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Comparative study of Hot Box Test Method using laboratory evaluation of thermal properties of a given building envelope system type

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ABSTRACT

This research mainly focuses on the experimental setup of the Hot Box Test Method and comparison of different models for measurement of thermal properties of building envelope systems. Hot Box Test Method has long been used to determine the thermal properties of building envelope systems, however, the steady-state assumption for calculation is not always desired, especially when the environmental conditions cannot be controlled. To utilize models considering the dynamic behavior of buildings for in-situ measurement, it is desired to first validate such models and compare the performances with hot box test. Therefore, the performances of several dynamic models, including Anderlind's Regression Model and R-C Network Model, have been studied. Hot box tests were performed in the Building Enclosure Testing Laboratory (BETL) at Penn State University and the results show the 3R2C model turns out to be the most accurate one among the dynamic models explored in this study. With a temperature difference larger than 20 °C, all dynamic models are validated with a percentage difference lower than 7% compared with the steady-state analysis, giving us alternatives for R-value measurement when in-situ measurement condition are applied.

1. Introduction

The thermal properties of building envelope (BE) systems can significantly influence the overall energy performance of buildings, and thus accurate determination of such properties is needed. Hot Box Test Method has been used as a reliable method for measurement of thermal properties of building materials and envelope assemblies in the U.S. for decades, starting with Mumaw [1]. ASTM C1363 standard provides guidelines for the use of hot box test in the U.S. [16]. This paper starts by discussing a review of the Hot Box Test Method, and then focuses on the experimental setup in the Building Enclosure Testing Laboratory (BETL) at Penn State University, as well as the validation of several data analysis models considering both the steady-state and dynamic behavior of the specimen. The specimen that is described in detail in Section 3.2 is an opaque wall panel with nine different segments with dimensions of the center concrete masonry unit segment, which is the subject of measurement in this study, being 110 cm long * 70.1 cm high and with 38.1 mm thick fiberglass insulation and 9.5 mm thick paging.

2. Literature review

2.1. Hot Box Test Method

Based on Hot Box Test Method, a specimen is located between two chambers: the metering chamber and the climatic chamber. The metering chamber is used to simulate the interior environment (hot side), while the climatic chamber is used to simulate the exterior environment (cold side). Heating and cooling systems are used in the metering chamber and climate chamber, respectively, to create the temperature difference. The thermal resistance of the panel can then be evaluated by using the measured heat flow from the metering chamber side to the climate chamber side passing through the specimen, and the measured temperature difference between the hot and cold sides. This test procedure requires defining areas of specimen where homogeneous thermal properties and steady-state heat transfer can be assumed [2]. As can be observed in Fig. 1, the heat flow directly passing through the specimen equals the heat input required to keep the metering chamber at constant temperature subtracts the heat loss through

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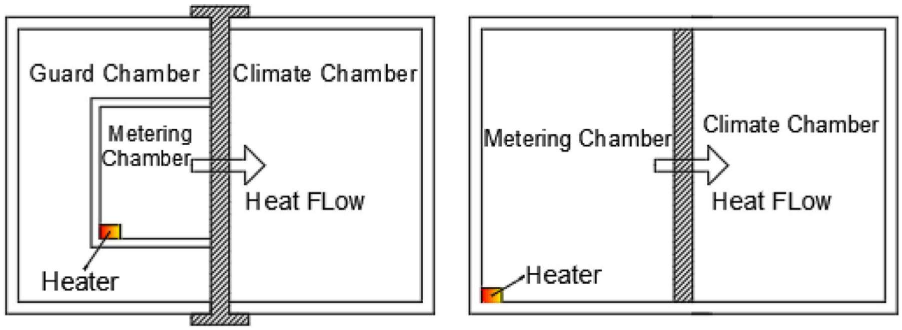

Fig. 1. Guarded hot box (Left) and Calibrated hot box (Right).

walls and surrounding panels. By maintaining the two chambers at constant temperatures, the steady-state condition can be reached.

There are two basic hot box setups: the "guarded hot box" that uses a metering chamber inside the "guard chamber", and the "calibrated hot box" that uses the surrounding environment as the "guard chamber". The guarded hot box is to keep the guard chamber and the metering chamber at the same temperature, thus the heat loss through metering box wall is not necessary to be determined [2]. The calibrated hot box, on the other hand, uses the outside environment as the "guard chamber", and by measuring the temperature difference between the surrounding environment outside of the chamber and the metering box, the heat loss through walls can be obtained. Both of these two setups need to have well-insulated interior. By making the assumption of steady-state condition, the 1-D heat transfer passing through the specimen can be expressed as:

$$q = \frac{1}{R_t}(T_{in} - T_{out}) \tag{1}$$

where R_t is the overall resistance of the wall specimen, including surface resistances R_{si} and R_{so}, T_{in} is the air temperature of hot (interior) chamber, and T_{out} the air temperature of cold (exterior) chamber. It should be noted that the specimen surface-to-surface resistance R_s can be expressed as:

$$q = \frac{1}{R_s}(T_{s,in} - T_{s,out}) \tag{2}$$

where $T_{s,\,in}$ is the interior surface temperature and $T_{s,\,out}$ is the exterior surface temperature. Generally, for engineering calculation of the overall R-value for building walls, it is appropriate to consider the total heat transferred from interior air to exterior air all by conduction, with two fictitious films considered at both sides of the wall to represent the effect of convection and radiation. The surface resistances for such air films (that is, the heat transfer coefficient between the specimen surface and the air) for both interior R_{si} and exterior R_{so} can be expressed as:

$$q = \frac{1}{R_{si}}(T_{in} - T_{s,in}) = \frac{1}{R_{so}}(T_{s,out} - T_{out}) \tag{3}$$

The parameters and variables used in above equations are defined as follows: $q=$ heat flux, $R_t=$ overall resistance, $R_s=$surface-surface resistance, $R_{si}=$interior heat transfer coefficient (film resistance), $R_{so}=$exterior heat transfer coefficient (film resistance), $T_{in}=$interior environmental temperature, $T_{out}=$exterior environmental temperature, $T_{s,\,in}=$interior surface temperature, $T_{s,\,out}=$exterior surface temperature.

It is clear that the equations above are based on steady-state assumption as the heat flux passing through each layer of the wall is assumed to be constant. The thermal resistance of the specimen R_s is the output of the hot box test and a very important coefficient for the commonly used building energy simulation tools such as BEopt, DesignBuilder, etc.

The Hot Box Test Method has been long used as a reliable tool for evaluation of thermal resistances of building elements. Some of the uses of the Hot Box Test Method by different authors are mentioned here to illustrate the broad applicability of the experimental approach. Burch et al. [3] studied a dynamic test method for determining transfer function coefficients for a wall specimen using a calibrated hot box. Fazio et al. [4] tested the hygrothermal performance of a large-scale envelope specimen by using Calibrated Hot Box Test Method. Fang [5] measured the U-factor for windows with a high-reflectivity venetian blind by using a two side-by-side hot box apparatus. Elmahdy et al. [6] studied the experimental procedure and uncertainty analysis of the Guarded Hot Box Test Method to determine the thermal transmission coefficient of skylights and sloped glazing. Wakili and Tanner [7] measured the U-factor of a dried wall made of perforated porous clay bricks by using a hot box test apparatus with a heat flow meter. Gao et al. [8] evaluated a reduced linear state model of hollow block walls and validated it by hot box test measurement. Wakili et al. [9] used a hot box test apparatus to measure the thermal transmittance of a balcony with integrated glass fiber reinforced polymer GFRP elements and compared the results with numerical analysis. Geoola et al. [10] tested the overall heat transfer coefficient for greenhouse cladding materials with and without thermal screens by using guarded hot box. Martin et al. [11] studied the effect of thermal bridge in walls though guarded hot box tests, which were designed and carried out both for steady-state to determine the R-value, and for dynamic state aimed at figuring out the amplitude and phase lag of internal heat flux. Kus et al. [12] tested a pumice aggregate concrete hollow block wall panel by means of Calibrated Hot Box Test Method. Kossecka and Kosny [13] discussed a simplified procedure for estimation of minimum time of a Hot Box Test for BE assemblies.

2.2. Dynamic calculation models

Even though it is appropriate to make steady-state assumption for Hot Box Test Method as we can maintain both the interior and exterior temperature at constant level in order to minimize the dynamic heat storage effect off the wall, it should be clear that an ideal steady-state condition is hard to be reached outside laboratory. Therefore, dynamic analysis is necessary for more accurate thermal property determination, especially when the exterior environmental condition keeps changing, as is the case for onsite measurement of the BE systems. Cesaratto and Carli [14] compared the results of using several methods for R-value calculation based on a number of in-situ tests and the corresponding influence on the net building energy demand. The results indicated that different methods lead to significant different results, up to 30% in the R-value. This then resulted in the net energy demand to vary between 11%–14%.

Jiménez et al. [24] performed a study to evaluate different dynamic analysis approaches to estimate the building component U-factor. A simple wall was built with only three layers to minimize the calculation error from using tabulated resistance value, as with this simplicity the whole wall R-value will be very close to the summation of tabulated R-value for each layer. The authors explored different data processing approaches such as the Linear R-C model, Linear ARX Model and the Linear Continuous Time State-Space Model, and then they compared the resulting U-factors to the design U-factor calculated by tabulated values. The Linear R-C Model and Linear Continuous Time State-Space Model that the authors explored are based on the same lumped-capacity assumption, which divides a wall into several lumped thermal mass and thermal resistances. However, the ARX Model is data-driven, meaning that it is a regression method rather than being physically interpreted. It was found that for the Linear R-C Models analyzed, the model without solar radiation and with heat flux as the output seems to stand out. For the Linear ARX Method, models with multi-outputs all fit well with the expected values. As for the Linear Continuous Time State-Space Model, it showed very good performance. These models explored by Jiménez et al. [24] help better understanding of the complicated methods that can be used for in-situ measurement data analysis. Accordingly, in-situ measurement results need to be treated with caution, because to obtain reliable test data great care is needed for testing and interpretation.

An-Heleen and Staf [25] did a comprehensive comparison of characterization methods determining the thermal resistance of building components by using HAMFAM simulation tool to simulate the in-situ environment condition. They compared the standard methods as well as the R-C network method (the grey-box stochastic state space model). Grey-box models rely on the physical knowledge to define the model structure and use statistical techniques to estimate the unknown parameters [22]. It is reported in An-Heleen and Staf's study that the Average Method requires a period of more than 20 days to show convergent and reliable result. Other methods, such as Anderline's Regression Method, the Black-Box Method and the Grey-Box Method show solid convergence with much shorter test period. However, Grey-Box modeling enables the use of a set of validation tools that is not included in the other methods, thus reportedly being used more often. There is also indication that the variation of results becomes dramatically large in summer season for all methods, and that for the Average Method is hard to show convergence even after a relatively long test period.

Atsonios et al. [20] proposed a study focused on comparison of several calculation models for in-situ measurement of thermal properties for BE systems. The steady-state method, dynamic method (which is an analogy to the Anderlind's Multiple Regression Method) and two other Sum of Least Square Methods are studied based on measurements of three wall types. The authors concluded that the steady-state method should not be used when the temperature difference is too low, or their criteria should be stricter. Based on the analysis of variability, they also concluded that the dynamic models appear to be only affected by the direction of heat flow.

Fonti et al. [21] studied the behavior of low-order R-C Network Models using MATLAB greybox package, based on the measurement data from a smart building. First-order, second-order and third order of R-C Network Models were considered in the study, and by comparing the output parameters such as the level of fit and final prediction errors, the authors concluded that the second-order R-C Network Models actually showed the best performance.

The dynamic models discussed above have been shown by different researchers to be feasible for thermal property measurement of BE systems, giving close results compared with the reference R-value (tabulated). However, the accuracy of such models still needs to be further validated and comparison of such models with a traditional hot box test and steady-state analysis is desirable, as the "reference R-value" is generally unknown for in-situ measurement of BE systems. The study reported here explored the Anderlind's Multiple Regression Model and the R-C Network Model, and compared their variance of results with the steady-state model. The detailed methodology is demonstrated in Section 4.

3. Experimental setup

This section introduces the test facilities in Building Enclosure Testing Laboratory (BETL) at Penn State University, including the metering chamber, the climate chamber, heating/cooling systems, and data acquisition systems used for sensor control as well as the tested wall construction. The chambers in BETL are controlled by Labview, where researchers can input the set points for temperatures and relative humidity levels to activate the corresponding systems. There are also air blowers and lighting facilities provided in BETL for such types of tests.

3.1. BETL hot box chamber

The chamber housed in the BETL facility provides approximately 9.3 m^2 (100 ft^2) of a controlled environment for testing various wall systems. The wall system is mounted in the middle of the chambers, separating it into two distinct chambers to simulate both the room and environment conditions. A resistance heater mounted on the ground is installed in the interior (metering) chamber and is able to heat up the room temperature up to 30 °C (86 °F). An air conditioner is used when the metering chamber needs cooling. The cooling system in the exterior (climate) chamber consists of two independent refrigeration systems, one is a medium temperature cooler system and the other is a low-temperature freezer system. An overview of the BETL hot box facility is shown in Fig. 2.

3.2. Specimen construction

The study presented in this paper makes use of an existing wall specimen located between the metering and climate chambers in BETL. The specimen was constructed by Repka and Kasal [15] and Wolfgang (B. M. Wolfgang, Hygro-thermal performance of imperfectly protected below-grade walls with interior insulation, Master's thesis, 2010) for the moisture behavior of below-grade walls and then used for this study as the test panel for the proposed hot box test. The wall was designed and constructed with nine different segments, which allowed simultaneous study of nine different wall systems. The frame was insulated by 5 cm XPS to ensure the 1-D heat transfer condition. Due to the amount of heat flux sensors available, all the measurements for this study are performed with respect to the center panel. The tested panel configuration has dimensions of 110 cm * 70.1 cm and consists of a 38.1 mm thick semi-rigid fiberglass with specified conductivity of 0.0338 W/mK, 192.5 mm thick concrete masonry unit (CMU) and 9.5 mm thick parging (stucco). The design R-value of the tested specimen is 1.528 (m^2K)/W.

The exterior (climate) chamber and interior (metering) chamber views of the wall are shown in Fig. 3(a).

The heating and cooling process is controlled by Labview program, and the thermistors and heat flux sensors are mounted on the surface of the tested specimen. An example of the sensors is shown in Fig. 3(b). The heat flux sensor is mounted on the hot side (metering chamber) of specimen.

(a) Overview (b) Cooling (left) and Heating (right) System (c) Air conditioner

Fig. 2. BETL hot box chamber.

(a) Climate Chamber and Metering Chamber View of the Specimen (b) Sensor Instrument

Fig. 3. Specimen and sensor instrument.

3.3. Data acquisition system (DAQ)

For the tests carried out and discussed here, Fenwall 192–103LEW-A01 thermistor was used to measure the surface temperature and Vaisala HMW40Y RH & Temperature transmitter to measure the environment temperature. For heat flux measurement, HFP01 HukseFlux heat flux sensor was used. The temperature sensor (192–103LEW-A01) has an accuracy of ± 0.1 °C and the heat flux sensor has an accuracy of ± 5% on walls. To measure the sensor reading as well as to control the heating/cooling system, Labview was used with NI Fieldpoint system, which is an integrated modular system to communicate between sensors and the computer. The ADC (Analog-Digital Converter) is FP AI-110 with 16-bits resolution.

3.4. Example of temperature and heat flux measurement

Four hot box tests (1)–(4) were performed for the same panel in BETL under the following four temperature set point gradients, respectively: 10 °C, 20°C, 25°C and 40 °C.

To show an example of the measured temperature and heat flux profile, data obtained from Test 2, with a set point difference of 20 °C is used and plotted in Fig. 4. Results of other test groups are summarized in tabular forms in Section 5.2. It can be observed that after 15 h, the metering chamber and climate chamber have reached quasi-steady state condition, meaning that the temperatures will not show further tendency of increase or decrease, but just oscillating around the mean set point temperature. The oscillation of the temperature is due to the working mechanism of the heater and the cooler; for example, when the temperature sensor detects the room temperature has reached the set point, the heater then stops heating, and after a short period of time, if the sensor detects the room temperature has dropped to below the set point, the heater is then re-activated to heat up the metering chamber to the set point. This explains the reason why the temperatures in both metering and climate chambers show oscillation around the set point. Fig. 4(b) also shows that the measurement of heat flux is relatively sensitive, because the heat flux sensor's output signal is in the level of microvolts, thus making it difficult to measure the heat flux at a constant level due to the temperature oscillation in metering and climate chambers. This is also part of the reasons why for in-situ measurement, when the environmental conditions keep changing, more advanced dynamic models are preferred over steady-state analysis.

4. Methodology

This section briefly illustrates the dynamic models that were explored aside from the steady-state method. To consider the dynamic behavior of the building walls, especially for the onsite environmental conditions with changing temperature, several dynamic methods have been developed: the Anderlind's Multiple Regression Model and R-C Network Models.

4.1. Anderlind's Multiple Regression Model

This model was developed by Anderlind [17] for determination of thermal resistance of a wall by considering the dynamic behavior of the wall through multiple regression. The heat flux passing through a wall is considered in three separate parts: the first part is a steady-state thermal behavior of the wall for which the R-value is being sought, which is primarily due to the steady-state conduction heat flow through the wall. The second and third parts reflect the dynamic response of the heat flux due to the temperature changes of indoor and outdoor surfaces.

$$q_i = \frac{1}{R}\left(T_{i,surf,\,int} - T_{i,surf,ext}\right) + \sum_{l=1}^{p} A_l\left(T_{i-p+l,\,surf,\,int} - T_{i-p+l-1,\,surf,\,int}\right) + \sum_{l=1}^{p} B_l\left(T_{i-p+l,\,surf,\,ext} - T_{i-p+l-1,\,surf,\,ext}\right) \tag{4}$$

At the ith measurement, q_i is the heat flux at that moment, $T_{surf,\,int}$ is the interior surface temperature, $T_{surf,ext}$ is the exterior

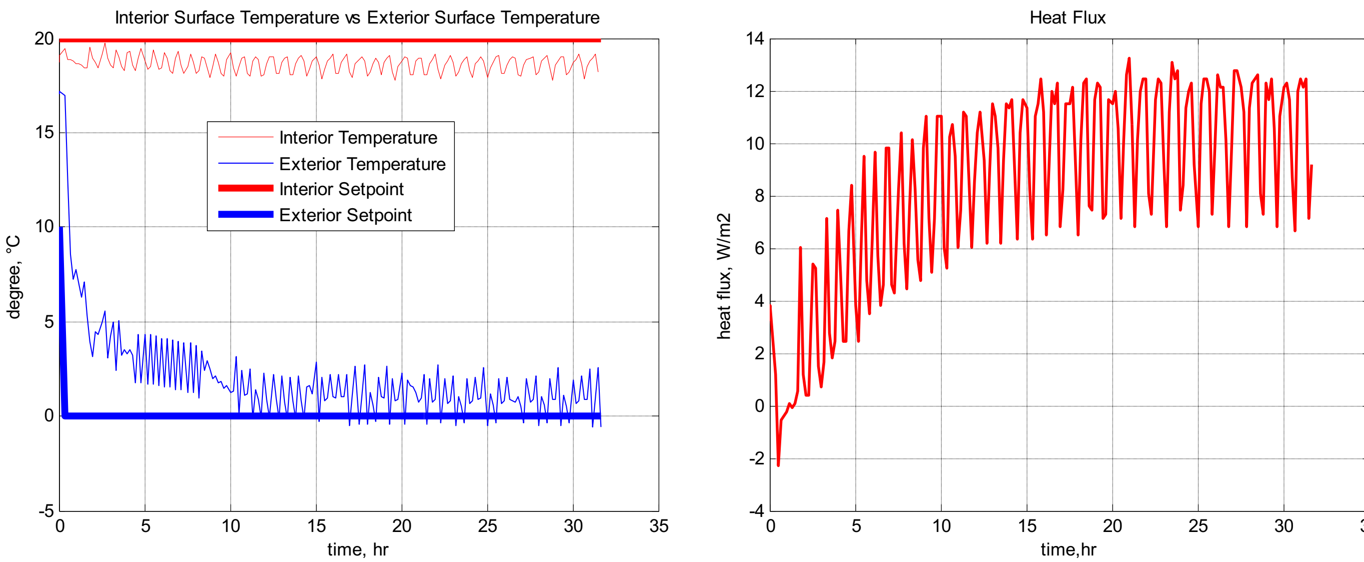

Fig. 4. Test 2 results. (a) Temperature measurement (left). (b) Heat flux measurement (right).

surface temperature, and p is the number of historical data points that one wants to use.

In Eq. (4), the first term just considers the temperature difference between the interior and exterior surfaces at the ith measurement. The second term is to consider the effect of previous interior surface temperature change on the current heat flux, while the third term is to consider the effect of the previous exterior surface temperature change on the current heat flux. R, A's and B's are multiple regression coefficients that we solve for, in which the R coefficient is the R-value and A's and B's are regression coefficients. It should be mentioned that in this model, the user decides the number of historical data to be used for regression. For example, if $p = 20$, then 20 historical points will be used, and it means for any ith measurement, the previous 20 measurement data will be considered to have an effect on the ith measured heat flux. Different choices of p will influence the regression results. For example, if we decide to use 20 historical points to consider the effect of temperature changes, then for each A's and B's we will have 20 coefficients. This model can be a powerful tool for in-situ measurement data processing. However, it should be noted that this model considers the dynamic behavior not based on the transient heat transfer principles, but as a means to evaluate the “goodness of fit” of the data, as also can be observed from Eq. (4) that there is no heat capacity terms included. This model was applied by using MATLAB regression tool, which can also evaluate how well the regression parameter fits the data.

To show a practical example of this method, as it is more straightforward compared with the R-C Network Model, consider a case where five historical points ($p = 5$) are used for both the exterior and interior temperature changes. Thus, the heat flux measured at the sixth time step can be expressed as Eq. (5).

$$\begin{aligned} q_6 = {} & \frac{1}{R}\left(T_{6.surf,\,int} - T_{6,surf,ext}\right) \\ & + \left\{A_1\left(T_{2,\,surf,\,int} - T_{1,\,surf,\,int}\right)\right. \\ & \left. + A_2\left(T_{3,\,surf,\,int} - T_{2,\,surf,\,int}\right) \ldots + A_5\left(T_{6,\,surf,\,int} - T_{5,\,surf,\,int}\right)\right\} \\ & + \left\{B_1\left(T_{2,\,surf,\,ext} - T_{1,\,surf,\,ext}\right) + B_2\left(T_{3,\,surf,\,ext} - T_{2,\,surf,\,ext}\right)\right. \\ & \left. \ldots + B_5\left(T_{6,\,surf,\,ext} - T_{5,\,surf,\,ext}\right)\right\} \end{aligned} \tag{5}$$

Such expression can be written for heat flux measured at each time step with the same coefficients to be determined, that is, R,

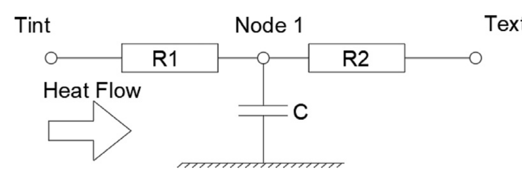

Fig. 5. 2R1C model.

A_1, …,A_5, B_1,…,B_5. These coefficients can then be regressed with the experimental data and R is the thermal resistance to be sought.

4.2. R-C Network Model

The R-C Network Model is an analogy to the electric circuit, regarding the heat flux passing through the wall as the current. This concept has been explored by researchers such as An-Heleen and Staf [25] and Jiménez et al. [18] to test its feasibility for the data analysis of in-situ measurement for BE systems. The model uses a lumped capacitance assumption and considers that the total thermal resistance of a wall can be modeled as several resistances in series, *R1, R2*, etc., while the thermal mass of the wall can be modeled as several heat capacitances, *C1, C2*, etc. Each node is assumed to be lumped with only one capacitance. The heat flux passing through each resistance, and at each node some of the heat will be stored into it while the remaining will keep moving on. This model can be implemented with different arrangements or orders such as 2R1C (two resistances, one capacitances), 3R2C (three resistances, two capacitances), etc. However, a higher order does not necessarily mean better accuracy. A simple 2R1C case is illustrated in Fig. 5, with T_{int} the interior temperature and T_{ext} the exterior temperature.

The energy balance at node 1 is given by Eq. (6), with T_1^j the temperature at node 1 for the jth time step.

$$C\frac{dT_1^j}{dt} = \frac{\left(T_{int}^j - T_1^j\right)}{R_1} - \frac{\left(T_1^j - T_{ext}^j\right)}{R_2} + ke(t) \tag{6}$$

The heat flux q inputted into R_1 at the jth time step is given by Eq. (7).

$$q^j = \frac{1}{R_1} * \left(T_{int}^j - T_1^j\right) + e(t) \tag{7}$$

Eq. (6) is the state-space equation for T_1; therefore with the measured experimental data, the unknowns R's and C's can be estimated by grey-box estimation. The last term in Eqs. (6) and (7) is the disturbance of the model, representing some arbitrary error such as measurement error, and k is the disturbance matrix defined in MATLAB grey-box model. The error term $e(t)$ is defined as a Gaussian white noise in this linear state-space model. If we have multiple nodes, the energy balance equation can be written for each node. For example, if we use 3R2C model, we will have 2 nodes, and for 4R3C model, we will have 3 nodes. If we have multiple nodes, for example, three nodes, then the state-space equations will be a set of ordinary differential equations for T_1, T_2 and T_3. The grey-box estimation can be performed for evaluating the coefficients $R_{1,}$ R_2 and C. To perform the grey-box estimation, it is necessary to choose some of the measured data as input, which are used to estimate the R and C values, and choose some of the measured data as output, which is used to compare how good the estimated parameters are and to minimize the error. For the study carried out and reported here, the interior surface temperature and exterior surface temperature are selected as the model inputs, and the measured heat flux as the output. Such choices are completely arbitrary. Two R-C models with different orders: 2R1C and 3R2C, were explored. MATLAB grey box package was used to numerically solve for this model. The MATLAB grey-box model tool provides estimation for the parameters together with some identification parameters such as FPE (final prediction error) to show the grey-box estimation accuracy.

For example, if 2R1C model is to be used, then there will be only one node located in the middle of the two resistances, and the governing equation will be the same as Eq. (6) and (7). The inputs used for the estimation of C, R_1 and R_2 are T_{int} and T_{ext} measured from the experiment, the error term $e(t)$ will be automatically generated by using MATLAB grey box estimation tool. Then the model will generate a set of estimated heat flux q values, that is, q^1, q^2,…,q^j, by applying Eq. (7), which can be compared with the real measured heat flux. The values of C, R_1 and R_2 that can minimize the difference between the estimated heat flux and the measured heat flux will be selected.

The fundamental difference between the Anderlind's Model and R-C Network Model is that R-C Networks Model is based on the physical energy balance differential equations, in which the value of thermal capacitance C can be considered in the model. But the Anderlind's Model considers the dynamic behavior of the wall as a linear relation of the previous temperature changes, which focus more on how well the parameters fit the test data instead of their physical interpretation.

The advantage of the R-C Network Model is that it is able to take the thermal capacity of the wall into consideration because it is based on the physical transient heat transfer principle, that is, the energy balance at each node. As we can calculate both the thermal resistance and capacitance of the wall, thus making it more convenient to consider the transient behavior for in-situ measurement. Also, we can obtain both the thermal resistance and capacitance of the measured wall by implementing such model, which makes the energy simulation for existing buildings become more accurate. It is worth noting that those internal "nodes" do not refer to any specific physical points inside the wall, neither those separate resistances refer to any specific layer's resistance; only the summation of these resistances has the physical meaning of the overall resistance of the wall.

5. Results and discussion

This section shows the detailed results obtained from using the steady-state and dynamic models as well as the interpretation and implication of the results. The goal of the tests reported here is to show a detailed experiment design and setup for the hot box test performed in BETL, the general outputs and measured quantities of a traditional hot box test as well as a brief comparative study about the performance of several dynamic models are discussed in Section 5.2. To better compare the performance of the models, four tests were performed with different temperature gradients, which cover a common range of temperature difference between interior and exterior up to 40 °C.

5.1. Example of R-C Network Model

While the Anderlind's Model is based on multiple linear regression, meaning that all the measured data are used as inputs to estimate the best-fitting parameters including the R-value, the R-C Network Model is a "prediction" model. It means that some measured quantities are used as the inputs to estimate the R-value and C-value, and such estimation will generate an output prediction that can be compared with the other measured quantities. The grey-box estimation tends to minimize the difference between the predicted values and the measured values. For example, for this study, the interior and exterior surface temperatures were used as the inputs of our R-C Network Model, and the measured heat flux was used as the output. Therefore, the model uses the interior and exterior surface temperatures to estimate the R values and C values, and any R values and C values that can lead to a prediction of heat flux whose difference with the measured heat flux is minimized is the most desirable estimation. The MATLAB grey-box tool is able to compare the predicted and the measured output. To show an example of this comparison, data obtained from Test 2 is used again and by performing a 2R1C model, we can get the comparison shown in Fig. 6. It can be observed that the estimated heat flux (shown in blue) and the measured heat flux (shown in grey) match relatively well. A detailed comparison of the R-values is given in Section 5.2 for all four tests. The 3R2C output for Test 2 is shown in Fig. 7.

5.2. Calculation of R-value

This section summarizes the results of R-value determination based on the four test sets with different models implemented. The four models are: the steady-state method, the Anderlind's Multiple Regression Method, 2R1C model and 3R2C model. For each test, these four models were used and thus four R-values were obtained. To evaluate the performance of each model, especially for those dynamic models, the steady-state R-value was selected as the baseline, and other three R-values were compared with respect to the steady-state one. As the steady-state R-value is calculated for each time step, the last 1/3 part of the calculated steady-state R-values (to minimize the error of the dynamic response of the specimen during the early stage of the test) were averaged to represent the mean value of steady-state R-value for each test. For example, for Test 2, the calculated steady-state R-value can be plotted as in Fig. 8. It can be observed that when the Test 2 started, since it did not reach steady state condition, the calculated steady-state R-value kept decreasing and after about 10 h, the steady-state R-value stopped decreasing and oscillated around a stable value. Thus, to minimize the error caused by the first few hours of Test 2, only the last third part of Fig. 8 were used to obtain the averaged steady-state R-value for Test 2. Unlike the steady-state model that generated a Fig., each dynamic model outputted a single R-value for Test 2 as shown in Table 1, thus no average is needed. The averaged steady-state R-value calculation is the same for other tests. It should be noted that for each test (Test 1, 2, 3 and 4), there is a respective steady-state R-value. Thus, these averaged steady-state R-values for each test should then be averaged again to get

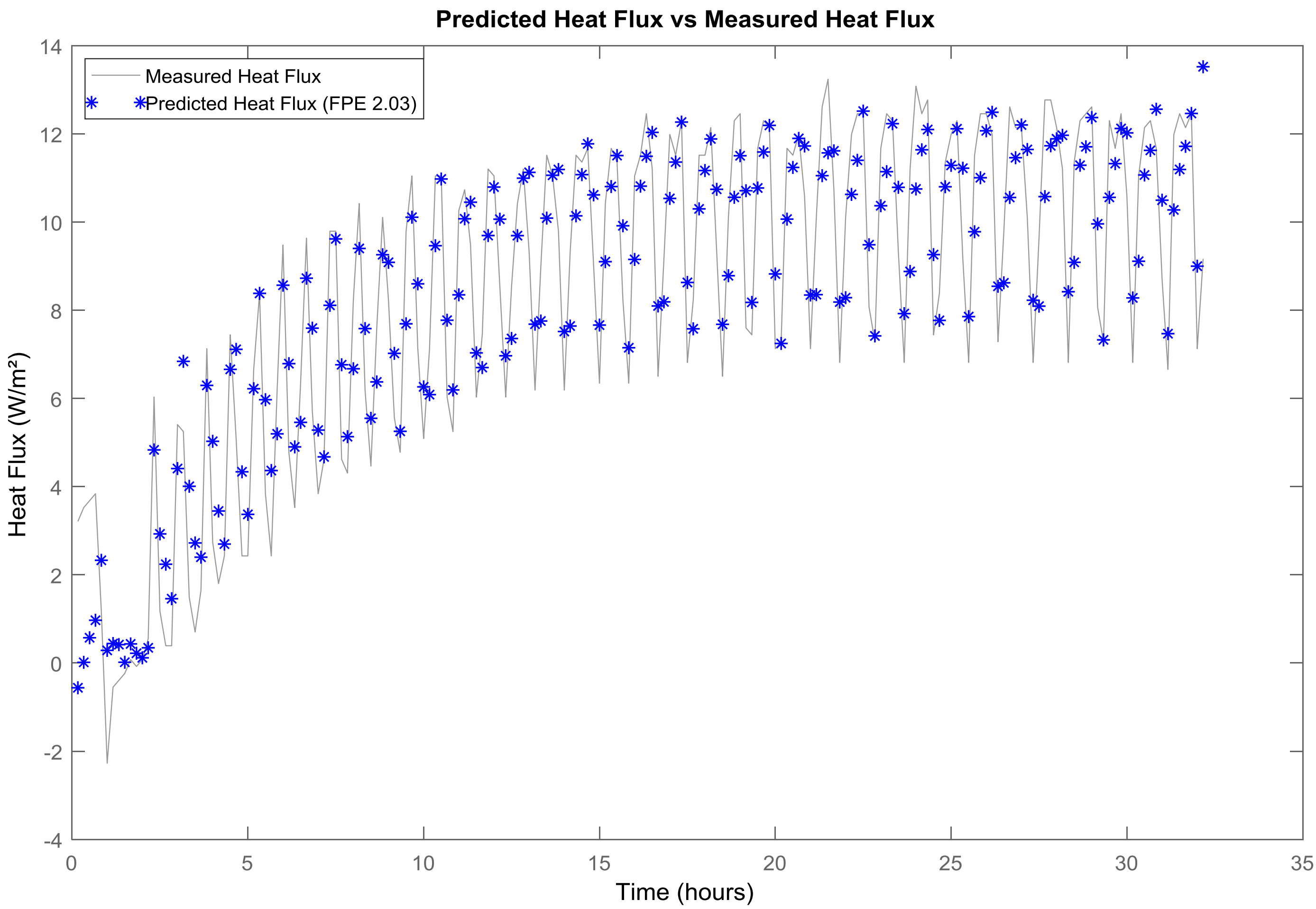

Fig. 6. 2R1C model results for test 2 (Heat flux sensor uncertainty: ± 5%).

Table 1
R-value comparison for each test (m^2K/W).

Test Number	Temperature difference	Steady-state model	Multiple regression	2R1C model	3R2C model
1	10	2.20	2.26	2.22	2.12
2	20	1.72	1.82	1.68	1.62
3	25	1.76	1.88	1.73	1.69
4	40	1.73	1.69	1.66	1.68
Column average (Exclude Test 1)		1.74	1.80	1.69	1.66

the overall averaged steady-state R-value to serve as the comparison baseline. This is due to the fact that the design R-value of the tested panel may not be accurate, thus an average R-value obtained from a single test is not enough.

It can also be observed from Table 1 that all the calculated R-values from measurements show a noticeable difference compared to the design R-value (1.528 m^2K/W), meaning that the design R-value does not reflect the real performance of BE systems. Therefore, for energy evaluation and simulation of the real performance of buildings, it is desired to obtain the R-values from experimental measurement.

Then as mentioned above, the averaged steady-state R-values of Tests 2, 3 and 4 (1.72, 1.76 and 1.73 m^2K/W) are summed and averaged to get an overall average steady-state R-value (1.74 m^2K/W), which serves as the baseline and is compared with R-values calculated from other dynamic models. It should be noted here that to calculate the overall averaged steady-state R-value (baseline) for the tested panel, the steady-state R-value from Test 1 (2.20 m^2K/W) was not used. The consideration here is that since the temperature difference of Test 1 is the smallest (10 °C), larger error may take place and thus it is desired to exclude this effect from the overall averaged steady-state R-value. The results are summarized in Table 1, Table 2 and Fig. 9. Table 1 contains the R-values calculated for each test with all types of models, and Table 2 shows the percentage difference of the R-value obtained from those three dynamic models compared with the overall average steady-state R-value. To show an example of the calculation of this percentage difference, consider the 2R1C model for Test 2. In Test 2 the 2R1C model gives an R-value of 1.68 m^2K/W, thus the percentage difference is (1.74–1.68)/1.74, which is 3.33% shown in Table 2. Fig. 9 shows the change of calculated R-value from all four models with respect to the temperature difference, and the design R-value is also shown in Fig. 9 as a reference.

The uncertainty estimation of the hot box measurement is based on ISO/IEC Guide (GUM) [23]. As also mentioned in Section 3.3, the uncertainty of temperature sensor is ± 1.0 °C and ± 5% for the heat flux sensor. Therefore, according to Sections 4–6 in ISO/IEC Guide (GUM) [23], the uncertainty of the measurement

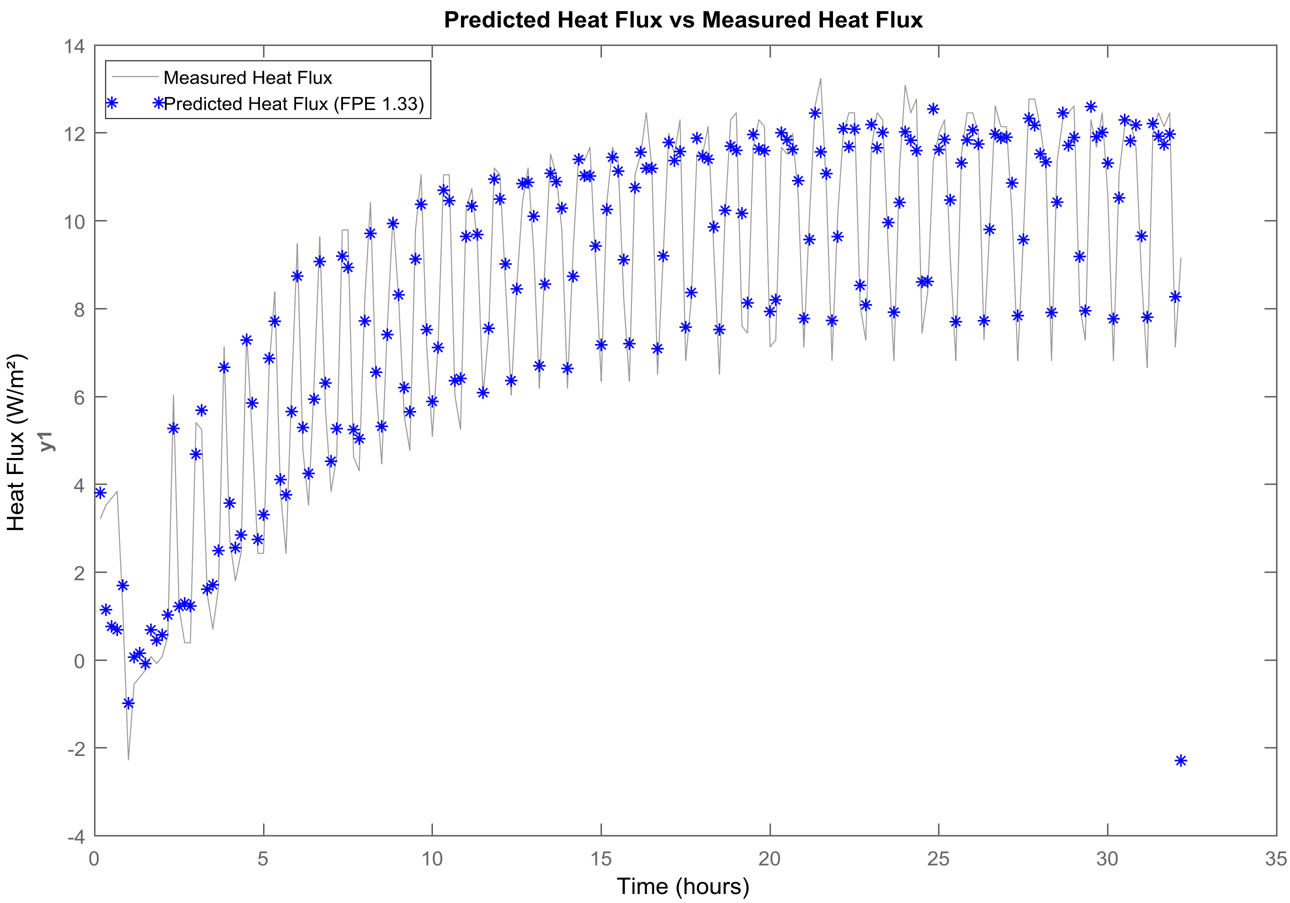

Fig. 7. 3R2C model results for test 2 (Heat flux sensor uncertainty: ± 5%).

Table 2
Percentage difference of dynamic models with the overall averaged steady-state R-value as the baseline.

Test Number	Temperature Difference	Steady-state Model (%)	Multiple Regression (%)	2R1C model (%)	3R2C model (%)
1	10	26.3	29.7	27.7	21.9
2	20	0.879	4.78	3.33	6.76
3	25	1.24	3.91	0.770	2.74
4	40	0.672	3.04	4.34	3.20
Column Average (Exclude Test 1)		0.930	3.91	2.81	4.23

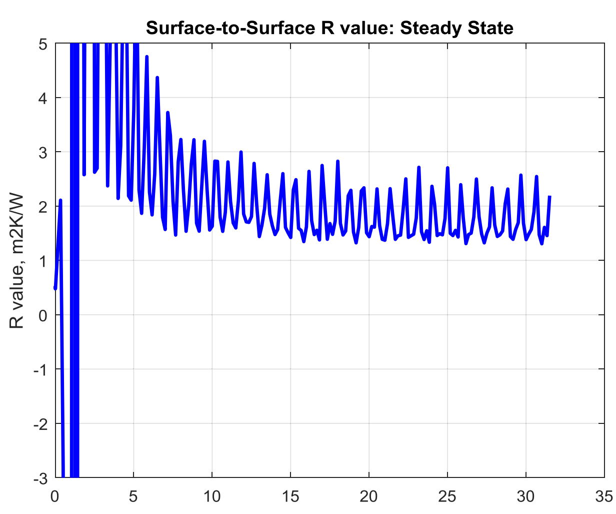

Fig. 8. Steady-state *R*-value of Test 2.

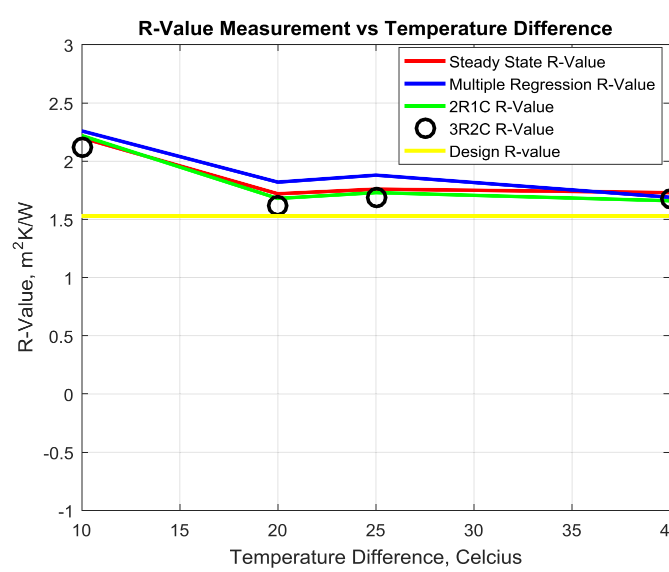

Fig. 9. *R*-value calculation vs temperature difference.

Table 3
Estimation of uncertainty.

Test number	Uncertainty
1	± 0.136(m^2K/W)
2	± 0.101 (m^2K/W)
3	± 0.103 (m^2K/W)
4	± 0.0993 (m^2K/W)

Table 4
Identification parametes of the dynamic models for Test 1.

	Anderlind's regression model	2R1C model	3R2C model
RMSE	0.376	0.253	0.214
FPE		0.0661	0.0485
Level of fit		66.8%	71.9%

Table 5
Identification parametes of the dynamic models for Test 2.

	Anderlind's regression model	2R1C model	3R2C model
RMSE	1.63	1.40	1.11
FPE		2.03	1.33
Level of fit		62.3%	70.0%

Table 6
Identification parametes of the dynamic models for Test 3.

	Anderlind's regression model	2R1C model	3R2C model
RMSE	1.53	1.36	0.516
FPE		1.91	0.284
Level of fit		69.6%	88.5%

Table 7
Identification parametes of the dynamic models for Test 4.

	Anderlind's regression model	2R1C model	3R2C model
RMSE	1.10	0.430	0.357
FPE		0.196	0.141
Level of fit		79.7%	83.1%

was calculated and summarized as in Table 3 with a coverage factor of 2.

It can be observed from Table 2 that the R-values obtained from those dynamic models are within an acceptable range (approximately within 7% when the temperature is above 20 °C) compared with the R-value obtained from steady-state model, which indicates that the outputs from the dynamic models can be validated by the traditional steady-state analysis in the hot box test with a controlled environment. Therefore, the dynamic models are suitable for measuring the thermal properties, and due to their capabilities of considering the dynamic behaviors of BE systems, the dynamic models become more applicable for in-situ measurement with uncontrolled environmental conditions compared to the steady-state analysis. It should be noted that because the comparison baseline is the averaged R-values of those steady-state R-values calculated from Tests 2, 3 and 4, the steady-state analysis shows smaller percentages in Table 2, which does not imply steady-state model is more accurate than the dynamic models.

To evaluate the accuracy of dynamic models, the identification parameters are presented for each test, as shown in Tables 4 to 7. The "root-mean-square-error" (RMSE) are used to evaluate all three dynamic models. As for the R-C Network models, two other identification parameters, "FPE" (final prediction error) and "level of fit", are used. The "FPE" parameter indicate the model accuracy, with the most accurate models having the smallest FPE. The "level of fit" indicates the goodness of fit. For the grey-box model, the identification parameters are outputted by *greyest* function in MATLAB. For Anderlind's Multiple Regression Model, the RMSE parameter is outputted by *regress* function.

By comparing the RMSE, FPE and level of fit of R-C Network Models in Tables 4 to 7, it can be observed that 3R2C model performs better than 2R1C model for all four tests. Since for each test, the RMSE and FPE of 3R2C model are lower than those of 2R1C model and the level of fit for 3R2C model is always higher than 2R1C model, it can be concluded that 3R2C model has a better accuracy than 2R1C model. This result is consistent with the results of the study by Fonti et al. [21]. Furthermore, by also considering the RMSE parameter of Anderlind's Multiple Regression Model, the 3R2C model shows the lowest RMSE among all three dynamic models. Therefore, it may also be concluded that 3R2C is the most suitable model among the three dynamic models explored in this study.

Fig. 9 shows a general trend of the change in R-value measurement with respect to the temperature difference. It can be observed that all models turn out to converge at the same point at a temperature difference of 40 °C, with the R-C Network Models showing a stable trend starting from the temperature difference of 20 °C. Compared with other models, the temperature difference turns out to have a larger influence on the Anderlind's Multiple Regression Model. It can also be shown in Fig. 9 that there is a noticeable difference between the design R-value and the measured R-values Therefore, to evaluate the real performance of BE systems, experimental measurement is desired.

6. Summary and conclusion

This paper presented a review of the determination of thermal properties for BE assemblies by using the Hot Box Test Method for increased accuracy. Factors that will influence the uncertainties include the accuracy level of sensors, the heating/cooling control systems, the level of temperature difference, the steady-state assumption as well as other environmental conditions. Such influencing factors will result in inaccuracy of the measured R-values and therefore the accuracy of building energy simulation. The most effective way to minimize the uncertainty caused by transient environmental conditions is to use some dynamic models to account for the dynamic behavior of the specimen. When in-situ measurement is needed to evaluate the thermal properties for existing buildings' envelope systems, by taking the transient effect into consideration, more advanced dynamic models are also preferred, and therefore the accuracy of such dynamic models should be estimated by the Hot Box Test Method under controlled test conditions.

The study reported consisted of performing a set of four hot box tests with different temperature gradients. An overview of the test chambers, data acquisition systems, heating/cooling systems and the construction of tested specimen was described after the literature review. The results of evaluating the following three dynamic models were explained: Anderlind's Multiple Regression Model, 2R1C Model and 3R2C Model. The measurement results showed that the measured R-values have noticeable difference compared with the design R-value; therefore for energy evaluation and simulation of buildings, experimental measurement is desired to obtain the real performance. By comparing the results of hot box steady-state analysis with the outputs of dynamic models, all the dynamic models show a relative small percentage difference and therefore are validated and appropriate for use in on-site measurement of existing buildings. Finally, by comparing the accuracies of the studied models, it was shown that the 3R2C model works best among the three dynamic models discussed in this study.

As summarized above, it can be concluded that the dynamic models explored in this study are effective tools to calculate the R-value of the wall specimen, especially when the steady-state assumption is disturbed by the environmental conditions. The Anderlind's Multiple Regression Method is the easiest dynamic method for practical use and is purely data-driven. However, when the calculation of thermal capacity is also desired, the R-C Network Models should be applied. Some other researchers, such as Cesaratto et al. [19], also studied the performance of the Steady-State method and the R-C Network Method and found that the R-C Network Method is more accurate especially under transient conditions. Therefore, the use of dynamic models seems to be more appropriate for the measurement of R-value, especially when the environmental condition is hard to maintain stable.

Declarations of interest

none

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