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# Novel hybrid modeling approach for utilizing simple linear regression models to solve multi-input nonlinear problems of indoor humidity modeling

Tao Lu [a,*], Xiaoshu Lü [a,b,c,d], Heidi Salonen [d], Qunli Zhang [c]

[a] Department of Electrical Engineering and Energy Technology, University of Vaasa, P.O. Box 700, FIN-65101, Vaasa, Finland
[b] College of Construction Engineering, Jilin University, Changchun, 130026, China
[c] Beijing Key Lab of Heating, Gas Supply, Ventilating and Air Conditioning Engineering, Beijing University of Civil Engineering and Architecture, Beijing, 100044, China
[d] Department of Civil Engineering, Aalto University, P.O. Box 11000, 02150, Espoo, Finland

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A B S T R A C T

Investigating indoor humidity is important because abnormal moisture levels can damage building structures and result in poor indoor air quality. Outdoor humidity, ventilation rate, and internal moisture load are the three dominant factors affecting indoor humidity. State-of-the-art methods, particularly full-scale field studies for determining these three factors and indoor humidity can be both time consuming and labor intensive. This study proposes a radically new methodology to effectively model the influence of these three factors on indoor humidity for a mechanically ventilated building/space. The methodology starts with a simple linear regression (SLR) constructed by measuring indoor and outdoor humidity and then hybrids a novel analytical approach that accurately predicts the impact of ventilation rate and internal moisture load on indoor humidity. The proposed upgraded SLR model was successfully validated with high accuracy by both experiments and numerical simulations using TRNSYS commercial software. The results demonstrate the ability of the developed SLR to accurately model indoor humidity and account for the moisture exchange between indoor air and building structures/furnishings. Inferring these relationships and their influences on indoor humidity presents a challenging task. The developed model is generic and unique and supports fast and inexpensive field studies by ensuring that the measurements of indoor and outdoor humidity are sufficient to derive field tests of the impacts of outdoor humidity, ventilation rate, and internal moisture loads on indoor humidity. The proposed model can be further developed as a standardized moisture assessment tool for benchmarking building performance.

## 1. Introduction

Indoor humidity is one of the most important factors determining indoor air quality (IAQ) and human thermal comfort [1]. Meanwhile, moisture is one of the most serious factors that deteriorates building structures and decreases energy efficiency. Thus, the evaluation of indoor humidity has become a part of the work concerning IAQ and building system optimization. In general, such evaluations can be performed using physics-based models or field studies.

Physics-based models are mostly constructed based on first principles to investigate the hygrothermal behavior of building materials [1–9] and also combined building envelopes and indoor air [10–14]. For building materials, Maliki et al. [9] proposed a two-phase, liquid and vapour, moisture flow model with capillary pressure and temperature gradients as driving potentials based on mass and energy conservation for multilayered porous materials. Further, Tariku et al. [14] developed a holistic heat, air and moisture (HAM) model in order to study the dynamic heat and moisture interactions between the building envelope, indoor air and building energy systems. Two primary balance equations from conservation principles of mass, energy and momentum were separately constructed to model the performances of the building envelope and indoor air and then integrated to form a whole building hygrothermal model on Simulink environment. Validation of the holistic HAM model showed a good agreement with internationally published test cases. Comparative analysis of simulation results demonstrated the importance of the coupled effects of the dynamic HAM transfer of the building envelope with the indoor environment and its components (i.e., HVAC system, moisture and heat sources [14]) for accurately predicting

* Corresponding author.
*E-mail address:* tao.lu@uwasa.fi (T. Lu).

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indoor humidity. Indeed, the level of indoor humidity is influenced by many factors, such as outdoor humidity, ventilation rate, internal moisture loads, airflow and temperature distributions in rooms, and moisture adsorption and desorption from surrounding surfaces (known as the moisture buffering capacity of building materials) [15]. However, modeling the moisture buffering of building materials is extremely complicated and requires detailed knowledge of the heat and moisture transfer for building materials (e.g., two-phase flow by Maliki et al. [9]) and for combined building envelopes and indoor air (e.g., holistic HAM model by Tariku et al. [14], Qin et al. [16]). Some parameters regarding the moisture buffering capacity of building materials can be determined only through time-consuming experiments. Rode et al. [17] defined a quantity called the moisture buffer value (MBV) to describe the ability of building materials and systems to exchange moisture with indoor environments. However, this remains a challenge. In addition, a test protocol was developed to determine how materials and systems should be tested for MBVs. A round-robin test was performed to determine the MBVs of eight different building materials and material systems. Similarly, ISO/DIS [18] and the Japanese Industrial Standard [19] have proposed experimental protocols for the determination of MBVs.

Because of the complexity in modeling heat and moisture transfer in buildings by considering moisture buffering effects, building simulation programs, such as EnergyPlus [20], TRNSYS [21], and WUFI [22], have also been adopted [23–26]. Qin and Yang [23] employed EnergyPlus to evaluate three different thermal models [21] for modeling moisture buffering effects on building energy consumption and indoor environments under different climate conditions. The three models were validated using measurement data from a test bedroom in Nanjing, China. A case study was then conducted to compare the models' accuracies. Martínez–Mariño et al. [24] validated a multi-zone building model developed by TRNSYS and TRNFLOW [25] for modeling indoor temperature and RH under complex and realistic situations. A multi-objective optimization was conducted to determine the optimal values of the surface and deep moisture buffering material masses. A relevant case study was carried out for twin houses in Germany. Ojanen [26] adopted WUFI Plus to simulate the indoor humidity in a log house with massive laminated logs as wall structures. The results demonstrated that the moisture buffering effect of the log walls helped to maintain the indoor conditions in a comfortable zone. Having the ability to assess the thermal response (i.e., indoor temperature and humidity) to different building parameters (e.g., ventilation rate, moisture load, wall structures, furnishings) is a great advantage for physics-based models. However, collecting and setting up these building parameters is time-consuming and requires significant effort and expert knowledge. Sometimes, parameters may not be available and model validation can be very difficult and expensive [27]. Therefore, physics-based models cannot be used as analysis tools for quickly processing large amounts of data involving many buildings.

In field studies, indoor humidity has often been investigated in different buildings using field measurements [28–31]. Kalamees et al. [32] conducted two years of measurements of indoor temperature and humidity for 101 single-family detached houses to analyze IAQ conditions and determine moisture production. Air change rates were measured during winter using a passive tracer gas air infiltration measurement technique. Psomas et al. [33] assessed the indoor humidity conditions in 678 Swedish residential buildings, 520 single-family houses, and 158 apartments in their investigation into the associations and correlations between RH levels and multiple building and system characteristics, occupancy patterns and behaviors, and health symptom complaints. Zhao et al. [34] monitored the indoor temperature, humidity, and $CO_2$ concentration in five mechanically ventilated and four naturally ventilated homes in Urumqi, China. The study suggested that the indoor climate was dry during winter, while it was comfortable in other seasons. Asif et al. [35] performed three months of measurements of the indoor $CO_2$ concentration, temperature, and humidity of four university buildings (15 classrooms) to analyze the performance of ventilation systems and thermal comfort. The results showed that the occupancy density, ventilation, outdoor thermal conditions, and orientation of the building had the most effect on the IAQ and thermal comfort parameters. Although field studies can provide researchers with information about real situations of indoor humidity levels, field studies are costly and limited by on-site conditions. For instance, if the ventilation system of a building is designed as a constant air volume (CAV) system, it is very difficult to study the correlation between the indoor humidity and the ventilation rate for the building because of insufficient information on the ventilation rate. For a mechanically ventilated space, outdoor humidity, ventilation rate, and internal moisture load are the three most influential and relevant factors. It would be more informative for a field study or data analysis if one could determine indoor humidity trends for all possible ventilation rates and internal moisture loads in a building/space.

With the widespread application of IoT (Internet of things) sensors, long-term measurements of indoor temperature and humidity are now available for buildings. The lack of a methodology in the literature that effectively utilizes long-term measurements of indoor and outdoor humidity to develop a model for studying the impact of outdoor humidity, ventilation rate, and internal moisture load on indoor humidity in a building/space hinders field studies and big data analysis. Data-based models often rely on sufficient experimental measurement data to solve multi-input nonlinear problems. It fails if there is insufficient information about one or more inputs. Therefore, it is challenging to develop such a methodology because of the difficulty in measuring internal moisture loads and the insufficient information on ventilation rate (e.g., many buildings have CAV systems). The objective of this study was to address this challenge by constructing indoor humidity models primarily using indoor and outdoor humidity measurement data. The constructed models can act like physics-based models with outdoor humidity, ventilation rate, and internal moisture load as three inputs if the current ventilation rates are known (e.g., knowing the daily average ventilation rate for the period when indoor humidity is measured).

To achieve this goal, we propose a novel methodology that couples hybrid modeling with a linear relationship generally held between indoor and outdoor absolute humidity (AH), which has been widely reported in many studies [15,36,37]). The potential of the simple linear regression (SLR) model derived from this relationship (i.e., indoor_AH = a(outdoor_AH) + b, where a and b are constants determined by measured indoor and outdoor AH, respectively) has been overlooked in the literature. The SLR model considers the moisture buffering effect, which is difficult to accurately model. Moreover, it not only shows a linear relationship between indoor and outdoor AH but also implies a linear relationship between indoor AH and internal moisture load because the internal moisture load can be considered as a part of outdoor AH brought into a space by ventilation. The concepts of the proposed novel methodology and SLR model are shown in Fig. 1.

The outdoor AH extension (OUT_AH_EXT) behaves like an outdoor AH. The sum of the outdoor AH and OUT_AH_EXT is called the extended outdoor AH (EXT_OUT_AH), which is used to replace the outdoor AH as the input for the SLR model. The SLR model describes a linear relationship between the indoor and outdoor AH by assuming a fixed ventilation rate and internal moisture load for the measurement period. If the outdoor AH remains the same, varying the ventilation rate and internal moisture load will induce a moisture change ($\Delta\dot{m}$). We presume that $\Delta\dot{m}$ is caused by a change in the outdoor AH rather than changes in the ventilation rate and internal moisture load, which are constants. Thus, this linear relationship between the indoor and outdoor AH still holds, and the SLR model constraint of a fixed (constant) ventilation rate and internal moisture load is released. The process of converting $\Delta\dot{m}$ (additional internal moisture load, Fig. 1) to OUT_AH_EXT via ventilation is modeled by physics-based models (see Chapter 2). The completed model can be regarded as a fast Excel-based indoor humidity estimation tool suitable for field studies and big data analysis that can easily create 3D surface plots, for example, showing the impact of outdoor humidity

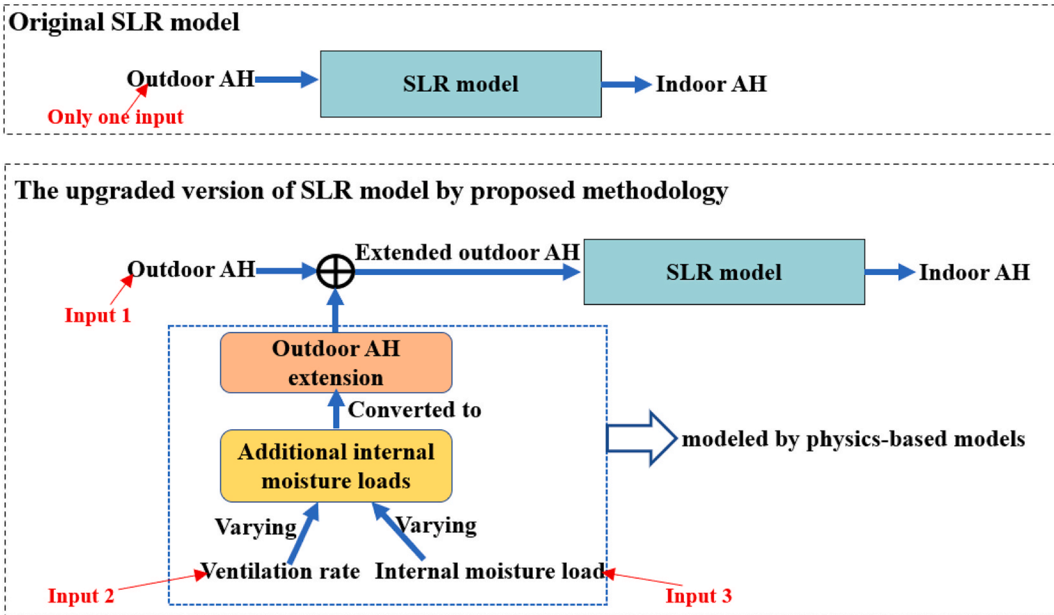


**Fig. 1.** Concept of proposed methodology.

and ventilation rate on indoor humidity in a mechanically ventilated building/space (CAV systems included). To the best of our knowledge, this is the first time that such a novel approach has been applied and used measured indoor and outdoor humidity to solve the multi-input nonlinear problem of indoor humidity modeling.

## 2. Methodology

To simplify the discussion, the following assumptions were made:

- indoor air is well-mixed,
- buildings use 100% outdoor air systems (this type of system is commonly used in Finland and other European countries), and
- there is no mechanical dehumidification or humidification for indoor air.

The governing equation of moisture transfer in a space is [38]:

$$V_{space}\frac{dAH_{in}}{dt} = \dot{V}_{ventilation}(AH_{out} - AH_{in}) + \dot{m}_{internal} - \dot{m}_{sorption} \tag{1}$$

where $V_{space}$ is the volume of the space ($m^3$), $AH_{in}$ and $AH_{out}$ are the indoor and outdoor AH ($g/m^3$), respectively, $\dot{V}_{ventilation}$ is the ventilation rate ($m^3/h$), $\dot{m}_{internal}$ is the internal moisture load (g/h), and $\dot{m}_{sorption}$ is the sorption of moisture into or desorption out of the building materials. Alternatively, $\dot{m}_{sorption}$ is also lumped with $V_{space}\frac{dAH_{in}}{dt}$ to form a new term $(EC)V_{space}\frac{dAH_{in}}{dt}$, where $EC$ is a positive number $\geq 1$ and has different names in the literature [38]. Therefore, it can be assumed that ventilation is the only means of introducing ambient moisture into a space. The methodology proposed in this study is based on this assumption and is an upgraded version of the following SLR model (Eq. (2)) that considers the ventilation rate and internal moisture load as two additional inputs.

$$AH_{in} = aAH_{out} + b \tag{2}$$

where $AH_{in}$ and $AH_{out}$ are the indoor and outdoor AH ($g/m^3$) values, respectively, and $a$ and $b$ are constants. It is preferable to use daily average values to create Eq. (2) because the internal moisture loads are significantly unbalanced for unoccupied and occupied periods in a day. Fig. 2 shows the three SLR models.

The three examples showed a very strong correlation between indoor and outdoor AH. Such strong correlations can also be found in houses [36] and apartments [37]. Before introducing the methodology proposed in this study, called NHMAHLR (novel hybrid modeling of AH linear regression), we define and explain the following terminologies:

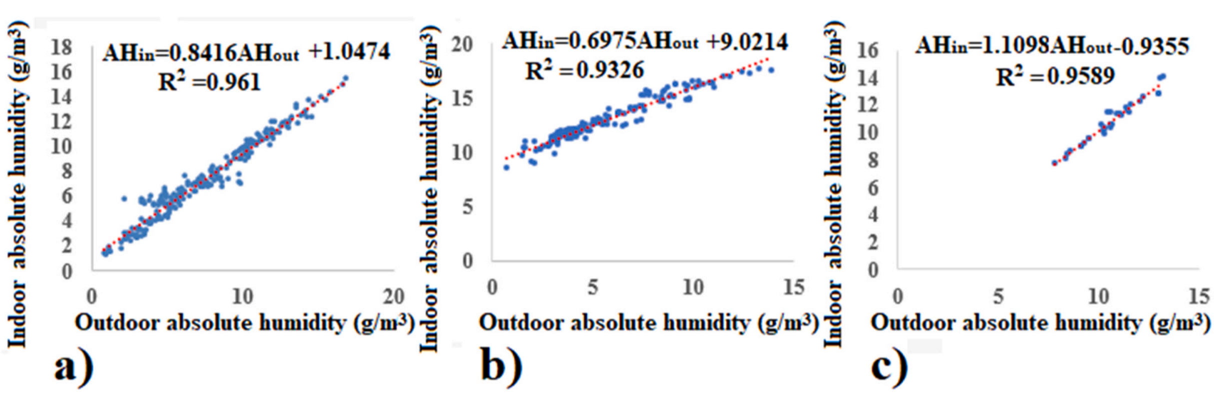


**Fig. 2.** a) The SLR model for a wooden church built in 2005 (one year's daily average values used). b) The SLR model for an indoor swimming hall built in 1990's (about half year's daily average values used). c) The SLR model for a sports center built in 1980's (about one month's daily average values used).

- *Base model*: the SLR model (Eq. (2)) manipulated by the NHMAHLR method to model the indoor AH for any outdoor AH, ventilation rate, or internal moisture load.
- *Reference ventilation rate and reference internal moisture load*: the ventilation rate and internal moisture load of a space for the period when the measurement was carried out to establish a base model. Unlike the reference ventilation rate, the reference internal moisture load is typically unknown.

The concept of NHMAHLR is shown in Fig. 1 and in the last paragraph of Chapter 1. The processes of generating additional internal moisture loads by changing the reference ventilation rate and/or reference internal moisture load and converting these additional internal moisture loads into OUT_AH_EXT were modeled using physics-based models (Fig. 1). We use an example and three scenarios to illustrate these processes, and we developed formulas for calculating EXT_OUT_AH, OUT_AH_EXT, and indoor AH for each scenario. Suppose that the indoor and outdoor humidity were measured for a space with a ventilation rate $\dot{V}_{example}$ $m^3/h$; then the SLR model created based on the measured indoor and outdoor humidity is

$$AH_{in} = a_{example}AH_{out} + b_{example} \tag{3}$$

In this case, the base model is $AH_{in} = a_{example}AH_{out} + b_{example}$, whereas the reference ventilation rate is $\dot{V}_{example}$. The aim of the NHMAHLR method is to employ a base model (Eq. (3)) to simulate the following three indoor humidity scenarios.

- Scenario 1: addition of $\dot{m}_{example}$ g/h moisture load to the space.
- Scenario 2: increase in the ventilation rate to $u$ (a positive number) times the reference ventilation rate (i.e., $u\dot{V}_{example}$).
- Scenario 3: addition of $\dot{m}_{example}$ g/h moisture load to the space and an increase in the ventilation rate to $u$ times the reference ventilation rate (i.e., $u\dot{V}_{example}$).

To model the above three scenarios, the NHMAHLR method substitutes EXT_OUT_AH for the outdoor AH in Eq. (3) to account for the changes in the reference ventilation rate and internal moisture load (see Fig. 1) to obtain

$$AH_{in} = a_{example}AH_{out}^{extended} + b_{example} = a_{example}\left(AH_{out} + AH_{out}^{extension}\right) + b_{example} \tag{4}$$

where $AH_{out}^{extended}$ is EXT_OUT_AH and $AH_{out}^{extension}$ is OUT_AH_EXT. The key is to develop physics-based models for computing EXT_OUT_AH.

### 2.1. Scenario 1: addition of $\dot{m}_{example}$ g/h moisture load to the space

Fig. 3 illustrates the concept of the NHMAHLR method and EXT_OUT_AH for Scenario 1.

EXT_OUT_AH is calculated as $AH_{out} + \frac{\dot{m}_{example}}{\dot{V}_{example}}$ for Scenario 1, where OUT_AH_EXT is $\frac{\dot{m}_{example}}{\dot{V}_{example}}$. Substituting $AH_{out} + \frac{\dot{m}_{example}}{\dot{V}_{example}}$ for $AH_{out}^{extended}$ in Eq. (4) obtains:

$$AH_{in} = a_{example}\left(AH_{out} + \frac{\dot{m}_{example}}{\dot{V}_{example}}\right) + b_{example} \tag{5}$$

Compared with the outdoor AH alone (left side, Fig. 3), EXT_OUT_AH introduces $\dot{m}_{example}$ $\left(=\left(\frac{\dot{m}_{example}}{\dot{V}_{example}}\right)\dot{V}_{example}\right)$ more moisture into the space equivalent to the addition of $\dot{m}_{example}$ internal moisture load in the space.

### 2.2. Scenario 2: increase in the ventilation rate to u times the reference ventilation (i.e., $u\dot{V}_{example}$)

Fig. 4 depicts the NHMAHLR method and EXT_OUT_AH for Scenario 2.

Compared with the internal situation of the base model (right side, Fig. 4), increasing the ventilation rate to $u$ times the reference ventilation rate (left side, Fig. 4) leads to $u-1$ times extra outdoor AH drawn into the space, and at the same time $u-1$ times extra indoor AH drawn out of the space. OUT_AH_EXT is calculated as: $(u-1)AH_{out} - (u-1)AH_{in}$, resulting in EXT_OUT_AH $= AH_{out} + (u-1)AH_{out} - (u-1)AH_{in}$. Substituting $AH_{out} + (u-1)AH_{out} - (u-1)AH_{in}$ for $AH_{out}^{extended}$ in Eq. (4) yields

$$AH_{in} = \frac{ua_{example}}{(1 + a_{example}(u-1))}AH_{out} + \frac{b_{example}}{(1 + a_{example}(u-1))} \tag{6}$$

If $u$ is infinity, Eq. (6) approximates to $AH_{in} = AH_{out}$; that is, the indoor humidity is equal to the outdoor humidity if the ventilation rate is infinity.

### 2.3. Scenario 3: addition of $\dot{m}_{example}$ g/h moisture load to the space and an increase in the ventilation rate to u times the reference ventilation rate (i.e., $u\dot{V}_{example}$)

By observing Figs. 3 and 4, the EXT_OUT_AH of Scenario 3 is

$$AH_{out}^{extended} = \left(AH_{out} + \frac{\dot{m}_{example}}{u\dot{V}_{example}}\right) + (u-1)\left(AH_{out} + \frac{\dot{m}_{example}}{u\dot{V}_{example}}\right) - (u-1)AH_{in} \tag{7}$$

where OUT_AH_EXT is $(u-1)\left(AH_{out} + \frac{\dot{m}_{example}}{u\dot{V}_{example}}\right) - (u-1)AH_{in}$.

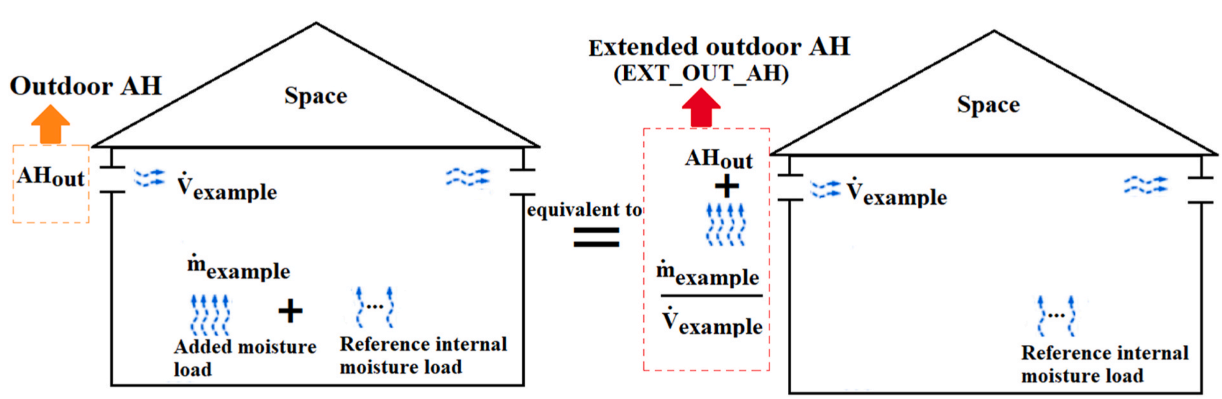


**Fig. 3.** Illustration of NHMAHLR method and EXT_OUT_AH for Scenario 1. Left: indoor situation for Scenario 1 (the base model, Eq. (3), is not valid owing to addition of $\dot{m}_{example}$ to the space). Right: indoor situation for base model (the base model is valid).

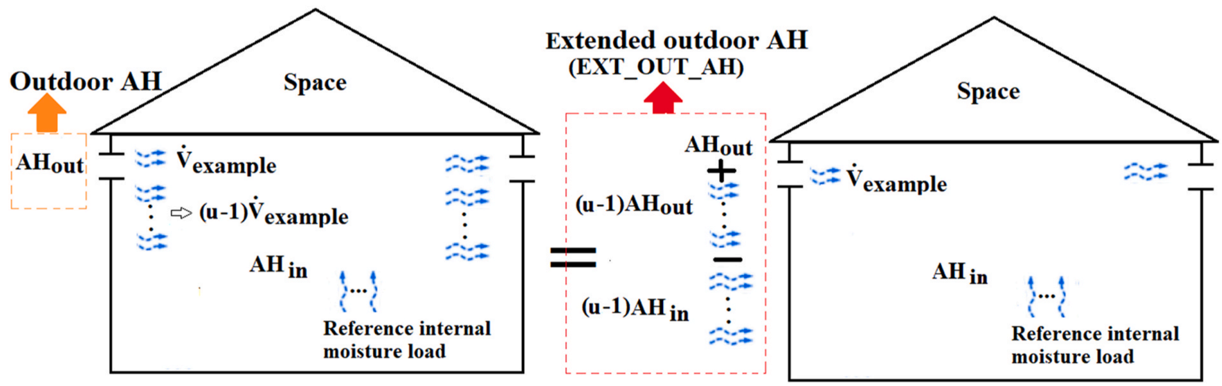


**Fig. 4.** Illustration of NHMAHLR method and EXT_OUT_AH for Scenario 2. Left: indoor situation for Scenario 2 (the base model, Eq. (3), is not valid owing to increase in reference ventilation rate). Right: indoor situation of base model (the base model is valid).

Substituting Eq. (7) for $AH_{out}^{extended}$ into Eq. (4) yields

$$AH_{in} = \frac{ua_{example}}{(1 + a_{example}(u-1))}\left(AH_{out} + \frac{\dot{m}_{example}}{u\dot{V}_{example}}\right) + \frac{b_{example}}{(1 + a_{example}(u-1))} \tag{8}$$

Eqs. (5), (6) and (8) were derived from the base model (Eq. (3)) to estimate the indoor AH for Scenarios 1–3. Eq. (8) is the general form of the hybrid model proposed in this study because all the inputs (outdoor AH, ventilation rate, and internal moisture load) appear in this formula.

## 3. Case studies

The case studies included simulated and experimental data.

### 3.1. Simulated data

The simulated data were produced by TRNSYS 18 [21] for a single-family, single-story house (Fig. 5). TRNSYS is a transient system simulation program used in renewable energy engineering and building simulations. It was developed at the University of Wisconsin approximately 40 years ago, and the latest version, TRNSYS 18, was released in April 2017. The main advantage of using a commercial software package to produce data is its low cost and flexibility. A commercial software package can use the same climate data to simulate the long-term thermal behavior for different building settings.

The structures and ventilation system of the simulated single-family house were based on an existing detached house in Finland [39] (see Table 1).

**Table 1**
Structures and ventilation system of single-family house.

| Element | Property | U-value (W/$m^2$K) |
|---|---|---|
| External wall | Gypsum board (13 mm), wooden frame + mineral wool (540 mm), wind shield board (9 mm) | 0.08 |
| Roof | Gypsum board (13 mm), wooden frame + mineral wool (650 mm), water proof sheet (10 mm) | 0.07 |
| Base floor | Parquet (14 mm), concrete (80 mm), EPS-insulation (365), ground layer (1000 mm) | 0.1 |
| Internal wall | Gypsum board (13 mm), wooden frame + air gap (50 mm), gypsum board (13 mm) | 2.42 |
| Windows | g-value: 0.26 | 0.80 |
| Ventilation system | | |
| Mechanical supply and exhaust ventilation system | Constant air volume system (100% outdoor air system) | |
| Operation schedule | Monday–Sunday 00:00–24:00 | |
| Supply and exhaust air flow rate | 0.4 $dm^3$/(s, $m^2$) | |

The effective capacitance humidity module (ECHD) of TRNSYS was selected to generate the indoor humidity data. Effective moisture capacitance has different definitions in the literature. The definition used by TRNSYS was adopted in this study. Sorption effects were

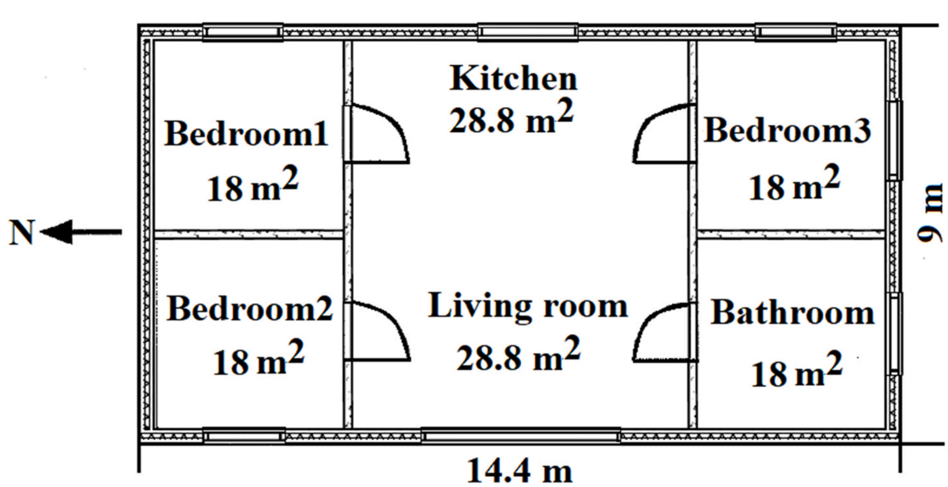


**Fig. 5.** Floor plan of single-family house (room height = 2.6 m).

considered by an effective moisture capacitance (unit: kg) defined as the product of the air mass and moisture capacitance ratio (MCR) (recommended value: 1–10) [21]. An MCR of 10 indicates that the building materials, plus the zone air, can absorb 10 times more moisture than the zone air alone. TRNSYS also offers a more sophisticated model called the buffer storage humidity module (BSHD) that models the moisture transfer between the indoor air and structures and within structures. BSHD is defined using six parameters. It is difficult to evaluate these six parameters for different wall structures and furnishings. Paralovo et al. [40] compared the ECHD and BSHD in a 29.4 $m^3$ one-person room in Austria using three different MCRs (1, 5, and 10). In general, the two models followed similar trends, but in summer, the structures and furnishings absorbed more moisture in the case of MCR = 10. Only the two-person Bedroom2 (18 $m^2 \times 2.6$ m) was investigated because it had the highest moisture load per square meter among all rooms. Weather data from Changchun, P. R. China (43.8171° N, 125.3235° E), were chosen for the case studies. Changchun has long cold winters (November–March) and hot humid summers. The annual average temperature in Changchun is approximately 6.1 °C, which is close to that in the southwestern part of Finland (5.0–7.5 °C). Four cases were simulated (Table 2).

The heating and cooling setpoints were 21 °C and 27 °C, respectively, for all rooms. Base Model 1 was created from Reference case (Table 2) as shown in Fig. 6.

By knowing Base Model 1 ($AH_{in} = 0.9897AH_{out} + 2.1105$) and the corresponding reference ventilation rate (25.92 $m^3$/h), the aim of the case study is as follows:

1. Use Eq. (6) to estimate the indoor humidity for Case 1 (ventilation rate increased from 25.92 $m^3$/h to 2 × 25.92 $m^3$/h).
2. Use Eq. (5) to estimate the indoor humidity for Case 2 (1.458 kg/day extra moisture load added to the space).
3. Use Eq. (8) to estimate the indoor humidity for Case 3 (ventilation rate increased from 25.92 $m^3$/h to 2 × 25.92 $m^3$/h, and 1.458 kg/day extra moisture load added to the space).

### 3.2. Experimental data

Two experiments were conducted in an empty wooden test house (Fig. 7) on a university campus in Finland from Mar. 30, 2016 to Apr. 9, 2016.

House details:

- Dimensions: 10.2 $m^2 \times 2.8$ m.
- Wall: ventilated façade, 25-mm wood-fiber panel, 400-mm insulation, 15-mm gypsum plasterboard (U = 0.1 $W/m^2K$).

**Table 2**
Simulated cases by TRNSYS[a].

| | Ventilation rate ($m^3$/h) | Moisture load (kg/day, assumed Bedroom2 had moisture load only for the occupied period, 22:00–7:00) |
|---|---|---|
| Reference case | 25.92 (0.55 ACH, 00:00–24:00) | 1.458 |
| Case 1 | 2 × 25.92 (2 × 0.55 ACH, 00:00–24:00) | 1.458 |
| Case 2 | 25.92 (0.55 ACH, 00:00–24:00) | 2 × 1.458 |
| Case 3 | 2 × 25.92 (2 × 0.55 ACH, 00:00–24:00) | 2 × 1.458 |

[a] No dehumidification or humidification of indoor and outdoor air.

- Roof: 2-mm polyvinyl chloride, 21-mm laminated veneer lumber panel, 400-mm insulation, 15-mm gypsum plasterboard (U = 0.09 $W/m^2K$).
- Floor: 25-mm cement-bound wood-fiber board, 400-mm insulation, 21-mm laminated veneer lumber panel (U = 0.1 $W/m^2K$).

The test house had a ventilation unit with rotary heat recovery (sensible heat only) mounted on the wall next to the door (Fig. 7). During the experiments, a 2000-W oil-filled electric heater with nine ribs and a thermostat was used to heat the test house at approximately 22 °C. Two experiments were performed using different ventilation settings (Table 3).

Airflow rates were calibrated using a Halton PRA-100 airflow damper and Swema 3000 airflow measuring device. Indoor temperature and RH were measured using a Grey Wolf Sensing Solution system [41] with RH accuracies of ±2% RH < 80% and ±3% RH > 80% and temperature (−25–70 °C) with an accuracy of ±0.3 °C. In each case, all the devices were placed on a 120-cm high tripod located at the center of the room. Measurements were recorded at 1-min intervals. The following two base models were built using half-hour average values.

- Base Model 2: $AH_{in} = 0.2968AH_{out} + 2.3994$ ($R^2 = 0.7465$ and the corresponding reference ventilation rate = 17.99 $m^3$/h built from the measurement of Case 4 (Table 3)).
- Base Model 3: $AH_{in} = 0.349AH_{out} + 2.5167$ ($R^2 = 0.7952$ and the corresponding reference ventilation rate = 37.82 $m^3$/h built from the measurement of Case 5 (Table 3)).

The goal of the case study was:

1. To use Eq. (6) and Base Model 2 to estimate the indoor humidity for Case 5 (ventilation rate increase from 17.99 $m^3$/h to 37.82 $m^3$/h, Table 3), and
2. To use Eq. (6) and Base Model 3 to estimate the indoor humidity for Case 4 (ventilation rate decrease from 37.82 $m^3$/h to 17.99 $m^3$/h, Table 3).

In addition, we also used an analytic solution (i.e., Eq. (1)) to model indoor humidity for the test house. Because modeling the moisture exchange between indoor air and interior cladding is extremely complicated, we ignored it (i.e., $\dot{m}_{sorption}$) and moisture load $\dot{m}_{internal}$ in Eq. (1) (the empty test house) giving the analytic solution as:

$$AH_{in}^{i} = AH_{out}^{avg} + \left(AH_{in}^{i-1} - AH_{out}^{avg}\right)e^{-I\Delta t} \tag{9}$$

where $AH_{in}^{i}$ is the indoor AH at time step $i$, $AH_{out}^{avg}$ is the average outdoor AH between time steps $i-1$ and $i$, $AH_{in}^{i-1}$ is the indoor AH at time step $i-1$, $I = \dot{V}_{ventilation}/V_{space}$ (air change rate), and $\Delta t$ is the time difference between time steps.

### 3.3. Model validation criteria

The root mean square error (RMSE), mean absolute percentage error (MAPE), and coefficient of determination ($R^2$) were used as criteria to evaluate the model fit.

$$RMSE = \sqrt{\frac{\sum_{k=1}^{N}\left(\hat{y}(k) - y(k)\right)^2}{N}} \tag{10}$$

$$MAPE(\%) = \frac{100\left(\sum_{k=1}^{N}\frac{|\hat{y}(k) - y(k)|}{y(k)}\right)}{N} \tag{11}$$

$$R^2 = 1 - \frac{\sum_{k=1}^{N}\left(\hat{y}(k) - y(k)\right)^2}{\sum_{k=1}^{N}\left(\hat{y}(k) - \bar{y}(k)\right)^2} \tag{12}$$

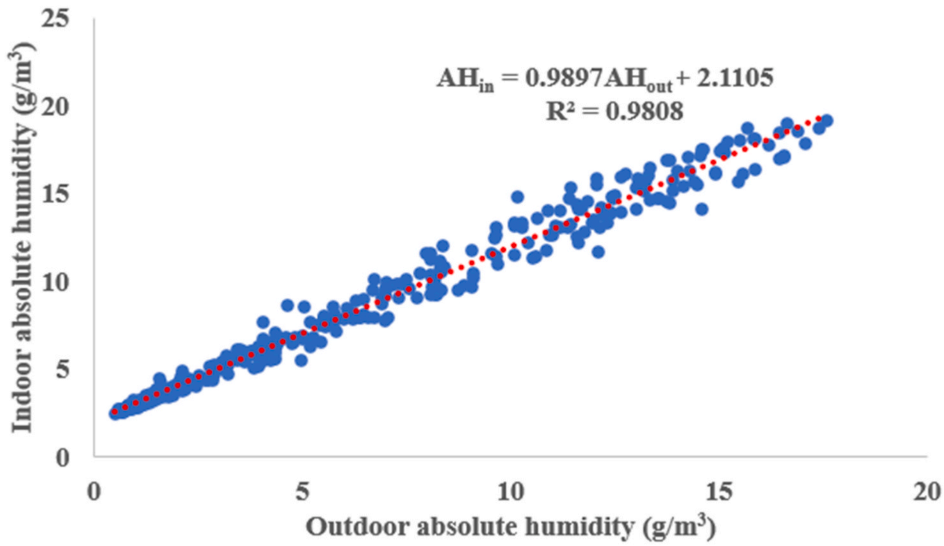


**Fig. 6.** Base Model 1 (daily average values were used, $R^2$ = coefficient of determination).

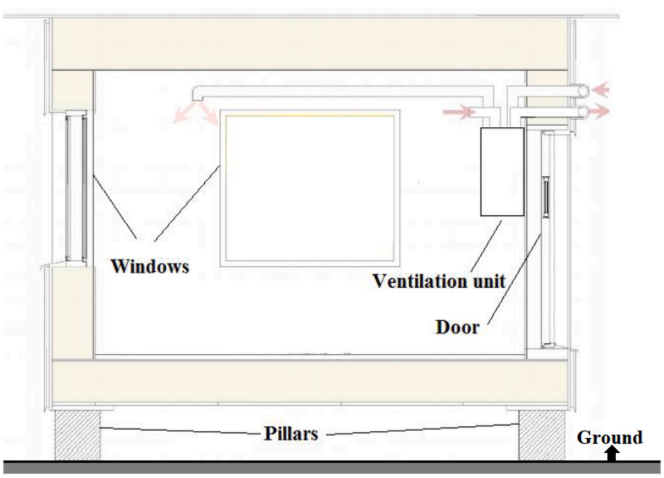


**Fig. 7.** Cross section of test house.

**Table 3**
Two case studies for test house.

| Case | Period | Ventilation setting | Measurement |
|---|---|---|---|
| Case 4 | Mar. 30, 2016–Apr. 2, 2016 | 17.99 $m^3/h$ | indoor temperature and RH |
| Case 5 | Apr. 4, 2016–Apr. 9, 2016 | 37.82 $m^3/h$ | indoor temperature and RH |

where $\hat{y}(k)$ is the simulated output, $y(k)$ is the measured output, and $\overline{y}(k)$ is the mean value of the measured output.

## 4. Results and discussion

### *4.1. Cases of increasing ventilation rate (Cases 1 and 5) and decreasing ventilation rate (Case 4)*

Fig. 8 shows a comparison between the data generated by TRNSYS and that estimated using Base Model 1 and Eq. (6) in Case 1. Figs. 9 and 10 show the comparisons of measurements and that estimated using

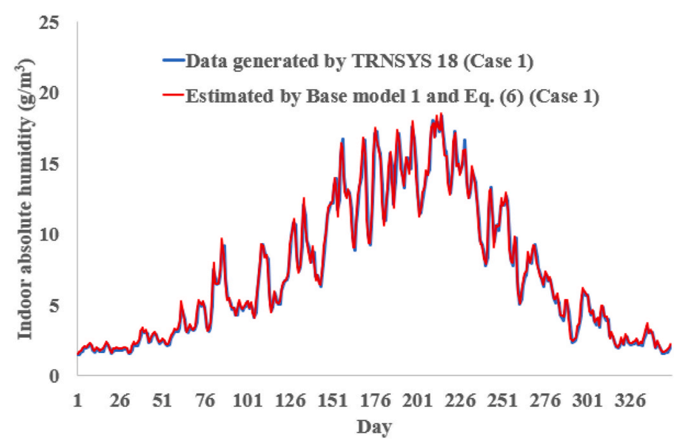


**Fig. 8.** Comparison between indoor AH data produced by TRNSYS (Case 1) and that estimated by Base Model 1 and Eq. (6). Base Model 1: $AH_{in} = 0.9897AH_{out} + 2.1105$, built from Reference case.

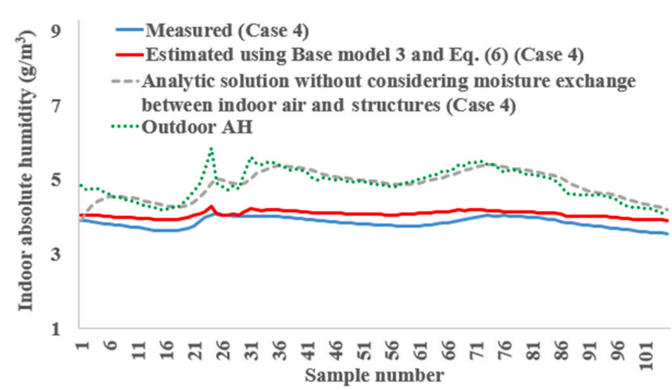


**Fig. 9.** Comparison of measurements and that estimated using Base Model 3 and Eq. (6) and the analytic solution without considering the moisture exchange between indoor air and structures for Case 4. Base Model 3: $AH_{in} = 0.349AH_{out}+2.5167$, built from Case 5.

Base Models 3 and 4 and Eq. (6) and the analytic solutions for Cases 4 and 5. Tables 4–6 display their performance.

Figs. 8–10 and Tables 4–6 show the ability of the NHMAHLR method

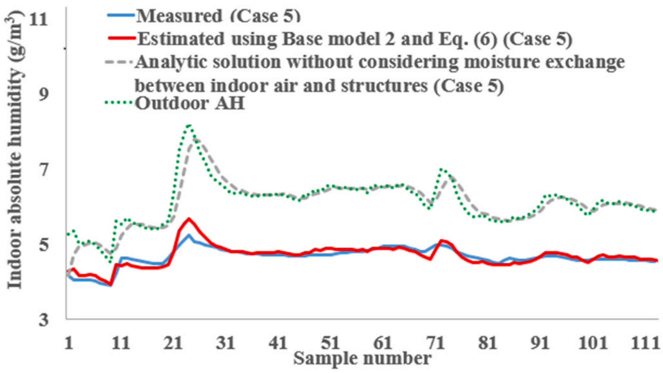


**Fig. 10.** Comparison of measurements and that estimated using Base Model 2 and Eq. (6) and the analytic solution without considering the moisture exchange between indoor air and structures for Case 5. Base Model 2: $AH_{in}$ = 0.2968$AH_{out}$+2.3994, built from Case 4.

**Table 4**
Performance of Case 1 (ventilation rate increased from 25.92 $m^3$/h to 2 × 25.92 $m^3$/h).

| | Case 1 |
|---|---|
| RMSE | 0.4 |
| MAPE (%) | 4.72 |
| $R^2$ | 0.99 |

**Table 5**
Performance of Case 4 (ventilation rate decreased from 37.82 $m^3$/h to 17.99 $m^3$/h).

| | Case 4 |
|---|---|
| RMSE | 0.24 (NHMAHLR)<br>1.11 (Analytic solution) |
| MAPE (%) | 5.94 (NHMAHLR)<br>26.27 (Analytic solution) |
| $R^2$ | 0.73 (NHMAHLR)<br>0.6 (Analytic solution) |

**Table 6**
Performance of Case 5 (ventilation rate increased from 17.99 $m^3$/h to 37.82 $m^3$/h).

| | Case 5 |
|---|---|
| RMSE | 0.13 (NHMAHLR)<br>1.5 (Analytic solution) |
| MAPE (%) | 2.14 (NHMAHLR)<br>30.63 (Analytic solution) |
| $R^2$ | 0.8 (NHMAHLR)<br>0.79 (Analytic solution) |

to simulate indoor AH with increased/decreased ventilation rates (Scenario 2) for both simulated (Case 1) and measured data (Cases 4 and 5). The results of the NHMAHLR method were very satisfactory, particularly for Cases 4 and 5 where it was superior to the analytical solutions.

As can be seen in Eq. (2), the terms $aAH_{out}$ and $b$ have physical meanings: $aAH_{out}$ indicates the contribution of outdoor air to the indoor AH, and $b$ implies the contribution of indoor moisture sources and sinks (e.g., occupancy, building structures, and furnishings) to the indoor AH. The moisture exchange between indoor air and structures/furnishings (inclusion of moisture storage and release), abbreviated as MEBTIAS in this section for simplicity, is included in $b$. Although the MEBTIAS cannot be explicitly calculated, it can be observed for an empty space; e.g., in Fig. 10, the gap between the indoor AH predicted by the NHMAHLR method (in red color) and indoor AH simulated by the analytic solution (grey color, MEBTIAS is ignored) can be clearly seen. The MEBTIAS is very difficult to accurately model because of the many factors involved in this process. Ignoring MEBTIAS can lead to significant errors as shown in Figs. 9 and 10. Even though Eq. (6) is derived from a regression model, it still describes how outdoor air, internal moisture load (or MEBTIAS), and ventilation impact indoor AH. For instance, if a space is empty, Eq. (6) implies that increasing the ventilation rate (i.e., $u$) increases the impact of outdoor air on the indoor AH (i.e., the value of the first term on the right-hand side of Eq. (6) increases), but it also reduces the influence of the MEBTIAS (i.e., the absolute value of the last term on the right-hand side decreases). A similar conclusion has been reported in many studies [37]. Therefore, the NHMAHLR method considers the MEBTIAS and the impact of the ventilation rate on the MEBTIAS, which improves the accuracy as shown in Figs. 9 and 10 and Tables 5 and 6. In Cases 4 and 5, the largest MAPE was 10.15% for the NHMAHLR method and 54% for the analytical solutions.

A higher MCR is normally set for a furnished place; for example, the MCR was set to 10 in the case study. Because furnishings absorb moisture, indoor AH often has a relatively slow response to changes in outdoor AH in a furnished space. The NHMAHLR method is a regression model; that is, a given outdoor AH value gives the possible trend and average value of indoor AH of measurements. As a result, the NHMAHLR method overestimated the indoor AH for an outdoor AH that experienced a large sharp change in Case 1. For example, the largest MAPE was 14.84% for Case 1; when the MCR changed from 10 to 5, the largest MAPE value decreased to 8.37%. The annual weather data in the case study came from the TRNSYS weather database, indicating that each month's weather data were actually from a different year. Therefore, a sudden and large change in outdoor AH often occurred when switching from one month to the next, resulting in a large MAPE for the NHMAHLR method.

### *4.2. Case 2 (addition of moisture load to the space) and Case 3 (addition of moisture load to the space and increase in ventilation rate)*

Figs. 11 and 12 plot the comparisons between the data generated by TRNSYS and that estimated using Base Model 1 and Eqs. (5) and (8) for

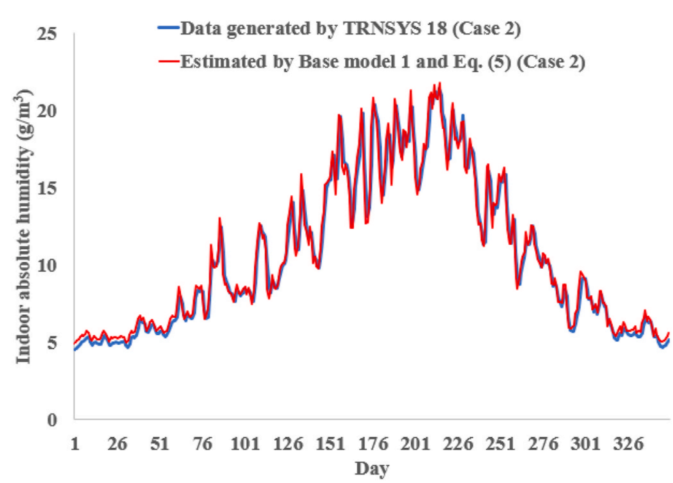


**Fig. 11.** Comparison between indoor AH data produced by TRNSYS (Case 2) and that estimated by Base Model 1 and Eq. (5). Base Model 1: $AH_{in}$ = 0.9897$AH_{out}$+2.1105, created from Reference case.

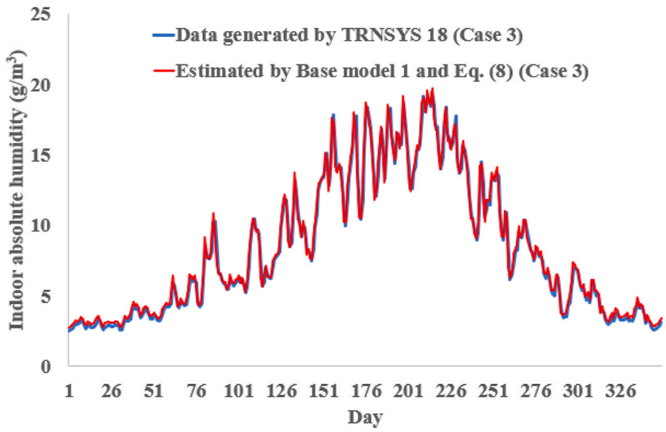


**Fig. 12.** Comparison between indoor AH data produced by TRNSYS (Case 3) and that estimated by Base Model 1 and Eq. (8). Base Model 1: $AH_{in}$ = 0.9897$AH_{out}$+2.1105, created from Reference case.

Cases 2 and 3, respectively, and Tables 7 and 8 display their respective performance.

By comparing Tables 4, 7 and 8, we can see that there is no significant difference between Cases 1–3 in terms of performance. They all matched the data produced by TRNSYS within ±10% for over 90% of the estimations and within ±15% for almost 100% of the estimations. The performance of the NHMAHLR method was also related to the choice of the MCR (see Section 4.1). The smaller the MCR, the smaller the NHMAHLR error.

The NHMAHLR method best fitted the field studies (or data analysis) for spaces that had mechanical ventilation systems and approximately constant daily average ventilation rates. In Finland, such spaces are common in both commercial and residential buildings. In some commercial buildings, the daily average ventilation rates on weekdays may differ from those on weekends. The NHMAHLR method is also very useful for experiments carried out in empty test houses such as that discussed in Section 3.2. The NHMAHLR method can simulate the indoor AH for occupied cases (see Eqs. (5) and (8) and Figs. 11 and 12) even though the experimental data were collected from an empty test house. This saves time and costs. However, if the daily ventilation rate varies significantly, it is better to use EXT_OUT_AH (see Chapter 2) instead of the outdoor AH to create a base model (Eq. (2)). For example, in an indoor swimming hall in Finland, outdoor air is used to remove excessive moisture from the pools. If the daily airflow rate ranges from 2.8 $m^3$/s to 3.75 $m^3$/s, we set 2.8 $m^3$/s as the reference ventilation rate. If the daily ventilation rate is 3.7 $m^3$/s, the daily outdoor AH is 3.9 g/$m^3$, and indoor AH is 11.4 g/$m^3$ for a day, the corresponding EXT_OUT_AH is computed using Eq. (7) as 1.49 g/$m^3$ (= (3.7/2.8) × 3.9 − (3.7/2.8–1) × 11.4). Using the computed EXT_OUT_AH and the measured indoor AH data, a base model can be easily established using tools such as Excel. Using EXT_OUT_AH to create a base model enhances the correlation between indoor and outdoor AH because fluctuations in daily ventilation rates are eliminated.

It is quite common for past measured outputs to be included as additional inputs to deal with the dynamic behavior of a system to improve accuracy. This strategy did not work in this study because we aimed to simulate indoor AH for unforeseen ventilation rates and internal moisture loads where the measurement of indoor AH was not available. Some illustrative examples of the novelty of the NHMAHLR method are described below.

**Table 7**
Performance of Case 2 (addition of 1.458 kg/day extra moisture load).

| Case 2 | |
|---|---|
| RMSE | 0.69 |
| MAPE (%) | 5.17 |
| $R^2$ | 0.98 |

**Table 8**
Performance of Case 3 (addition of 1.458 kg/day extra moisture load and increase in ventilation rate from 25.92 $m^3$/h to 2 × 25.92 $m^3$/h).

| Case 3 | |
|---|---|
| RMSE | 0.42 |
| MAPE (%) | 4.79 |
| $R^2$ | 0.99 |

First, the NHMAHLR method presents a new analytical modeling approach in comparison with the existing methods in literature [10–14,16,20–26,28–36,42–45]. The method starts with an SLR model that describes a linear relationship between the indoor and outdoor AH by assuming a fixed ventilation rate and internal moisture load for the measurement period. In order to use the SLR model for the cases of varying ventilation rate and internal moisture load, we adopted a fictitious outdoor AH (EXT_OUT_AH, extended outdoor AH, Fig. 1) and analytical modeling to account for changes in the ventilation rate and internal moisture load by assuming that the resultant changes in indoor AH are due to changes in outdoor AH (rather than changes in the ventilation rate and internal moisture load). This way, the linear relationship (the SLR model) always holds correctly or accurately. The introduction of EXT_OUT_AH ensures that, with the measurements of indoor and outdoor humidity only, the complex relationship of outdoor humidity, ventilation rate, and internal moisture load and their impact on indoor humidity can be accurately evaluated. This presents a unique feature in advancing literature studies of indoor humidity modeling.

Second, this unique feature greatly simplifies state-of-the-art field studies by ensuring that a varying outdoor humidity field test is sufficient to derive field tests for varying ventilation rates and internal moisture loads. In practice, it is difficult, or even impossible, to conduct different levels of ventilation measurements for a CAV system, as commonly used in Finland. In a separate field measurement, for example, for outdoor humidity, indoor humidity, and air change rate measured during winter using the passive tracer gas–air infiltration technique, a large number of measurements (101 family houses) were performed to investigate the IAQ conditions in Finland [32]. In a cold climate, indoor RH is of great concern in winter because it can drop to unacceptably low levels. The validation and simulation results of this study clearly show that the NHMAHLR method could be easily used to provide predictive scenarios of different air change rates for the 101 houses using only measured indoor and outdoor humidity (in the heating season, indoor temperature can be assumed to be constant regardless of the air change rate). Therefore, both the time and number of field measurements would be considerably reduced. As temperature and humidity sensors are commonly used in buildings, the NHMAHLR method can replace field measurements with good accuracy.

From a modeling and simulation point of view, constructing and running an SLR model of the NHMAHLR method takes only a few minutes. Considerable effort may be needed in constructing physics-based models for a single house as reported in [10–14,16,23,24,26]. Data-based models such as the existing artificial neural networks and multiple regression models [42–45] overly rely on the quality of measurements owing to their black-box modeling structures. They face challenges in collecting sufficient data to describe the influence of ventilation rate and internal moisture load on indoor humidity, selecting proper inputs, and solving overfitting issues. The NHMAHLR method resolves these challenges. For example, without any prior knowledge of the ventilation rate and internal moisture load for a measurement period, the NHMAHLR method evaluates the impact of ventilation rate on indoor humidity using a multiplier on the ventilation rate (see Eq.

(6)). To the best of our knowledge, no study in the literature has reported a method that matches the efficiency and effectiveness of the NHMAHLR method.

## 5. Conclusions and future work

A novel methodology, the NHMAHLR method, was developed using a hybrid model (Eq. (8)) to estimate the indoor AH based on the outdoor AH, ventilation rate, and internal moisture load. This study provides the following three original contributions.

- The recognition of a new concept: all internal moisture gains/losses can be assumed to be outdoor sources introduced into a space through a fixed ventilation rate.
- A new type of outdoor AH, EXT_OUT_AH, was developed to implement this new concept. EXT_OUT_AH includes outdoor AH and all extra moisture owing to changes in the reference ventilation rate and/or reference internal moisture load. The use of EXT_OUT_AH instead of outdoor AH introduces the ventilation rate and internal moisture load as two implicit inputs. Most importantly, the concept of EXT_OUT_AH is physically correct because outdoor humidity and internal moisture load have the same effect on indoor humidity in a mechanically ventilated space. This is the value of the NHMAHLR method.
- A hybrid modeling approach was proposed to utilize only the measured indoor and outdoor humidity to solve a multi-input nonlinear problem, a concept rarely mentioned in the literature of indoor humidity modeling.

The NHMAHLR method was validated by comparing its predictions with those of the data generated by commercial TRNSYS software and two experiments for various ventilation rates and internal moisture loads (five cases in total). The results discussed in Chapter 4 were promising, and the following conclusions were obtained.

- The new analytical modeling approach enables the utilization of a single-input linear regression model to accurately assess the indoor humidity based on multiple factors. This finding is important because it can significantly simplify multi-input nonlinear modeling processes.
- Using a smaller time step (hourly for Cases 4 and 5) still achieves acceptable accuracy despite the static feature of SLR models. However, further investigations are required.
- The impact of ventilation rate on the moisture exchange between indoor air and structures is considered in the NHMAHLR method. Ignoring these factors can result in significant errors.
- The NHMAHLR method creates SLR models comparable to physics-based models. However, it is considerably simpler and faster than most existing physics-based models and can be easily used to model the indoor humidity of dozens of different buildings. This advantage makes the NHMAHLR method attractive for field studies and big data applications.
- The experimental costs can be dramatically reduced using the NHMAHLR method. Using a single solo experiment, the indoor humidity scenarios of experiments under different ventilation rates and/or internal moisture loads can be accurately predicted.

The limitation of the NHMAHLR method is that it relies heavily on the base models. Measurement errors, climate conditions, and experimental conditions all affect the performance of the NHMAHLR method. Improving the performance of the base models should be a top priority for future work. One solution is to use EXT_OUT_AH (see Section 4.2) instead of the outdoor AH to build the base models. The internal moisture loads of the experimental spaces should also be included in the EXT_OUT_AH. However, it is challenging to accurately estimate internal moisture loads for spaces because of the involvement of the moisture exchange between indoor air and structures. Glass and TenWolde [46] discussed several existing approaches for estimating internal moisture loads; however, these approaches require further verification to correctly calculate EXT_OUT_AH for occupied periods.

## CRediT authorship contribution statement

**Tao Lu:** Conceptualization, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Xiaoshu Lü:** Writing – original draft, Writing – review & editing, Supervision, Resources. **Heidi Salonen:** Writing – review & editing. **Qunli Zhang:** Writing – review & editing.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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