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Further validation of a method aimed to estimate building performance parameters

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Abstract

A further validation of an earlier developed neural network method for estimating the total heat loss coefficient (K_{tot}), the total heat capacity (C_{tot}) and the gain factor (α) based on measured diurnal data of internal–external temperature difference, supplied heat for heating and "free heat" is presented. The validation was performed in laboratory scale, using a test cell, for three different cases of ventilation, without (constant)-, natural-, and forced ventilation. Earlier measurements from a building was also used in order to simulate a realistic energy use pattern and a rather stochastic behavior of α, which also was transformed to represent existing and future buildings in terms of the composition of their energy use. For all three types of ventilation and different types of buildings, the method was capable of estimating the three different performance parameters and their different dependencies. For K_{tot}, the RMSE was between 3 and 20% and for α, the deviation was between 9 and 19%.

Keywords: Buildings; Heat gain; Heat capacity; Heat balance; Time constant; Neural network; Identification; Heat loss

1. Introduction

The total energy use in buildings differs substantially depending on the year of construction, where the energy use is considerably lower for new buildings compared to older buildings. The reason for this is that newer buildings are often better insulated, often have ventilation heat recovery, more efficient white goods, etc. Further, the energy use in buildings varies strongly over the year, mainly due to increasing demand for heating during the winter. The use of electricity and hot water is fairly constant during a year with a slight increase during the winter. Household electricity and hot water are in contrast to space heating, first of all, strongly correlated to the occupant behavior.

With ever-greater demands for an efficient use of energy in buildings, the need for knowledge of the performance parameters is increasing all the time. The total heat loss coefficient and the heat capacity are two such fundamental performance parameters, which provide information about the envelope's thermal performance. In inhabited buildings, another important performance parameter is the ability of the heating system to use available "free" heat from solar radiation and internal heat sources (in this work designated as the gain factor), such as household equipment and HVAC systems.

The aim of this paper is to report on further development and experimental validation of an earlier presented method for estimation of these building performance parameters [1–4]. The method is based on an analysis of a neural network (NN) model that is trained on measured data of internal–external temperature difference and free heat. Generally, the method includes pre-processing in order to remove correlations between data used as model input before training the NN. Finally, an analysis is performed to extract the unknown parameters, i.e. the total heat loss coefficient, the total heat capacity and the gain factor.

In this paper, we have validated the method for more realistic ratios between supplied heating and the energy use

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pattern during a year. Moreover, the validation considers three different cases of ventilation: without (constant)-, natural- and forced ventilation.

2. Neural network method

Lundin et al. [1] have reported on a NN method for the estimation of performance parameters K_{tot}, α and C_{tot} and their variations. The method is based on a lumped description of a $1-R$, $1-C$-type model:

$$K_{tot}\theta = P_{heat} + \alpha P_{dom} + C_{tot}\frac{d\theta}{dt} \tag{1}$$

where K_{tot} is the total heat loss coefficient, θ the internal–external temperature difference, P_{heat} supplied heat to the heating system, α the gain factor, P_{dom} the domestic load, C_{tot} is the total heat capacity.

A key part of the method is the use of a NN model to map dependencies between input and output parameters. This is done in three steps: data pre-processing, training and testing and finally the results are interpreted in terms of Eq. (1).

The data set was first pre-processed in order to remove all correlations between the measured parameters that are used as inputs to the NN, and this was done by performing a simple linear regression. After training, the NN weights were fixed. Since the correlation between the input parameters is zero, the output from the NN can be studied as a function of each individual input parameter, and thus, we were able to obtain information about the different performance parameters.

In order to obtain information about the variation in the performance parameters there has to be a detailed mapping of the training set. An NN architecture consisting of three hidden layers of 60 process elements (PE), followed by an output layer of one PE together with an epoch size of one was used [1]. This is contrary to the approach used when the NN is aimed for prediction. In that case, a very detailed knowledge of the training is negative, since the NN should ideally only learn the general features in order to provide good predictions. The problem of too detailed knowledge of the training set is often referred to as over-training. The idea behind our approach is to force the NN model to learn the data set in detail to be able to analyze the NN in terms of various input parameters.

By using a NN model, trained on data of P_{heat}, P_{dom} and $d\theta/dt$ as inputs and θ as output, the parameters K_{tot}, α and C_{tot} were extracted by analyzing the NN model in terms of Eq. (1). The method have been improved regarding to how the time derivative ($d\theta/dt$) for a given time step is estimated. In our previous work, we used a backward difference as an approximation of $d\theta/dt$. In this paper, the $d\theta/dt$ is estimated by the derivative of a second-order polynomial fitted to the two previous temperatures and the present temperature.

3. Experimentals

To validate the accuracy of the NN method, a number of experiments were designed. For this, a test cell was used which was developed in a previous work [1,2] and is briefly described below.

3.1. Experimental setup

The dimensions of the test cell were 365 mm high, 400 mm wide and 400 mm long. The walls, floor and ceiling were made of PVC plates and insulated with polystyrene cellular plastic. The test cell was also designed to make air changes possible in order to simulate natural and forced ventilation. Two vents together with a variable fan allowed the desired air renewals to be made. Fifteen thermocouples (type T) were used for measuring the temperatures at different points inside and outside the test cell. The varying internal–external temperature difference across the envelope was experimentally realized by controlling the heat supply in order to induce different internal temperatures of the test cell, while the ambient temperature equaled the indoor temperature of our laboratory. The temperature condition of our experimental setup was, thus, reversed compared to the situation for a real building. Three power resistors were used as heating sources to regulate the internal air temperature. Measurements were made every second and averaged for minute intervals. The accuracy of the individual temperature measurements was calibrated to ± 0.3 °C. The thermocouple readings, nine inside and six outside the test cell, were averaged to give the internal and external temperatures, respectively.

3.2. Calibration

A first-order model ($1-R$, $1-C$) was used to model the thermal performance of the test cell, which gives

$$\theta(t) = \frac{P}{K_{tot}} + \left[\theta(0) - \frac{P}{K_{tot}}\right] e^{-t/\tau} \tag{2}$$

with $\theta(t) = T_i(t) - T_e$ and $\tau = C_{tot}/K_{tot}$; where T_i is the internal temperature, T_e the external temperature, τ the time constant and P is the supplied heat. The solution of the first-order model (Eq. (2)) is only valid for constant K_{tot}, C_{tot} and P.

To determine the thermal performance, the test cell was supplied with a constant P and $\theta(t)$ was measured during 6 h and this was done for different steps in P. The unknown parameters K_{tot} and $\tau = C_{tot}/K_{tot}$ can then be determined by non-linear least square curve fitting to the measured values of $\theta(t)$ and P.

3.3. Experimental design

In Sweden, the energy demand for many single-family buildings, here referred to as existing building, can roughly