2018 Building Performance Analysis Conference and
SimBuild co-organized by ASHRAE and IBPSA-USA
Chicago, IL
September 26-28, 2018

MODEL-BASED ESTIMATION OF BUILDING INFILTRATION

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ABSTRACT

Building infiltration measurement is a challenge. To address current challenge, a scalable and low cost Building Infiltration Estimator with Ultrasonic Thermometry (BLAST) is proposed. The proposed method contains the physical measurements and a model-based estimation. This paper is focusing on the model-based estimation part, which uses an Extended Kalman filter (EKF) to inversely estimate the building infiltration using measurements of surface temperature and total heat flux, and a low-order state-space model. An EnergyPlus-based emulator is used to generate a virtual building and measurements to test the proposed estimation method. Nearly 80% estimated infiltration resistances are within the 20% error band compared to the calculated infiltration resistance from EnergyPlus. This preliminary study shows the EKF based estimator with the proposed measurements is promising for building infiltration estimation.

INTRODUCTION AND BACKGROUND

Building consumed 38.61% total energy consumed in the U.S. According to a recent DOE report (U.S. Energy Flow 2016), the estimated energy use associated with the infiltration loss through the building envelope in the U.S for the year 2010 is 4 quads BTUs annually, which accounts for nearly 10% of the total energy use in buildings. Building infiltration increases total energy consumptions of both existing building and new construction. In general, air infiltrates through windows and opaque building envelope elements of building enclosures. Infiltration diagnostic technologies can be used to establish the extent of infiltration in an existing building or verify the performance of new construction. According to Department of Energy (DOE 2011), the infiltration measurement techniques should meet the criteria as follows: suitable for all building types, usable in occupied buildings, accurate regardless of outdoor weather conditions, low-effort for setup, and capability to quantify both the location and extent of infiltration. Currently, there are two most commonly used infiltration measurement techniques, which are blower door testing and tracer gas methods.

Blower door testing mount a fan into an existing exterior door. The purpose of that fan is to lower inside air pressure, then due to the higher outside air pressure, the air flows through all unsealed leakages. A frame with a flexible panel, which fits the doorway, a variable-speed fan, and a pressure gauge, which is used for measuring pressure differences, are three main components of the blower door infiltration techniques. The variable-speed fan pulls the air to the outside, which lowers the air pressure inside the building. Because the indoor air pressure is lower, the air will flow through the building envelope crack or the unsealed wall. The infiltration rate can be measured due to the imbalance of air pressure between the inside and the outside (DOE 2018). It is easy to establish a blower door testing for small commercial buildings and homes. However, it is hard to apply on large commercial buildings and industrial facilities. Also, a blower door testing can only quantify air leakages, but cannot identify the location of the air leakage. Moreover, a blower door testing needs to setup at the building pathway, which may create some difficulties for the normal operations in the testing buildings.

Another common method for measure infiltration is to use the tracer gas. Unlike the blower door method which cannot accurately estimate the amount of the infiltration air flow under particular driving force, the tracer gas method is a direct measurement. There are two types of tracer gas testing, single zone test, and multi-zone test. The single zone test measures the whole house or building air exchanges, and the multi-zone test measures the air flow from the outside room by room. The gas used for such testing should be non-toxic, colorless, inert, and stable. As a result, the commonly used tracer gas includes Carbon Dioxide, Nitrous Oxide, Freon, Helium, and Sulfur Hexafluoride (Hancock et al. 2002). Several types of equipment are needed to accomplish the tracer gas test, which includes a zone mixing fan and a space heater. The decay rate of tracer gas is used to determine the infiltration rate. According to ASTM E741 (ASTM 2000), the air should be maintained well mixed, and heaters are used to control the room temperature during the test. The singe zone tracer gas test can measure the infiltration when the air handler is on, or the ventilation system is operated. Similar to the blower door method, the tracer gas testing also has some limitations. For the single zone tracer gas test method, the testing result is heavily based on the test day weather condition. Also, since the pressure difference used to calculate the infiltration could be caused by the duct leakage, it is difficult to separate the infiltration from the duct leakage. The multi-zone tracer gas infiltration test will provide an overall view of building infiltration together with the infiltration rate for individual zone under a specific operation or specific weather conditions.

There are some ongoing building envelope infiltration measurement methods such asacoustic building infiltration measurement system (ABIMS). Unlike blower door and tracer gas methods which depends on the pressure difference between the indoor and outdoor environment, the ABIMS uses the acoustic leakage to estimate infiltration (Muhleisen 2017). However, according to 2017 building technologies office peer review (Muhleisen 2017), the research team currently is still trying to address the following issues:

1) The measurement needs to be low cost.
2) This method needs to be able to measure the inflitration during the construction or when building is occupied.
3) There is a need to derive a relation between the infiltration and the acoustic data.

In summary, measuring and quantifying building envelope infiltration is challenging. The existing infiltration diagnostic technologies normally required significant effort (e.g., blower door testing and Tracer gas methods). To address the preceding challenge, we propose a scalable and low cost Building Infiltration Estimator with Ultrasonic Thermometry (BLAST) to detect and quantify the infiltration (quantitative location and extent) through the building envelope for residential and commercial buildings, empowered by inverse modeling coupled with ultrasonic thermometry. The flow chart for the proposed method is shown in Figure 1. The proposed appoach consists of two steps: measurement and estimation. Total heat flux and outside surface temperature are measured using ultrasonic sensors. A model-based estimator then takes these two measurements to estimate the inflitration through data fusion using EKF.

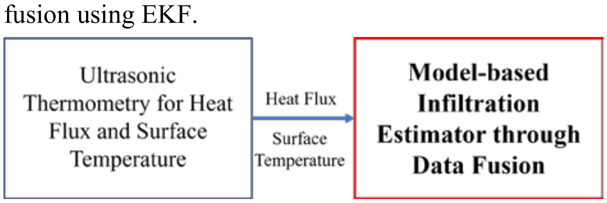

Figure 1 The flow chart for BLAST

This paper focuses on the second step of a model-based estimation, which is the red box in Figure 1. An EnergyPlus-based emulator is used to generate simulation data to test the proposed estimator.

In general, there are three types of building models, which are white-box model (i.e., physics-based model, black-box model (i.e., data-driven model), and grey-box model (Zhou, Wang et al. 2008). Available whole building simulation models such as EnergyPlus (2018), eQuest (2018), etc., are typical detailed white-box models. However, a large number of parameters are needed as inputs for simulation, and the process of collecting and inputting physical descriptions is time consuming, and sometimes, physically impossible. Moreover, users cannot access the states easily in these whole building simulation programs, which is critically important for the purpose of model-based estimation.

A state-space equation is usually required for a model-based estimation. One approach is using stochastic differential equations (SDE's). A set of SDE's describing the dynamics of the system form into a continuous-discrete stochastic state space model, which allows the decomposition of noise added the system into process and measurement noise. With an appropriate setting of the prediction error, the continuous-discrete state space model can be used to estimate unknown parameters (Jimenez et al. 2008). Such approach was used in estimating some parameters of the HVAC components (Andersen et al. 2000). Another widely used building state-space equations are derived from thermal resistance and capacitance (RC) network. The RC network model is able to simulate the building dynamics better than the black models (Li and Wen 2014). It has been recently used for simulating the transient building load prediction (Braun and Chaturvedi, 2002) and control algorithms testing (ASHRAE 1997).

Together with the RC network model of state-space equations, filter-based estimators such as Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF) have been used to estimate unknown parameters or states for building applications. For example, an EKF was used to estimate building load related to internal heat gains based on a 3R2C thermal network model (O'Neill, Narayanan et al. 2010). A UKF was used to estimate unknown parameters of the resistance and capacitance of the wall by Radecki and Hencey (2012).

In this paper, we will present an EKF based estimator using 3R2C thermal network model for inflitration estimation. First, a low-order, state-space 3R2C model of building envelope dynamics and the underlying filter theory will presented, then an EnergyPlus-based emulator will be used to generate simulation data to test the proposed estimator. The preliminary testing results illustrate the feasibility and acceptable accuracy of the proposed model-based estimation approach.

SIMULATION

EnergyPlus Emulator

An EnergyPlus-based emulator is used to provide the simulated data to test the proposed estimator. In this emulator virtual environment, measurements used in the estimator will come from the virtual sensor (i.e., outputs) from EnergyPlus instead of actual physical sensors. The infiltration of one exterior wall in the working room of a small commercial building is estimated in this study. There are three office rooms, one waiting room, one store, and one working room in this building. The selected wall, as shown in red square in Figure 2b, is an exterior wall of the working room located at the corner of the test building. For this preliminary study, there are no windows in this working room.

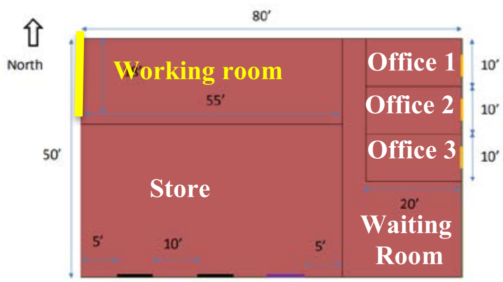

Figure 2a Floor plan of the simulated building

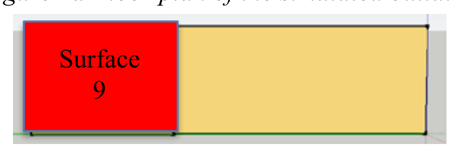

Figure 2b Side view of the simulated building with selected wall surface

In this study, inputs and outputs from EnergyPlus are used as the data source (e.g., virtual measurement) for the proposed estimator. To build the EnergyPlus model, the Google Sketchup Make with Openstudio was used to create building geometry, then the building envelope model was imported to EnergyPlus IDF editor. Only information related to the proposed estimator will be briefly introduced as follows.

The test wall is a three layers composite wall with wood, foam, and concrete. Each wall layer's physical parameters are listed in Table 1.

Table 1 Wall material characteristic by layers

	WOOD	FOAM	CONCRETE
Specific heat (J/kg*K)	900	1400	1000
Density (kg/m^3)	530	10	1400
Thickness (m)	0.009	0.0615	0.1
Conductivity (W/m^{2}K)	0.14	0.14	0.51

This small commercial building has a variable air volume (VAV) system. For this VAV system, it has DX AHU with a gas burner. Each thermal zone has its own VAV box and its own thermostat. The thermostat with a dual setpoint for the working room, where the testing wall is located, is set to 19.4 °C for the heating season, and 24°C for the cooling season. The building infiltration is set as 0.4 air change per hour (ACH) for each zone.

The following EnergyPlus variables are outputs for this study:

1) Zone mean air temperature
2) Outdoor air dry bulb temperature
3) Surface 9 inside surface solar radiation heat gain rate
4) Surface 9 inside face temperature
5) Surface 9 outside face temperature
6) Surface 9 outside face convection heat gain rate
7) Surface 9 inside face solar radiation heat gain per area
8) Zone total infiltration heat gain energy
9) Zone total infiltration heat loss energy
10) Surface 9 wall inside face convection heat transfer coefficient
11) Surface 9 outside face convection heat transfer coefficient
12) Surface 9 outside face solar radiation heat gain rate
13) Surface 9 outside face solar radiation heat gain rate per area

Outputs (8) and (9) are used to calculate the building infiltration, output (2), (6), (11), and (13) are related to inputs for the estimator. Other outputs are used as references for the initial conditions. Chicago O'Hare TMY3 weather file was used for this simulation. The time step was set to be 2-minute. We are assuming that during a given hour, the weather date is the same.

RC Model and Energy Balance Equation

A low-order, state-space model of building envelope dynamics based on non-linear algebraic and differential equation formulation is used for estimating unknown parameters and states. For this specific problem, a 3R2C thermal network model is used. The 3R2C model is shown in Figure 3.

This 3R2C model uses the solar air temperature, $T_{sol\text{-}air}$, to consider the solar radiation impact on the outside surface, which is a widely used approach to simplify the procedure to calculate the solar radiation heat flux on the exterior surface. Therefore, the outside surface solar radiation flux is not included in this model. The governing equation for the test wall can be described as:

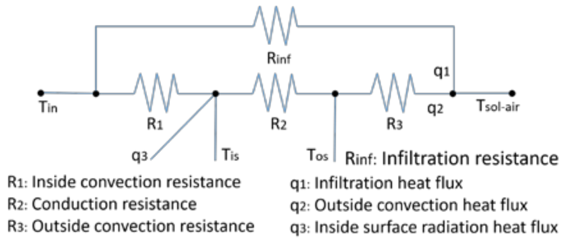

Figure 3 The proposed 3R2C model for the testing wall

$$C\frac{dT_{os}}{dt} = \frac{T_{is}-T_{os}}{R_2} + q_2 \tag{1}$$

$$C\frac{dT_{is}}{dt} = \frac{T_{in}-T_{is}}{R_1} + \frac{T_{os}-T_{is}}{R_2} + q_3 \tag{2}$$

$$q_2 = \frac{T_{sol-air}-T_{os}}{R_3} \tag{3}$$

$$q_1 = \frac{T_{sol-air}-T_{in}}{R_{inf}} \tag{4}$$

$$q_{total} = q_1 + q_2 \tag{5}$$

$$\frac{dT_{in}}{dt} = 0 \tag{6}$$

Equations (3), (4), and (5), can be combined and plugged into Equation (1), then Equation (1) can be rewritten as:

$$C\frac{dT_{os}}{dt} = \frac{T_{is}-T_{os}}{R_2} + q_{total} - \frac{T_{sol-air}-T_{in}}{R_{inf}} \tag{7}$$

The total wall conductive resistance, which is R_2 in equation (8) and (9) follows:

$$R_i = \frac{L}{k} \tag{8}$$

$$R_2 = \sum_{i=1}^{3} R_i \tag{9}$$

There are two thermal capacitances in the RC model, which are used to represent whole wall thermal capacitance. In this work, two capacitances are assumed to have the same value. Then, thermal capacitance C can be represented by:

$$C_i = \rho C_p L A \tag{10}$$

$$C = \frac{1}{\sum_{i=1}^{3}\frac{1}{C_i}} \tag{11}$$

Please note that for this preliminary study of the black room, there are no windows. Impacts of windows on the model formulation will be in the future work.

Extended Kalman Filter

The EKF has been commonly used for the non-linear estimation. The advantage of using Kalman Filter (KF) is that KF is capable of estimate unknown states with given model and inputs. For this study, an EKF is implemented because the underlying model is non-linear. The non-linear system dynamics for EKF can be represented by (Wan and Van Der Merwe 2000):

$$X(k+1) = F[x(k), u(k), v(k)] \tag{12}$$

$$y(k) = G[x(k), w(k)] \tag{13}$$

The EKF is a useful tool to estimate a non-linear system, which a linearization is required for the estimation. The linearization process takes a state-space equation F, and a measurement equation G, with only considerations of the first derivative, to linearize the system. The Jacobian matrix is commonly used in this approach, which is shown in Equation (14):

$$J\big((k+1|k)\big) = \frac{\partial F}{\partial X}$$
$$H\big((k+1|k)\big) = \frac{\partial G}{\partial X} \tag{14}$$

After the linearization, the system can be treated as a linear system, where state-space equation and its covariance can be represented, as shown in Figure 4.

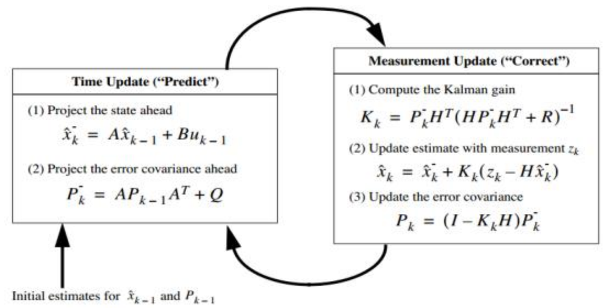

Figure 4 Extended Kalman filter update process

After the initial state and its associated covariance, the linearized state-space equation, and covariance equation are chosen, the EKF uses the predicted state and the covariance to calculate a new Kalman gain. The last step of a single prediction is to update or correct the predicted state and the covariance by using the new Kalman gain. Then, the updated state and covariance become the new input parameters for the next state estimation.

State-Space Equation

To use the Kalman Filter for the estimation, a state-space equation is required. In this study, a state-space matrix is used to represent a single wall energy balance equation. The system model has the form of:

$$X = \dot{F}(x,u)$$
$$Y = G(x) \tag{15}$$

The inputs, u, in this preliminary study, include total surface heat flux and solar-air temperature. The state-space matrix for the proposed 3R2C thermal network model can be described as:

$$x = \begin{vmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \\ x_7 \\ x_8 \end{vmatrix} = \begin{vmatrix} T_{os} \\ T_{is} \\ T_{in} \\ R_{inf} \\ q_3 \\ R_1 \\ R_2 \\ C \end{vmatrix}$$

$$\dot{x} = f(x) = \begin{vmatrix} \frac{x_2-x_1}{x_7x_8} + \frac{u_{qtot}}{x_8} - \frac{u_{Tsolair}-x_3}{x_4x_8} \\ \frac{x_3-x_2}{x_6x_8} + \frac{x_1-x_2}{x_7x_8} + \frac{x_5}{x_8} \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{vmatrix} \quad (16)$$

Equation (16) formed the state space matrix, which represents x in *F(x,u)*. To use the EKF to estimate unknown states, it also requires a measurement equation. For this study, the outside surface temperature is only measurement, which is the first state for this model. The measurement equation is as follows:

$$y = [1\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ ]X \quad (17)$$

Filter Design

The estimation accuracy not only depends on the fidelity and accuracy of the underlying model, it also affected by the parameters used in the filter itself. Thus, a right filter design is a key factor for an accurate estimation. The filter design includes accurate inputs, and an appropriate design of the covariance. The inputs may come from the direct field measurements or some calculations using measurements. In this study, there are two inputs, namely, solar air temperature and total surface heat flux.

The solar air temperature can be calculated from outdoor air temperature, the wall outside layer solar absorptivity, the total solar radiation incident on the surface, and the outside convection heat transfer coefficient (Niu and Yu 2016). One assumption is used to calculate the solar air temperature. The outside layer solar absorptivity (α) is assumed as 0.75, which is a common value for the wood sliding. The solar air temperature can be calculated by:

$$T_{sol-air} = T_{oa} + \frac{\propto q}{h_{os}} \quad (18)$$

Since the radiation effects on the surface heat flux, the solar-air temperature are considered using in this model. The total heat flux through an exterior wall consists of infiltration heat flux and outside convection heat flux. The infiltration heat flux is not a direct output from EnergyPlus, but it can be calculated by using an output of the infiltration heat transfer energy and the simulation time step, the calculation follows:

$$q_1 = \frac{E_{inf}}{t} \quad (19)$$

For this study, the simulation time step is set as 120 seconds in the EnergyPlus, and infiltration heat transfer energy is from EnergyPlus output (8) and (9). Once infiltration heat flux is calculated, the total heat flux on the exterior wall can be written as:

$$q_{total} = q_1 + q_2 \quad (20)$$

Please note, for the proposed BLAST, this total heat flux will be directly measured. Both inputs (i.e., solar-air temperature and total surface heat flux) and one measurement (i.e., total surface heat flux) are from the EnergyPlus simulation.

A Matlab Kalman Filter toolbox is used for the filter. The appropriate design of the covariance, the process noise, and the measurement noise is another important step for the proposed model-based estimator. In this paper, the process noise covariance, Q, the measurement noise covariance, R, and initial state error covariance matrix P0 are assumed as follows:

$$Q = 1 * 1(8,8)$$
$$Q(4,4) = 10{,}000{,}000; \quad Q(6,6) = 10{,}000{,}000$$
$$R = 1\ ;\ P_0 = 10{,}000{,}000 * 1(8)$$

The state 6 of the indoor heat convection resistance is assumed as a constant, which is not always true. Therefore, a high process noise is given. The infiltration resistance is also highly an uncertain non-constant. A high process noise is used to compensate this uncertainty from the model. Other process noise covariance is set as one. To improve the estimation accuracy for the initial states, a high initial state error covariance is given. The measurement is considered to be accurate. Thus, the measurement noise covariance is set to one. We are assuming that the room air is in a quasi-steady-state with a relatively constant value during the given time step, which is shown in the state space equation (16).

Constraint

Constraints based on the physics are used in the filter such that the estimated values don't violate the physics. For this study, the soft constraints with given bands are applied to the estimation model. The lower bound of all states of temperatures is set at -60 °C, and the upper bound of temperatures is set at 120 °C. This constraint is applied for the outside surface temperature, the inside surface temperature, and the zone mean air temperature. Another constraint is set for the infiltration resistance with a lower bound of 0.00001 K/W. This makes the estimated infiltration resistance to be always greater than 0. For this study, the testing wall is in the black room without windows. Therefore, a constraint of the inside surface solar heat flux (q_3) is set to 0.00001 W to ensure this heat flux to be zero.

RESULTS

In this section, estimation results for the testing black wall using the simulated data from the EnergyPlus are presented. The estimation starts at January 1st, and the estimation period is set to be 5,400 time steps. The outside surface temperature estimations are shown in Figure 5.

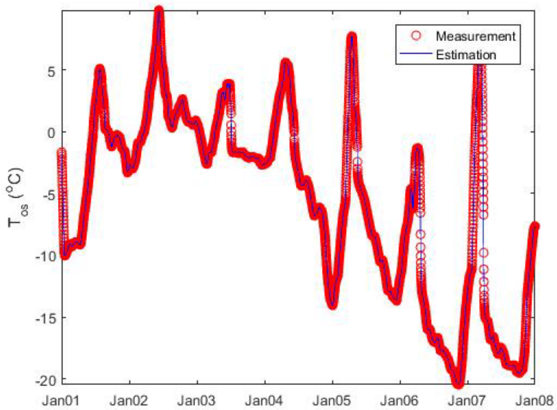

Figure 5 Outside surface temperature estimation

The red dot is virtual measurements from EnergyPlus, and the blue line is the estimated outside surface temperature from the estimator. As shown in Figure 5, the estimated and measured outside surface temperature match with each other very well, which is expected due to the filter design. Because outside surface temperature is the only measurement for the EKF, the covariances are chosen to trust this measurement.

Our real interest is to estimate building infiltration using the proposed estimator. The infiltration estimation of the infiltration resistance is shown in Figure 6. The known infiltration resistance from the EnergyPlus is defined as:

$$R_{inf} = \left|\frac{T_{sol-air} - T_{in}}{q_1}\right| \quad (21)$$

Where T_{in} is a directly output from EenergPlus, while $T_{sol-air}$ and q_1 (i.e., infiltration heat flux) are calculated using outputs from EnergyPlus.

The EKF estimated infiltration resistance is shown as the blue line. This is compared with the actually known values from the EnergyPlus.

Figure 6 shows that the EKF estimated infiltration resistance has the same trend compared with true values. There are 21 time steps that the estimated infiltration resistance reached the upper bound of the constraint. This occurred at the end of January 2nd. The reason is unknown currently and is being investigated. Most likely, this is due to relatively small infiltration resistances during that period, which causes the challenges for the filter design. Besides the EKF that was used in this conference paper, we are actively exploring other estimation methods such as unscented KF. In the same time, we are reexamining the proposed thermal-network based state-space physics model to see whether the modeling can be improved with some state observers.

To better determine the estimation accuracy, statistic metric including coefficient of variation of root-mean-square error (CV-RMSE), R^2, and mean based error (MBE) are used.

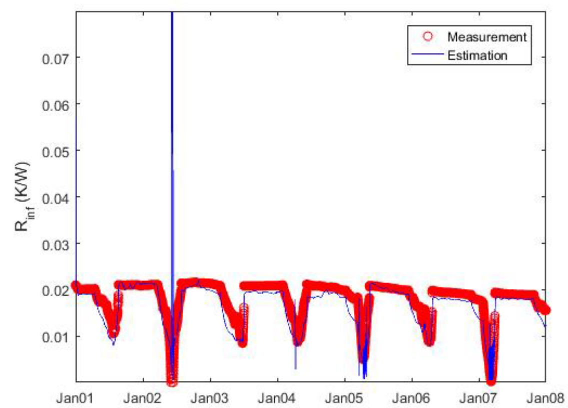

Figure 6 Building infiltration resistance estimation

The CV-RMSE can be calculated by:

$$CV - RMSE = \frac{RMSE}{\bar{x}}$$

$$RMSE = \sqrt{\frac{\sum_1^n (x_{EKF} - x_{E+})^2}{n}} \quad (22)$$

The R^2 is calculated by:

$$R^2 = 1 - \frac{\sum_1^n x_{EKF}^2}{\sum_1^n x_{E+}^2} \quad (23)$$

Another statistic metric used to evaluate the estimation accuracy is MBE:

$$MBE = \frac{\sum_1^n \frac{x_{EKF} - x_{E+}}{x_{E+}}}{n} \quad (24)$$

The statistic metric for the infiltration estimation is shown in Table 2.

Table 2 Statistic metric for infiltration resistance estimation

CV-RMSE (%)	**R^2**	**MBE (%)**
0.1216	0.1083	0.1645

This statistic metric analysis shows that the proposed model-based estimator gives a reasonable accuracy using the data from the EnergyPlus emulator. Figure 7 gives an evaluation of the proposed estimator in terms of the count of the percentage error in a 10% bin.

For this estimation with a 2-minute sampling frequency, there are 5,400 estimation points. Figure 7 shows that 3,446 (63.81%) estimations are within the 10% error band, and 778 (14.41%) estimation errors are between 10% to 20%. 78.22 % estimations fall in the range of 20% error band. Another 873 (16.17%) estimation points are within the 20% to 30% error band. 106 out of 5,400 estimation points (1.96%) have more than 50% estimation error.

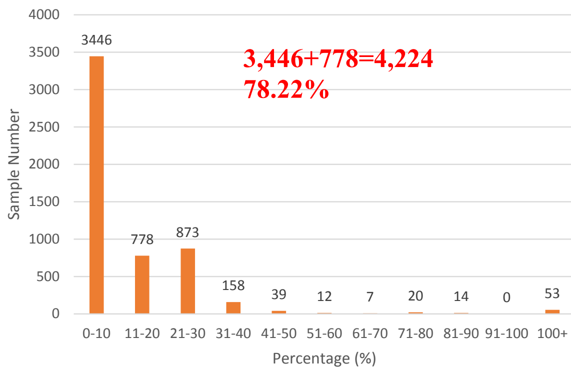

Figure 7 Count of the estimation error

The following factors could contribute to the non-perfect estimation of the infiltration resistances: 1) The state-space equation can be improved further to better reflect the building envelope heat transfer. The current state-space model (i.e., 3R2C model) has been successfully applied to estimate the building internal loads and the wall physical parameters in the literature (Lee and Braun 2008). However, it may need some adjustments for estimate the building infiltration. 2) Using the solar-air temperature to consider solar radiation impacts on the exterior surface could cause some error.

The estimated wall conduction thermal resistance and capacity are nearly constants during the whole estimation period, which is as expected since the wall conduction thermal resistance and capacity are set as constant in the EnergyPlus emulator. These constant values are almost identical to the values used in the EnergyPlus, which demonstrates that the proposed EKF-based estimator performed well for the parameter estimation.

CONCLUSIONS

This paper demonstrates the feasibility of using a model-based estimation to quantify the building infiltration. A lumped and dynamic state-space model of the room with infiltration was developed. An Extended Kalman Filter was utilized to estimate the states and unknown parameter. Data from the EnergyPlus emulator was used to test the proposed estimator. Testing results show that it is promising to use EKF as an estimator for building infiltration. Most of estimation are within 20% error band of the true values.

Ongoing and future work of this model-based estimation of building infiltration includes:

1) Improvement of the physics-based dynamic model. For example, the state-space models need to include the window. In addition, a solar heat flux distribution model needs to be investigated to understand inside surface heat flux.
2) Investigations on other estimation method. For example, an unscented Kalman Filter could be considered.
3) Inclusion of an uncertainty wrapper into the estimator. This is particularly true when the real sensor measurements are utilized.
4) The testing of the proposed estimator is being tested using the proposed emulator for the summer days. The estimation, in general, is matching with the virtual measurements. However, we are experiencing some oscillation issues related to the filter design. We are currently redesigning the EKF and investigating the Unscented Kalman Filter to solve this oscillation issue.

The proposed infiltration estimation method is a model-based infiltration estimator through data fusion using filters (e.g., Extended Kalman Filter). Fused data includes heat flux and surface temperatures measured from ultrasonic thermometry. This conference paper is only focusing on the inverse modeling with data assimilation assuming that measurements from ultrasonic thermometry are known. This is totally different with the traditional forward infiltration model such as the infiltration model used in EnergyPlus (Gowri et al.), which requires the inputs of infiltration air flow rate at the design condition and some specific coefficients. The infiltration air flow rate at design conditions often are not easy to obtain for a given building unless a blower door or tracer gas method is used. The proposed inverse modeling approach with filters have been widely used in aerospace and automobile industry, while little has been explored in building science. The beauty of the proposed approach stems from the combination of physics and measurement. The key to the proposed method is how to intrusively measure heat flux and surface temperatures on the external surface. We are actively conducting the research in this area as well.

ACKNOWLEDGMENT

This study is partially supported through the ASHRAE Innovation Research Grant Award (IRG-030-1718).

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NOMENCLATURE

T_{os}: (°C) outside surface temperature
T_{is}: (°C) inside surface temperature
T_{in}: (°C) zone air temperature
q_1: (W) zone infiltration heat flux
q_2: (W) outside surface convection heat flux
q_3: (W) inside surface solar radiation heat flux
R_1: (K/W) inside convection resistance
R_2: (K/W) wall conduction resistance
R_3: (K/W) outside convection resistance
C: (J/K) wall heat capacitance
R_i: (K/W) thermal resistance for single layer
L: (m) wall thickness
k: (W/m^{2}K) thermal resistance
ρ: (kg/m^3) single wall layer material density
C_p: (J/kgK) specific heat
α: solar absorptivity
h_{os}: (W/m^{2}K) outside surface convection heat transfer coefficient
q: (W) outside surface solar incident radiation heat transfer rate.
q_1: (W) zone infiltration heat loss or heat gain
q_2: (W) outside convection heat flux
F: EKF state-space equation matrix
x: EKF state
u: EKF input
v: EKF process noise
G: EKF measurement equation mater
w: EKF measurement noise
J: the Jacobian matrix for state space matrix
H: the Jacobian matrix for measurement matrix
RMSE: root-mean-square error
$\overline{x}$: mean value of EKF estimation
X_{EKF}: EKF estimated infiltration resistance
X_{E+}: EnergyPlus Calculated infiltration resistance
n: the total estimation time step number