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# Calibrating numerical model by neural networks: A case study for the simulation of the indoor temperature of a building

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## Abstract

This paper proposes a method using neural networks to calibrate numerical models. The approach passes the output of numerical model to a neural network for calibration. An experimental study was conducted using a simulation of unheated and uncooled indoor temperature of a sports hall. The proposed neural network-based model improves the results and produces more accurate calibrated indoor temperature. Furthermore, the developed calibration method requires only measurements of indoor temperatures as the necessary inputs, thus significantly simplifying the calibration procedure needed to model the building performances.

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*Keywords:* Numerical model; Neural networks; Model calibration; Generalization; Unheated and uncooled indoor temperature simulation;

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## 1. Introduction

Building simulation models the physical performances of facilities to ensure that they are designed, built, and operated as intended. It often involves decision-making and repeating assessment of the thermal response (e.g. indoor temperature, humidity) to building parameters (e.g. ventilation rate) for the purpose of articulating energy-efficiency strategies [1], hence, it is fast, economical, and particularly powerful for studying conditions that are too difficult and expensive for actual experimentation.

Building simulation, physical and data-driven based broadly, is normally underpinned by a numerical model [1-4]. In general, numerical approaches are not as accurate as black-box models (e.g. artificial

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neural networks). Errors result from a variety of sources, for example, incomplete information regarding building properties, the introduction of assumptions and simplified representations of complex physical processes, and other uncontrollable factors. Diagnosing error sources can be very difficult, time consuming, and expensive and, therefore, is an area of research itself [5]. Some efforts have been made to increase the accuracy of numerical models. However, limited improvements have been achieved regarding test rooms and boundary conditions only [2, 6]. Refining of inputs (e.g. building characteristics) is widely applied to calibrate building simulation [7], which demands significant investigation of building systems and structures. Artificial neural networks (ANNs), on the other hand, are the most popular black-box models and effective at modelling high levels of non-linearity and handling tasks involving uncertainties, complexities, and ill-defined problems. Because ANNs depend entirely on experimental data, they can offer much more accurate results.

To address these modeling challenges in building simulation, this paper emphasizes one key issue aiming at improving the accuracy of numerical models without tedious and difficult error analysis to minimize the time and cost of model calibration. An ANN calibration model is proposed and described with a case study of unheated and uncooled indoor temperature for buildings. The proposed model takes estimated unheated and uncooled indoor temperature from numerical model as input to calibrate the numerical model. The proposed ANN approach improves the results and produces more accurate calibrated indoor temperature. The calibration requires only the measurement of unheated and uncooled indoor temperatures without detailed building system data, thus significantly reducing the effort needed to model the building performances.

## 2. Methodology

The main components of the proposed ANN calibration model are illustrated in Fig.1 and briefly described below:

- ANN is trained to learn simulation error patterns based on the difference between the measurement and the output of the numerical model. The error includes all error sources in both the simulation and modeling, e.g. inaccuracies in the mathematical solution of the numerical model. Hence the output of the numerical model is the deviation from the true value due to the inclusion of all errors.
- Other inputs in Fig.1 are those related to possible error sources of the model that can help increase calibration accuracy of the ANN.

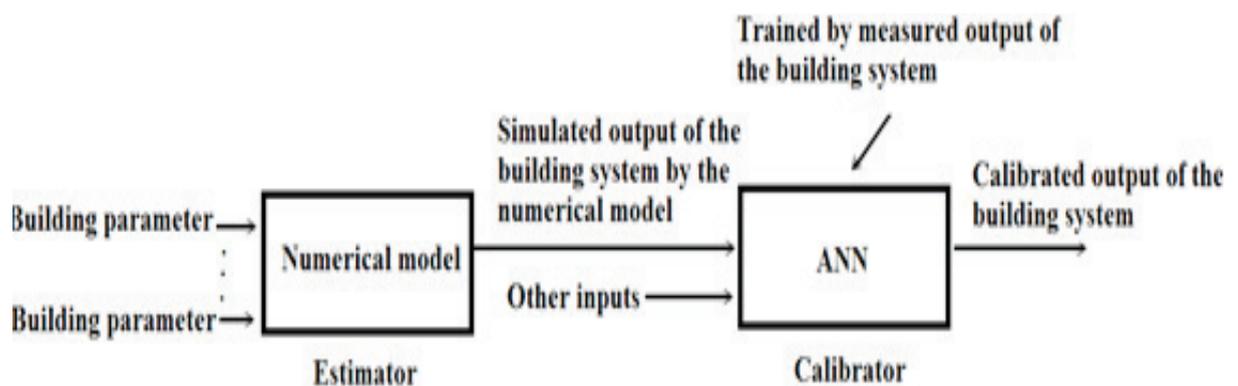


Fig.1 Illustration of the proposed ANN calibration model framework.

### 3. Case Study

We take indoor temperature simulation for an unheated and uncooled single-zone building as a case study to illustrate the proposed ANN calibration model. The case study was conducted in a sports center situated in the south of Finland.

#### 3.1. Building description

The sports center contains two zones: a sports hall and a recreation area. The study was undertaken for the sports hall, which utilizes 100% outdoor air system (Fig.2) and consists of two floorball courts (gym and judo training courts). The supply air flow rate is around  $2.6 \text{ m}^3/\text{s}$  during operating hours (9 am – 10 pm) and  $1.3 \text{ m}^3/\text{s}$  during non-operating hours (10 pm – 9 am).

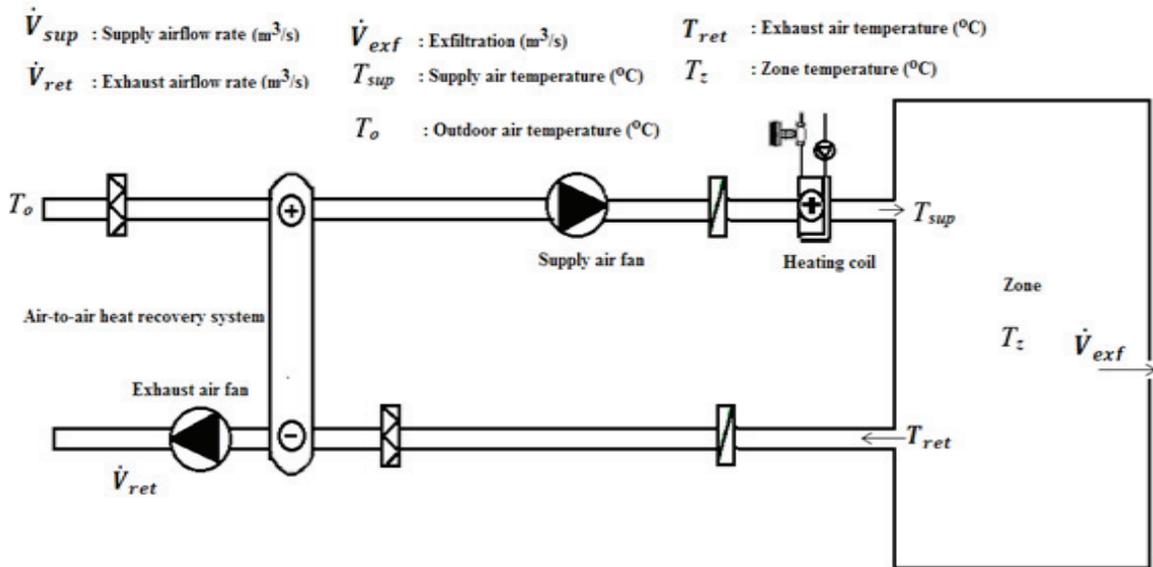


Fig. 2 Schematic of the ventilation system for the sports hall.

Some additional information regarding the sports center is as follows:

Volume:	17220 m <sup>3</sup>
Exterior walls:	1 mm steel + 150 mm mineral wool + 1 mm steel
Roof:	2 mm steel + 175 mm mineral wool + 2 mm steel
Floor:	80 mm concrete + 75 mm insulation + gravel fill (220 mm)

There is no window in the sports hall. The exterior surfaces of the sports center, including exterior walls and roof, are painted in light colours with low solar absorptance. The return indoor temperature data were collected from the building automation system at a 20 min interval. There are 2357 data points, where the first 1200 samples (51%) were used for training and the rest (49%) for testing. During the period of data collection (18.7.2007 – 20.8.2007), the rotary air-to-air heat recovery system was switched

off without heat exchange between return air and supply air and, therefore, the sports hall was unheated and uncooled.

The heat balance for the sports hall (Fig.2) is shown in Eq. (1) [6]:

$$\rho \cdot c \cdot V \frac{dT_{ret}}{dt} = \sum_{i=1}^{N_{surfaces}} h_i A_i (T_{si} - T_{ret}) + \dot{Q}_{int} + \dot{V}_{sup} \cdot \rho \cdot c (T_{sup} - T_{ret}) + \dot{Q}_{sol} \quad (1)$$

where  $\rho$  is density of the air [kg/m<sup>3</sup>];  $c$  heat capacity of the air [J/kg K];  $V$  volume [m<sup>3</sup>];  $N_{surfaces}$  the number of internal surfaces;  $h_i$  heat transfer coefficients [W/m<sup>2</sup> K];  $A_i$  surface area [m<sup>2</sup>];  $T_{si}$  surface temperature [K];  $\dot{Q}_{int}$  internal heat gains [W];  $\dot{Q}_{sol}$  solar input which leads directly to an increase in air temperature or furniture [W]. Note that  $T_{si}$  presents internal surface temperature without considering the impact of solar radiation due to the unavailability of solar radiation data. Therefore,  $T_{si}$  is a bit lower than actual one. Eq. (1) uses the return air temperature  $T_{ret}$  to represent the average indoor temperature, leading to an approximation of a uniform temperature condition for the hall.  $\dot{Q}_{sol}$  takes zero value since there is no window in the sports hall.  $\dot{Q}_{int}$  includes heat gains from (1) occupants, (2) lights, (3) supply air fan, (4) equipment (e.g. jogging machine) and (5) unknown sources. The measured lighting is about 7000 kW and the heat released from the supply air fan is around 2200 kW during operating hours and 450 kW during non-operating hours. The heat gains from occupants and equipment are difficult to estimate and, hence, are ignored here.

Heat transfer through the building envelopes is expressed as transient heat conduction [3]:

$$\frac{\partial T_{structure}}{\partial t} = \alpha \frac{\partial^2 T_{structure}}{\partial x^2} \quad (2)$$

where  $x$  is the length coordinate,  $T_{structure}$  is the temperature at a point in  $x$  direction in a building structure (e.g. exterior wall, roof) and  $\alpha$  is thermal diffusivity [m<sup>2</sup>/s]. As the sports hall has a slab-on-ground type of floor/foundation/ground system, its heat conduction was treated as two-dimensional problem with boundaries prescribed for a much larger area. The details can be found in [3].

The numerical model (Eqs. (1) and (2)) was implemented using HMTB program developed and verified earlier [3]. It provides a graphical interface to facilitate the inputs of building envelope information, ventilation system, lights, and occupants. Building material property data, the interior surface heat transfer coefficient (i.e.  $h_i$ ) and the exterior surface heat transfer coefficient were provided by the Finnish Association of Civil Engineers (RIL) [3]. The indoor temperature of adjacent zone (i.e. recreation area) was assumed to be 20°C.

Both simulated and measured indoor temperature data were naturally split into two parts for ANN calibration: the first 1200 samples (51%) were used for training and the rest (49%, 1157) for testing. Because lightning, exercise and sports activities were scheduled, they are **related to time within certain degrees**. Time was, therefore, chosen as another input and coded in an hour representation format (e.g. 10:30 am is coded as 10.5=10+30/60). The number of hidden units was set as three. The ANN was trained by using a training algorithm based on Bayesian Regulation Backpropagation, which updates the weight and bias values according to the Levenberg-Marquardt optimization to improve generalization. Before training, all data were normalized.

### 3.2. Model validation criteria

Several model performance measures, including the mean of the sum of square errors (MSE), the mean of absolute errors (MAE), the mean of absolute percentage errors (MAPE), the index of agreement (IA), and the coefficient of determination ( $R^2$ ) are used as criteria to evaluate the model fit:

$$MSE = 1/N \sum_{k=1}^N (\hat{y}(k) - y(k))^2 \quad (3)$$

$$MAE = 1/N \sum_{k=1}^N |\hat{y}(k) - y(k)| \quad (4)$$

$$MAPE(\%) = 100/N \sum_{k=1}^N \left| \frac{\hat{y}(k) - y(k)}{y(k)} \right| \quad (5)$$

$$IA = 1 - \frac{\sum_{k=1}^N (\hat{y}(k) - y(k))^2}{\sum_{k=1}^N (|\hat{y}(k) - \bar{y}(k)| + |y(k) - \bar{y}(k)|)^2} \quad (6)$$

$$R^2 = 1 - \frac{\sum_{k=1}^N (\hat{y}(k) - y(k))^2}{\sum_{k=1}^N (y(k) - \bar{y}(k))^2} \quad (7)$$

where  $\hat{y}$  is simulated output,  $y(k)$  measured one and  $\bar{y}(k)$  the mean value of measured.  $\frac{100 * |\hat{y}(k) - y(k)|}{y(k)}$  (See Eq. (5)) is called Absolute Percentage Error (APE), which will be discussed later.

IA and  $R^2$  validate “goodness-of-fit” of a model, which will be used only for ANN.

## 4. Results and discussion

The comparison results are given in Table 1 and Fig.3.

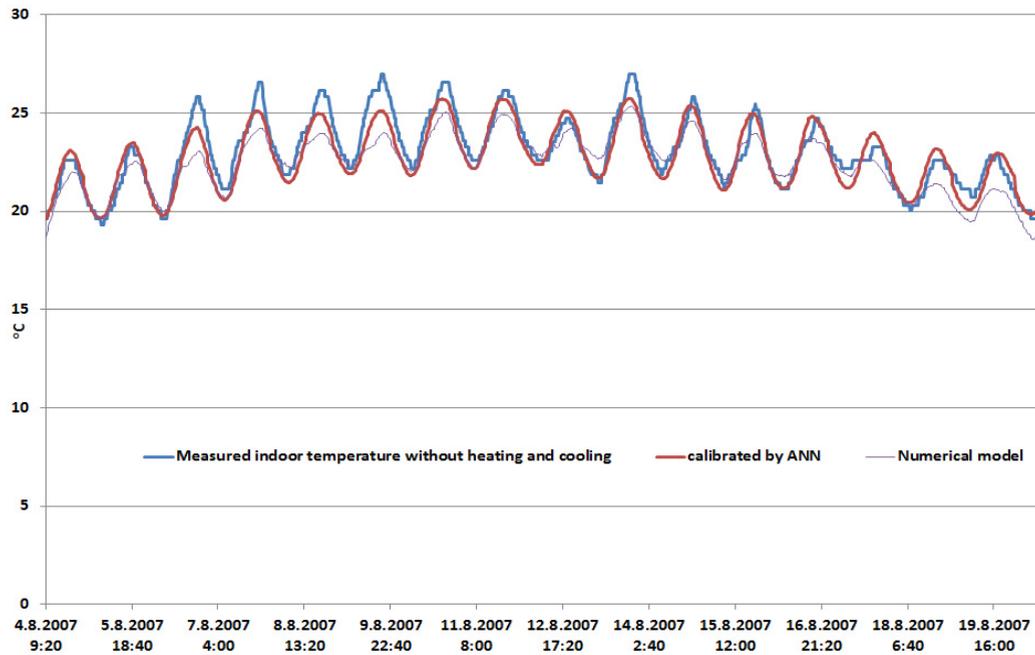


Fig.3 Comparison of measurement, numerical model and calibrated ANN model.

Table 1. Performances of the numerical model and calibrated results of the numerical model by ANN

	Numerical model	Calibrated by ANN
<b>MSE</b> (Mean Square Error)	0.97	0.43
<b>MAE</b> (Mean Absolute Error)	0.77	0.48
<b>MAPE</b> (%) (Mean Absolute Percentage Error)	3.4	2
<b>IA</b> (Index of Agreement)		0.95
<b>R<sup>2</sup></b> (Coefficient of Determination)		0.87

The accuracy is improved by employing ANN as a calibrator, with the maximum APE decreasing from 11.5% (the numerical model) to 6.5% (calibrated by ANN). Error analysis for numerical model is extremely difficult as demonstrated in Fig.3: the simulated indoor temperature from the numerical model is declining during non-operating hours during 16-19.8.2007 due to decreasing outdoor temperature. however, the measured data set does not behave in the same fashion. During non-operating hours (22:00 pm – 9 am) during 18-19.8.2007, the measured temperature is actually higher than the temperature during 17-18.8.2007, resulting in poorer simulation results (MAE=2.7 and MSE=7.6 for 22:00 18.8.2007 – 8:40 19.8.2007). The explanation for such a phenomenon is difficult since its underlying physical mechanisms are poorly understood. For example, the internal heat gains (e.g. occupants, lighting, solar radiation through exterior walls and roof) are very small that the contribution is negligible during non-operating hours. However, the calibrated result by ANN basically follows the measurement's trend, giving MAE =0.53 and MSE =0.43 (22:00 18.8.2007 – 8:40 19.8.2007). The performances do not change much (Table 1). This shows the ability of the proposed ANN to handle highly nonlinear problems with uncertainties.

## 5. Conclusions

An ANN based calibration model was developed for the simulation of indoor temperature or/and humidity for unheated and uncooled buildings and is extensible to other building simulations. Compared to the numerical model alone, the calibrated model by ANN is much more accurate. Diagnosis-related analysis of the error sources is not needed using the proposed ANN calibration model which greatly simplifies the modelling processes.

## 6. Copyright

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