OCCUPANCY ESTIMATION BASED ON CO_2 CONCENTRATION USING DYNAMIC NEURAL NETWORK MODEL

Hwataik Han*[1], Kyung-Jin Jang[2], Changho Han[3], and Junyong Lee[4]

1 Mechanical Engineering, Kookmin University
861-1 Jeungneung-dong, Seongbuk-gu
Seoul 136-702, Korea
**Corresponding author: hhan@kookmin.ac.kr*

2 Thermal Environmental Lab, Kookmin University
861-1 Jeungneung-dong, Seongbuk-gu
Seoul 136-702, Korea

3 Graduate School, Kookmin University
861-1 Jeungneung-dong, Seongbuk-gu
Seoul 136-702, Korea

4 Graduate School, Kookmin University
861-1 Jeungneung-dong, Seongbuk-gu
Seoul 136-702, Korea

ABSTRACT

Demand-controlled ventilation has been proposed to improve indoor air quality and to save energy for ventilation. It is important to estimate occupancy in a building precisely in order to determine adequate ventilation airflow rates, especially when people are the major source of indoor contaminants such as in office buildings. In this paper, we investigate occupancy estimation methods using a dynamic neural network model based on carbon dioxide concentration in a space. We conducted an experiment in a single room to measure carbon dioxide concentration and actual occupancy continuously in the room. We trained and tested the dynamic neural network model TDNN (time-delayed neural network) by varying the number of tapped delay lines and the number of neurons. Networks were trained using the first-day data and results were obtained for the rest of the days. The estimated results were compared with the actual number of occupants measured by a number counter installed at the entrance door. The root mean square (RMS) errors were obtained depending on system parameters. The dynamic model with tapped delay showed smaller errors in general than conventional static neural network models. The RMS errors were reduced, as the tapped delay line increased up to 15 minutes for the present experiment. The time delay has been found to be related to the dispersion time of contaminants in the space, which is again related to the dimensions of the space and the source locations relative to the sensor locations. Further research is needed to include the effect of the concentration in the adjacent rooms and the effect of other contaminants such as humidity and particle concentrations.

KEYWORDS

Occupancy estimation, Dynamic neural network, Demand-controlled ventilation, Carbon dioxide

1 INTRODUCTION

It is important to maintain indoor air quality as well as energy conservation in buildings. Energy consumption of buildings constitutes approximately 24% of the total energy consumption in Korea, more than 25% of which is consumed in ventilation for maintaining an adequate indoor environment (KEITI, 2012). Most people currently spend more than 90% of their time per day, and think it is important to provide adequate ventilation rates to maintain indoor air quality. Meanwhile, energy is wasted as buildings are often over-ventilated, especially in vacant buildings.

Recently, demand-controlled ventilation (DCV) has been investigated widely, and various DCV schemes have been developed to conserve energy for building ventilation (Emmerich and Persily, 2001). The American Society of Heating, Refrigeration and Air-Conditioning Engineers (ASHRAE, 2013) provided a standard for ventilation requirements by distinguishing the contaminants by occupants and from those by building materials. If the number of occupants in each zone is known, unnecessary ventilation can be shut off in vacant zones, and an adequate amount of ventilated air can be provided according to the occupants in the zones. Klein (2011) conducted multi-agent simulations and operated an air-conditioning system according to the number of occupants. He reported that energy consumption was saved by 12-17%, and that the indoor comfort level was improved by 5%. Xu and Wang (2007) reported that energy consumption can be reduced by as much as 8-33% by utilizing various DCV schemes.

Occupancy information can be used in various fields, such as security, lighting, fire protection, and HVAC control. Conventional methods for estimating the number of occupants include motion recognition by sensors such as passive infrared (PIR), image processing by video camera images, etc. Occupancy should be measured without hindering occupants' behavior or offending their privacy. In this context, methods using environmental sensors have been preferred, even though they can be inaccurate. Various methods have been tried by many authors in the literature. Federspiel (1997) conducted an experiment to estimate CO_2 generation rates using a Karman filter. Kar and Varsheny (2009) suggested a moment method of integration to reduce the errors occurring inherently in the process of differentiation of fluctuating CO_2 concentration data. Dong et al. (2010) revealed the correlations of occupancy with CO_2, CO, total volatile organic compounds (TVOC), particulate matter 2.5 (PM2.5), and temperature, and compared the results using the following methods: support vector machine (SVM), artificial neural network (ANN), and hidden Markov model (HMM). Lu et al. (2011) used the maximum likelihood estimation method in a mechanically ventilated room, and Mamidi et al. (2011) used a rule-based heuristic method and Gaussian process. Other than the indoor concentrations, various parameters have been tested (Hailermarium et al., 2011; Yang et al., 2012; Dodier et al., 2006) to improve accuracy in estimating occupancy, including light intensity, noise intensity, electric usage, internet usage, etc. In this paper, we investigate a simple dynamic neural network model and apply it to a single office room to figure out optimal system parameters in estimating occupancy.

2 THEORETICAL BACKGROUND

2.1 Ventilation Model

In case the indoor carbon dioxide concentration is assumed to be uniform in a zone, as shown in Fig. 1, mass conservation can be expressed as Eqn. (1). The amount of CO_2 generated in the zone is assumed to be linear with respect to the number of occupants, N. The metabolic emission rate per person is assumed to be constant, and there is no other generation of carbon dioxide in the room.

$$V\frac{dC}{dt} = Q\left(C_{\mathrm{out}} - C(t)\right) + mN(t) \tag{1}$$

where V is the volume of the room, Q is the ventilation rate, m is the CO_2 generation rate per person, and C_{out} is the outdoor CO_2 concentration.

Theoretically speaking, the number of occupants can be derived from the governing equation by differentiating CO_2 concentrations with respect to time. However, because of the uncertainties involved with the concentration measurements, reliable results cannot be obtained directly from the differential equation.

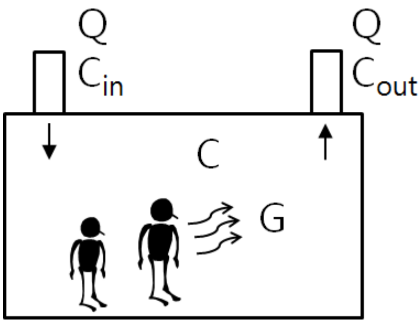


Figure 1: Concentration model in a single zone

2.2 Dynamic Neural Network

Neural networks are non-linear statistical data modeling tools that can be used to model complex relations between inputs and outputs. The design of artificial neural network was inspired by the biological neural network, which comprises neurons and synapses. ANN has been successfully applied to various fields such as system modeling, adaptive control, noise filtering, image processing, and speech recognition. ANN can be considered a black box in which the model inputs are the number of neurons in the input layer, the model parameters are the number of neurons and the values of interconnection weights, which do not have any physical meaning, in the hidden layers, and at last, the outputs are the number of neurons in the output layer.

The most common type is a static feed-forward configuration that allows the approximation of any nonlinear static mapping between input and output variables provided that certain conditions are met (Castilla, 2013). A multilayer feed-forward neural network shows outstanding performance for various functional approximations and pattern recognitions, but time series cannot be handled properly. A dynamic neural network has been developed to conduct time-series analyses (Sinha et al., 2000). A dynamic neural network uses either a tapped delay line (TDL) to delay inputs or an output feedback to provide memory functions so that time-series analyses can be conducted. Figure 2 shows the structure of a TDNN (time-delayed neural network) using a TDL. Inputs, *p*, are inputted to a hidden layer along with delayed inputs. The number of delayed inputs is *k*. The inputs are summed with weighting values, *w*, and are added with biases, *b***,** and the output values, *a***,** are transferred through a transfer function, *f*. For complex problems, an ANN has a large number of neurons and many hidden layers.

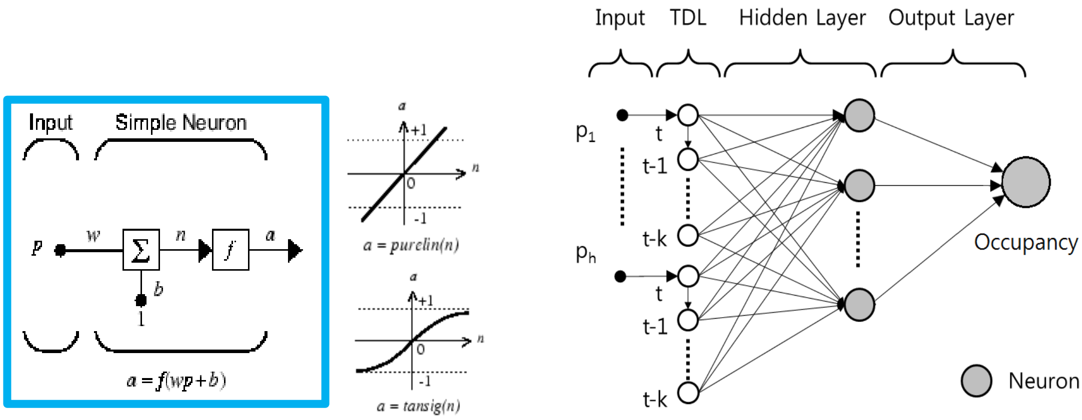


Figure 2: Structure of an artificial neural network

3 EXPERIMENTS

3.1 Test Room

The test room is located on the third floor of the five-story College of Engineering building of Kookmin University in Seoul, Korea. The configuration of the room is shown in Fig. 3. The room is an office for graduate students and is equipped with various sensors and facilities for environmental control. The room has been remodeled to conduct various DCV experiments.
Carbon dioxide concentrations were measured using a non-dispersive infrared (NDIR) type of CO_2 sensor. The measurement range is 0-20000 ppm, and the resolution is 1 ppm. Uncertainty of the CO_2 sensor is known to be within 1%. Magnetic sensors have been installed at the door and windows to detect when they are opened. A motion counter has been installed at the door to count the number of people entering and exiting the room. There are two infrared beams in the counter, which are apart horizontally to detect the direction of movement by the sequential cut-offs. Output signals were analyzed by the Lab-View counter function. The actual number of occupants is calculated by integrating the number of pulses. The time interval of data acquisition is 1 minute. The total number of data points is 1440 in 24 hours.

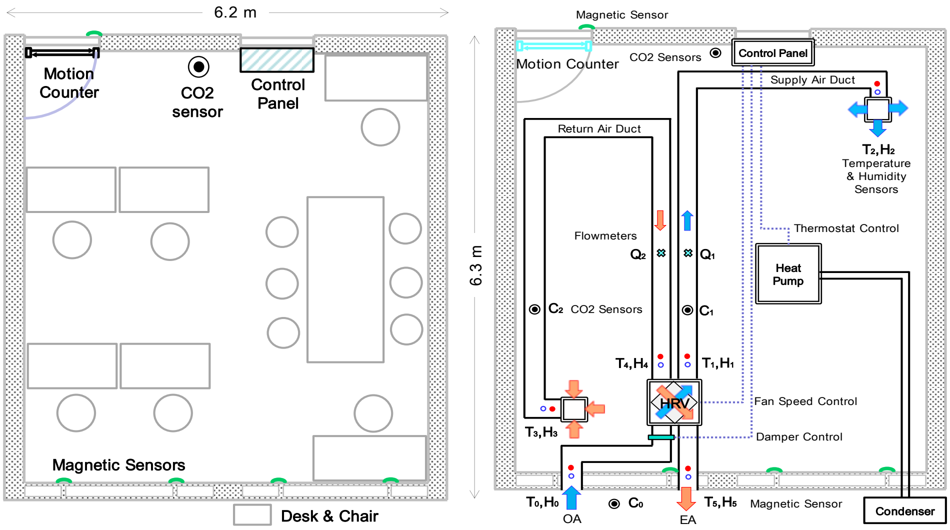


Figure 3: Test room configuration

3.2 Procedure

Experiments were conducted from May 7 to 13, 2013. Data from five days were used excluding the weekend. The number of occupants in the room varies from zero to eight irregularly. The windows were closed, and the mechanical ventilation system was not operated throughout the period. The average infiltration rate of the room is 0.29 air changes per hour (ACH) ±10%, which is obtained from the decay rate measured overnight when the room is vacant. The infiltration rate of the room is not required for neural network modeling but is shown as a reference. The infiltration rate is assumed to be constant regardless of outdoor weather conditions.
The Matlab R2012a Neural Network Toolbox was used to estimate the varying number of occupants. Network inputs are CO_2 data measured from the gas sensor, and network outputs are the number of occupants. A tangent hyperbolic function is used for the transfer function of the hidden layer, and a linear function is used for that of the output layer. In order to train

neural networks, Marquardt algorithm and Bayesian regulation were used for normalization. The maximum iteration for training is 1000, and the criterion of convergence is 10^{-10}. Training is repeated 15 times, and the output results with the minimum error were selected. Data from day 1 is used to train the neural network, and the occupancy is estimated for the rest of the days: days 2-5. The estimated occupancy is compared with the actual occupancy measured by motion sensors. The RMS of the differences is calculated according to Eqn. (2).

$$RMS = \sqrt{\frac{1}{n_{\text{total}}} \quad N_{\text{true}} - N_{\text{estimate}} \;^{2}} \tag{2}$$

where n_{total} is the number of data points.

4 RESULTS AND DISCUSSION

In order to find an optimal number of TDLs, the number of input TDLs was tested from 1 to 30. The RMS error in estimating occupancy is shown in Fig. 4. As the number of TDLs increases, the RMS error decreases rapidly at first but remains nearly constant when the number of TDLs is greater than 15. The TDL value of 15 means that the inputs to the neural network are the 15 data points measured at the previous 15 time steps. The number of hidden neurons has been also tested. As the number of hidden neurons increases, the RMS error increases. The dynamic neural network model with a single hidden neuron achieves the best results and was used in the present experiment.

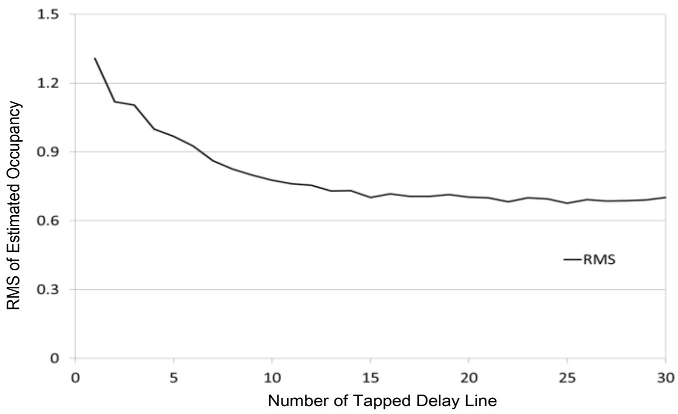


Figure 4: Effect of number of TDLs on the RMS results

The static model can be considered as a neural network with no TDLs. Without implementing the data at previous time steps, the output would be proportional to the current input. Figure 5 compares the results by the static and dynamic models. The static model gives quite a large error in estimating occupancy. The dynamic model gives much better results compared with the static model, but there remains a slight time delay in the results.

The RMS values of the dynamic model are shown in Fig. 6 with respect to the time shift of the results. The RMS error exhibits a minimum when the time shift is approximately 7 minutes. The time lag generated by the dynamic model is believed to be due partly to the sensor response time but mainly to the gas dispersion in the space. The dispersion time is considered to be proportional to the dimension of the space.

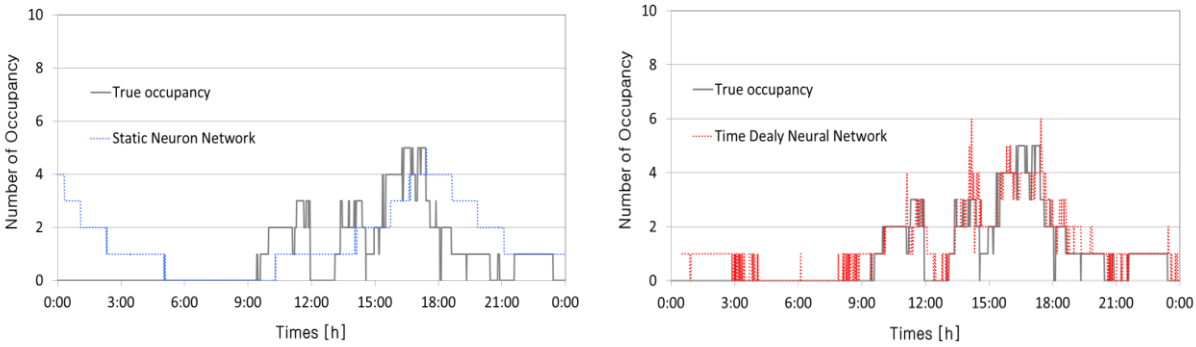


Figure 5: Comparison of static (left) and dynamic (right) models (Day 2)

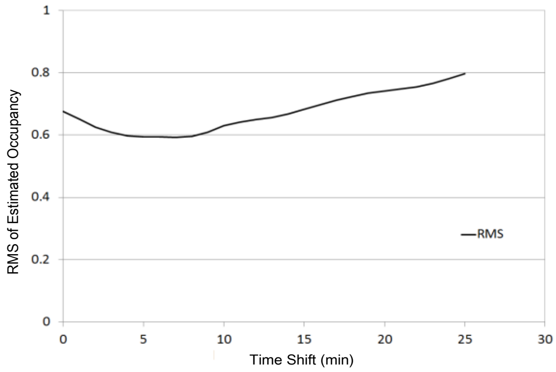
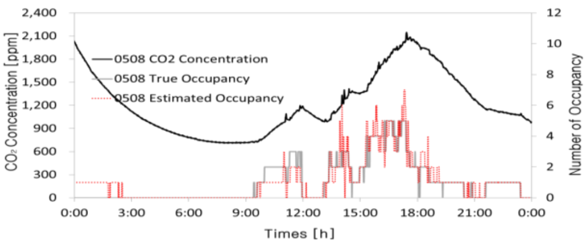
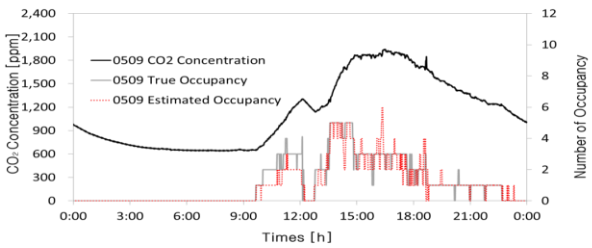


Figure 6: Effect of time shift

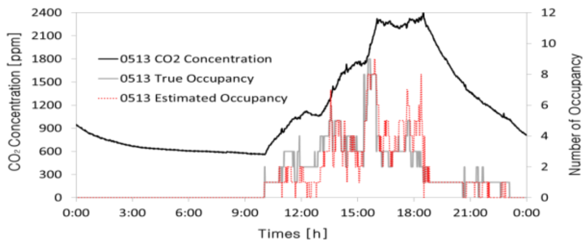
Figure 7 shows the final results of the estimated occupancy for the rest of the days. The figure shows the results in comparison with the actual occupancy along with the concentration variations measured in the room. The results are in good agreement with the true values. The RMS errors are found to be 0.63, 0.58, 0.63, and 0.88 respectively for days 2-5. Based on the first-day training, the average of the RMS errors is 0.68. In case we increase the number of days of training, the average RMS error decreases slowly. The average of the RMS errors by various combinations of two-day training has been found to be 0.64.



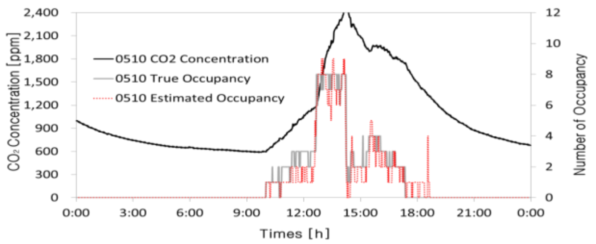
(a) Day 2 (May 8)



(b) Day 3 (May 9)



(c) Day 4 (May 10)



(d) Day 5 (May 13)

Figure 7: Comparison of estimated occupancy with true occupancy

5 CONCLUSIONS

We investigated occupancy estimation methods using the dynamic neural network model based on carbon dioxide concentration in a room with irregularly varying numbers of occupants. We trained and tested a dynamic neural network model of TDNN by varying the number of TDLs. The network model was trained using the data collected during the first day, and results were obtained for the rest of the days for various system parameters. The following conclusions have been drawn from the experimental results.

1. The dynamic model with tapped delay shows improved results compared with the conventional static neural network model. The RMS error decreases as the number of TDLs increases. The optimal number of TDLs has been found to be 15 for the present configuration.
2. Because the system-governing equation is not complicated, a simple neural network structure is sufficient to model the system with a single hidden neuron in a single layer. The RMS error rather increases as the number of hidden neurons increases.
3. The time delay of a few minutes remains in estimating occupancy using the dynamic neural network model with optimized system parameters. This issue is considered to be related to the dispersion time of contaminants in the space, which is again related to the dimensions of the space and the source locations relative to the location of sensors.

Further research needs to be conducted to include the effect of the concentration in the adjacent rooms and the effect of other parameters such as humidity and particle concentrations to improve the accuracy of the method.

6 ACKNOWLEDGMENTS

This research was supported by the Converging Research Center Program funded by the Ministry of Education (No. 2012K001383), and by the Research Policy/Infrastructure Development Program funded by the Ministry of Land, Infrastructure and Transportation (No. 11 Technique Standardization 03-01), Republic of Korea.

7 REFERENCES

KEITI. (2012). Indoor Environment Management Technology Trends of Building based on Eco-Energy. *KEITI Report*, 2012-86, 77.

Emmerich, S.J. and Persily, A.K. (2001). State-of-the-Art Review of CO_2 Demand Controlled Ventilation Technology and Application. *NISTIR 6729*.

ASHRAE. (2013). *Handbook-Fundamentals.* Atlanta: American Society of Heating Refrigerating and Air-Conditioning Engineers.

Klein, L. (2011). Coordinating Occupant Behavior for building Energy and Comfort Management using Multi-agent Systems. *Automation in Construction*, 22, 525-536.

Xu, X. and Wang, S. (2007). An Adaptive Demand-Controlled Ventilation Strategy with Zone Temperature Reset for Multi-zone Air-Conditioning Systems. *Indoor and Built Environment*, 16, 426-437.

Federspiel, C.C. (1997). Estimating the Inputs of Gas Transport Processes in Buildings. *IEEE Trans. Control System Tech.*, 5(5), 480-489.

Kar, S. and Varshney, P.K. (2009). Accurate Estimation of Indoor Occupancy using Gas Sensors, *ISSNIP*, 355-360.

Dong, B. Andrews, B. Lam, K.P. Hynck, M. Zhang, R. Chiou, Y.S. and Benitez, D. (2010). An Information Technology enabled Sustainability Test-Bed (ITEST) for Occupancy

Detection through an Environmental Sensing Network. *Energy and Buildings*, 40, 1038-1046.
Lu, X. Lu, T. and Viljanen, M. (2011). Estimation of Space Air Change Rates and CO_2 Generation Rate for Mechanically-Ventilated Buildings. *Advances in Computer Science and Engineering*, 237-260.
Mamidi, S. Maheswaran, R. Chang, Y. (2011). Smart Sensing Estimation and Prediction for Efficient Building Energy Management. In Multi-agent Smart Computing Workshop.
Hailermarium, E. Goldstein, R. Attar, R. and Khan, A. (2011). Real-time Occupancy Detection using Decision Trees with Multiple Sensor Types, *Proc. of 2011 Sym. on Simulation for Architecture and Urban Design*, 141-148.
Yang, Z. Li, N. Becerik-Gerber, B. and Orosz, M. (2012). A Non-Intrusive Occupancy Monitoring System for Demand Driven HVAC Operations, *Construction Research Congress*, 828-837.
Dodier, R.H. Henze, G.P. Tiller, D.K. and Guo, X. (2006). Building Occupancy Detection through Sensor Belief Networks, *Energy and Buildings*, 38, 1033-1043.
Castilla, M. Alvarez, J.D. Ortega, M.G. Arahal, M.R. (2013). Neural Network and Polynomial Approximated Comfort Models for HVAC Systems. *Building and Environment*, 59, 107-115.
Sinha, N.K. Gupta, M.M. and Rao, D.H. (2000). Dynamic Neural Networks: An Overview. *Industrial Technology 2000 Proc. of IEEE Int. Conference*, 1. 491-496.