, window to wall ratio, width to depth ratio, orientation of building
- Operation: set-point temperatures for heating and cooling, start and end times for heating and cooling
- Thermal properties of building envelopes: U-values of opaque envelopes (wall, roof), U-value and solar heat gain coefficient of windows
- Internal heat gain: density and activity level of occupants, lighting density(W/m$^2$), equipment density(W/m$^2$), infiltration rate
- HVAC system: four types of HVAC systems including variable air volume (VAV), constant air volume (CAV), electric heat pump (EHP) and fan coil unit (FCU), set-point temperatures for supply air, efficiencies of heat exchanger and economizer

- Cooling plant: four types of cooling plants including turbo chiller, absorption chiller (gas source or district cooling source) and absorption chiller heater and corresponding COP of plants, set-point temperatures of chilled water and cooling water
- Heating plant: three types of heating plant including gas boiler, district heating and absorption chiller heater and corresponding efficiency of heating plants, set-point temperature of hot water
- Service hot water plant: two types of domestic hot water plant including gas boiler and district heating, set-point temperature of service hot water

In particular, it is assumed that each floor has a rectangular plan composed of one interior zone and four perimeter zones with 5m perimeter depth. The window area is entered by the window to wall ratio, and the window is assumed to be located at the center of each exterior wall. The multiplier function of the EnergyPlus was used for a repeating typical floor except for the top and lowest floor. The capacity and flow rate of air, water or refrigerant were set to 'autosize' function offered by the EnergyPlus (Ahn et al. 2016b).

### 3.3 Monte Carlo for sampling of pre-simulation cases

In this study, the LHS method, one of the Monte Carlo techniques, was used to generate the pre-simulation cases. The LHS provides good coverage of the parameter space with relatively few samples compared to a standard brute force random sampling (Wyss and Jorgensen, 1998). The LHS method has proved suitable for complex nonlinear models and has been demonstrated in many building simulation studies (IBPSA 2001-2015). In the LHS, the range of each parameter was subdivided into N disjoint intervals with equal probability mass. In each interval, a single sample was randomly drawn from the associated probability distribution.

In this study, the samples of the inputs (Table 1) were generated using an 'lhsnorm' function in the MATLAB. Table 1 shows the min and max values of input variables, and their distributions were assumed to be a normal distribution. The min and max values were used for 97.5 percentile point of the normal distribution. Because there are a total of 86 combinations of HVAC system/cooling plant/heating plant/ service hot water plant, the samplings by LHS were done 86 times. Each LHS sampling generates 400 simulation cases, and a total number of EnergyPlus simulation cases is equal to 34,400 (=86*400) (Ahn et al. 2016b). The authors used MATLAB to automatically write 34,400 EnergyPlus input files (.idf), and the pre-simulations were conducted through the 'group simulation' function of EnergyPlus. The 34,400 LHS samples and outputs of EnergyPlus were used as training and test data for the ANN models which will be discussed in the following section.

Table 1: Min and max values of inputs (Ahn et al. 2016a; Ahn et al. 2016b; Ahn and Park 2017).

| Input variables | Unit | Min | Max | References |
|---|---|---|---|---|
| The Number of floors | - | 3 | 27 | NGII (2017) |
| Total floor area | $m^2$ | 3,000 | 40,000 | - |
| Window to wall ratio | % | 40 | 95 | PCAP (2012) |
| Width to depth ratio | - | 1.02 | 3.07 | NGII (2017) |
| Azimuth angle | Degree | 0 | 359 | NGII (2017) |
| Start time for heating | - | 6 | 9 | KEMCO (2011)<br>MOEL (2013) |
| End time for heating | - | 18 | 20 | KEMCO (2011)<br>MOEL (2013) |
| Set-point temperature for heating | $^oC$ | 18 | 24 | KEMCO (2011) |

| | | | | |
|---|---|---|---|---|
| | | | | Prime Minister's Office (2012) |
| Start time for cooling | - | 6 | 9 | KEMCO (2011) MOEL (2013) |
| End time for cooling | - | 18 | 20 | KEMCO (2011) MOEL (2013) |
| Set-point temperature for cooling | $^{o}C$ | 24 | 29 | KEMCO (2011) MOTIE (2013) |
| Outdoor air volume per person | $m^3/s$ | 0.006 | 0.015 | ASHRAE (2007) |
| U-value of wall | $W/m^2K$ | 0.17 | 0.76 | MOLIT (1999) MOLIT (2015) |
| U-value of window | $W/m^2K$ | 0.96 | 4.19 | MOLIT (1999) MOLIT (2015) |
| SHGC of window | - | 0.50 | 0.80 | PCAP (2012) |
| Occupant density | $W/m^2$ | 0.07 | 0.15 | PCAP (2012) |
| Occupant activity | W/person | 104 | 156 | PCAP (2012) |
| Lighting density | $W/m^2$ | 8.8 | 13.2 | PCAP (2012) |
| Equipment density | $W/m^2$ | 8.64 | 12.96 | PCAP (2012) |
| Infiltration rate | ACH | 0.1 | 1.5 | Heo (2011) |
| Set-point temperature for HVAC supply air | $^{o}C$ | 10.4 | 15.6 | ASHRAE (2012) |
| HVAC fan efficiency | % | 0.3 | 0.85 | ACE R&A (2017) |
| COP of EHP | - | 2.25 | 5 | MOTIE (2016) |
| COP of turbo chiller | - | 3.52 | 5 | MOLIT (2015) |
| COP of absorption chiller | - | 0.65 | 1.2 | MOLIT (2015) |
| COP of absorption chiller heater | - | 0.9 | 1.2 | MOLIT (2015) |
| Set-point temperature for chilled water | $^{o}C$ | 3 | 10 | ASHRAE (2012) |
| Set-point temperature for cooling water | $^{o}C$ | 27 | 32 | HDCC (2017) |
| Boiler efficiency | % | 76 | 98 | Heo (2011) |
| Set-point temperature for hot water | $^{o}C$ | 51 | 80 | EngineeringToolBox (2017) |
| Set-point temperature for service hot water | $^{o}C$ | 55 | 60 | KEMCO (2005) |

## 3.4 Artificial Neural Network models

The ANN is based on a multi-layer perceptron, and it has been widely used for engineering problems. The ANN composed of input, hidden and output layer modifies the weights between each layer to minimize the error between predictions by the ANN and target values using a back propagation algorithm. To conduct the back propagation algorithm that seeks optimal weights, the gradient descent method, the Gauss-Newton method, the Levenberg-Marquardt method and Bayesian Regularization method can be used (Kim et al. 2016; Ahn and Park 2017). In this study, the Bayesian Regularization method was selected since it is able to give accurate results rather than other methods in the case of using the large number of inputs (Kaur and Salaria 2013). The structure of ANN was composed of 2 hidden layers, one layer has 15 nodes and the other layer has 10 nodes (Ahn and Park 2017).

One of the advantages of the ANN model is its ability to deal with multi-input-multi-output (MIMO) for the time-series prediction (Li et al. 2017; Ahn and Park 2017). The ANN model in this study was structured to predict monthly energy use (e.g. cooling, heating, service hot water, lighting, fan) and energy sources (e.g. electricity, gas, district heating and district cooling) for an entire year (Ahn et al. 2016a; Ahn et al. 2016b; Ahn and Park 2017).

The learning process of the ANN model is an optimization problem to solve for the weights that minimize the difference between the predicted value by the ANN model and the target value from training data. In order to prevent an occurrence that optimal weights cannot be effectively found e.g., converging to a local optimum, the authors repeated the learning process 10 times (Ahn et al. 2016b). The weights that can provide the best prediction were selected in this study. The development process of the ANN models is summarized as follows:

(a) Selection of inputs and outputs: The inputs and outputs are shown in Tables 1-2, respectively.
(b) Training and test dataset: Among 400 simulation cases from each LHS sampling, 370 cases and 30 cases were used for training and test, respectively. In other words, 30 cases were not included for the training data.
(c) Iterative learning: As mentioned above, the training of the ANN model was purposefully repeated 10 times to find optimal weights. During the iteration, the calculated values of the Coefficient of Variation of the Root Mean Squared Error (CVRMSE) were saved. After each iteration, the weights of the ANN model with the lowest CVRMSE were selected.

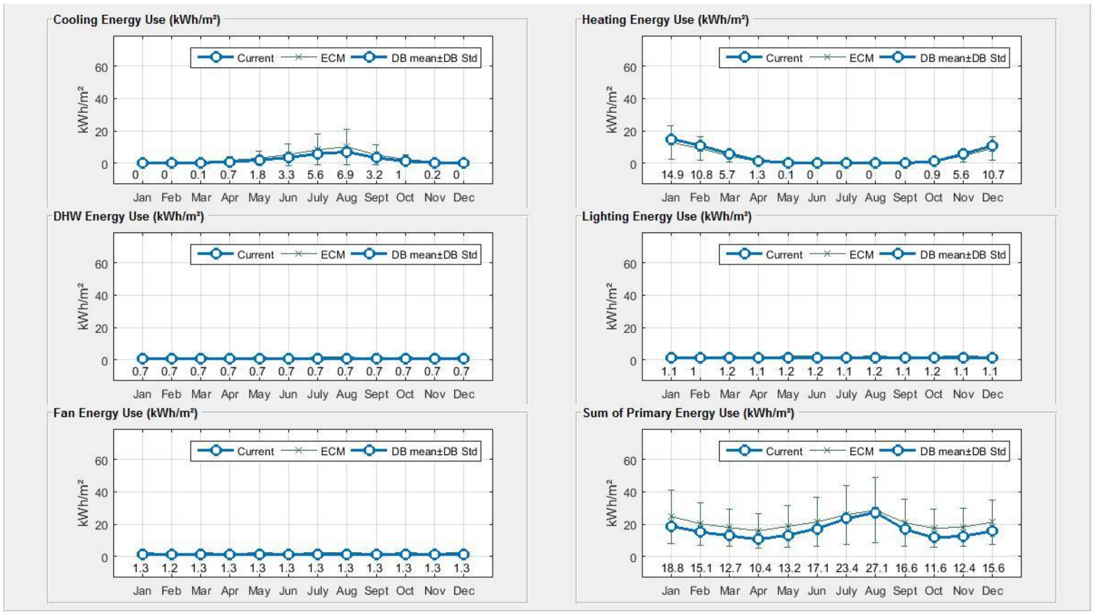
Table 2 shows the results of prediction performance the test dataset. According to ASHRAE Guideline 14-2002 (ASHRAE 2002), the Mean Bias Error (MBE) and CVRMSE of the model for monthly prediction should be less than 5% and 15%, respectively. As shown in Table 2, The ANN model is good enough except the prediction of Output #8.

Table 2: Comparison results between ANN models and EnergyPlus pre-simulation models in test cases (Ahn and Park 2017).

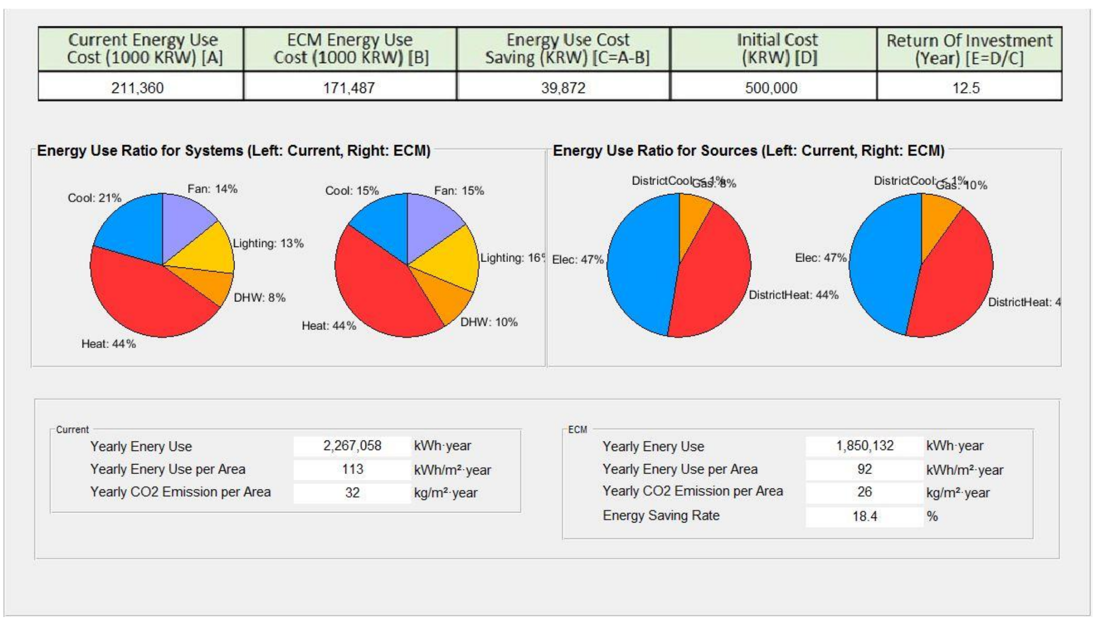
| Index | Use | Source | MBE(%) | CVRMSE(%) |
|---|---|---|---|---|
| Output #1 | Cooling | Electricity | 1.26 | 12.78 |
| Output #2 | Cooling | Gas | 0.62 | 2.27 |
| Output #3 | Cooling | District cool | 0.28 | 3.27 |
| Output #4 | Cooling (pump) | Electricity | 1.22 | 11.03 |
| Output #5 | Heating | Electricity | 4.64 | 7.97 |
| Output #6 | Heating | Gas | 1.24 | 10.18 |
| Output #7 | Heating | District heat | 1.65 | 8.24 |
| Output #8 | Heating (pump) | Electricity | 4.63 | 23.37 |
| Output #9 | Service hot water | Gas | 0.40 | 1.94 |
| Output #10 | Service hot water | District heat | 0.04 | 0.75 |
| Output #11 | Service hot water (pump) | Electricity | 0.46 | 1.56 |
| Output #12 | Lighting | Electricity | 1.80 | 8.41 |
| Output #13 | Ventilation | Electricity | 1.69 | 9.88 |

## 4 RESULTS

Figure 3 shows an user interface of the developed profiling system. The energy profiling system delivers the following results: (1) monthly energy use analysis (cooling, heating, domestic hot water, lighting, fan energy, primary energy) (Figure 2 (a)) and (2) energy performance before and after Energy Conservation Measures (ECMs) (Figure 2 (b)). The profiling system provides an opportunity to quickly assess the expected benefit of building energy retrofit strategies




(a) monthly energy use



| Current Energy Use Cost (1000 KRW) [A] | ECM Energy Use Cost (1000 KRW) [B] | Energy Use Cost Saving (KRW) [C=A-B] | Initial Cost (KRW) [D] | Return Of Investment (Year) [E=D/C] |
|---|---|---|---|---|
| 211,360 | 171,487 | 39,872 | 500,000 | 12.5 |



(b) before vs. after ECMs

Figure 2: User interface of the profiling system.

## 5 CONCLUSIONS

This paper presents the development process of the building energy profiling system for easy and quick building energy performance assessment. The profiling system is based on the ANN models trained by 34,400 pre-simulated EnergyPlus models. The averages of MBE and CVRMSE between EnergyPlus simulation models and ANN models are 1.53% and 7.82%, respectively, which meets ASHRAE Guideline 14-2002 (ASHRAE 2002). The current version of the profiling system is meant for office buildings in South Korea. In Phase 2, a variety of building types (e.g. educational, residential, institutional buildings) will be included.

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