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USE OF KALMAN FILTER FOR ESTIMATING UNKNOWN INTERNAL LOADS

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ABSTRACT

This paper addresses the estimation performance of a Kalman filter for an internal aggregated load. The internal aggregated load consists of heat gains from internal sources (people, lightings, equipment) and heat gain/loss from infiltration and air movement between zones. In general, it is difficult to quantify such load because of its dynamic nature (e.g. heat firstly absorbed and reradiated back to room air, bidirectional airflow through doors, windows, etc.). For this reason, crude estimate (or guess) is usually used for energy simulation of existing buildings. To address the aforementioned issue, a state estimation method, Kalman filtering, is proposed in this paper. Kalman filtering is well suited for situations when limited measured data are available under strong uncertainty. To validate its estimation performance, virtual and real experiment were conducted in this study. The preliminary results show that the Kalman filter can successfully estimate randomly varying loads, but its performance depends on model adequacy and measurement noise.

INTRODUCTION

For energy simulation of existing buildings, drawings (architectural, mechanical, electrical), daily records of operation of building systems, information gathered from site-visits/interviews, as well as measured (or monitored) data were compiled through several pre-processes for simulation run. The data entered into a simulation program can be classified into two: "static" and "dynamic". The data gathered from drawings such as geometric information and the thermal properties of materials can be regarded as static. In general, it is relatively easy to obtain static data because such static data are usually documented well and the nature of static data is literally 'static'. Examples of dynamic data are (1) system operation settings, (2) heat gains from internal sources (people, lightings, equipment), and (3) heat gain/loss from airflows (infiltration, mixing air between zones). Even though system operation settings are dynamic, they are easy to obtain because they are usually stored in computerized database such as Building Automation System (BAS) or Building Energy Management System (BEMS). However, it is difficult to obtain the second and third types of dynamic data due to the following:

- In most buildings, schedule information of individuals is not collected because of a privacy issue. Moreover, the heat gain from people varies based on age, sex, and activities (ASHRAE 2009) and hard to measure.
- Electric consumption by equipment and lightings is not sub-metered. Moreover, there are differences in heat emission for each equipment and lightings.
- It is difficult to quantify the amount of infiltration and air movement between zones (van der Maas, 1992). It would be even more challenging to measure in a real-life case (uncontrolled conditions).

For these reasons, crude estimate (or guess) is usually used for energy modeling of existing buildings. However, according to Hopfe and Hensen (2011), energy prediction is significantly influenced by such unknown inputs and more careful attention should be paid.

Incomplete information leads to deficient energy simulation model (Ahn et al, 2012), and there is always a gap between reality and simulation prediction. Various calibration techniques are proposed to overcome this issue: optimization-based parameter estimation (Reddy et al. 2006), rapid calibration (Liu et al, 2011), evidence-based calibration (Raftery et al, 2011), Bayesian calibration (Heo et al, 2012). Unfortunately, the aforementioned internal heat gains, infiltration and air movement have "time-varying" characteristics, leading to vast search space in optimization. Typical search algorithms cannot find optimal solutions within the limited time.

In this study, the authors propose Kalman filtering, a rigorous estimation technique, to estimate time-varying unknown parameters. The Kalman filter can effectively estimate unmeasured states (which evolve in time) with the use of knowledge of the system, dynamics of measuring devices and statistical descriptions of the system noise, measurement errors, and uncertainty in the dynamic models. The Kalman filter approach is well suited for situations when limited measured data are available under strong uncertainty.

In this study, the elements #2 (heat gains from internal sources) and #3 (heat gains from airflows) were estimated not separately but aggregately with regard to their contribution to the internal load. The following two experiments were conducted to verify estimation performance of the Kalman filtering.

1. Virtual experiment – the aggregated internal load (the sum of #2 and #3) was arbitrarily manipulated during the time horizon inside a full dynamic simulation model. The Kalman filter estimated the internal load and comparison was made between true heat gains and estimated heat gains.
2. Mini test-bed experiment – an experiment was conducted in a small-scale test-bed. In the same manner as mentioned in the virtual experiment, the real heat inputs were compared to the estimates by the Kalman filter.

ESTIMATION APPROACH

The Kalman filter algorithm estimates state variables in a noisy linear dynamical system by minimizing mean-squared estimation error of the current state as noisy measurements are received and the system evolves in time. Each update provides the latest unbiased estimate of the system variables together with a measure on the uncertainty of those estimates in the form of a covariance matrix. Since the updating process is general and relatively easy to compute, the Kalman filter often is implemented in real-time. A brief review on the Kalman filter can be found in Humpherys et al. (2012).

Also, the Kalman filter can be applied to state or parameter estimation problems using the state augmentation technique. The Kalman filter assumes white uncorrelated random sequences $w(i)$ and $v(i)$ for the process and measurement noise. In general, those statistical properties are assumed to be Gaussian distribution (Gelb 1974, Simon 2006; Crassidis and Junkins, 2012). The whiteness or colored content of stochastic processes, such as $w(i)$ and $v(i)$ can be characterized by those power spectrums. The power spectrum means how the power of random process is distributed over the different frequencies. If the power is distributed uniformly over all frequency components, such process is called white noise. To put it another way, if the random variable $w(t_1)$ is independent from the random variable $w(t_2)$ for all $t_1 \neq t_2$ then $w(t)$ is called white noise (Simon, 2006).

In contrast, the colored noise has non-uniform power distribution over the frequencies, or it is correlated with itself. The colored noise may be modeled as random walk, random ramp, exponentially correlated random variable, periodic random variable (Gelb 1974). A simple model of the colored noise process would be random walk (it will be explained in the later section), and its mathematical expression is as follows.

$$w(i+1) = w(i) + w'(i) \tag{1}$$

Where, $w'(i)$ is white noise. At this point, the state augmentation reduces the problem to a standard Kalman filter form. For that, the augmented state differential equation, driven by white noise $w'(i)$ is as follows.

$$\begin{bmatrix} x(i+1) \\ w(i+1) \end{bmatrix} = \begin{bmatrix} F & I \\ 0 & I \end{bmatrix} \begin{bmatrix} x(i) \\ w(i) \end{bmatrix} + \begin{bmatrix} G \\ 0 \end{bmatrix} u(i) + \begin{bmatrix} 0 \\ I \end{bmatrix} w'(i) \tag{2a}$$

$$z(i) = \begin{bmatrix} H & 0 \end{bmatrix} \begin{bmatrix} x(i) \\ w(i) \end{bmatrix} + v(i) \tag{2b}$$

where, x is the state vector, F is the system matrix, G is the input matrix, u is the control vector, z is the measurement vector, H is the measurement matrix, v is white, zero-mean measurement noise. The noise processes of w' and v have $N(0,Q)$, $N(0,R)$ respectively where Q is model noise covariance matrix and R is measurement noise covariance matrix. Eq.(2a) is discrete-time linear system, and Eq.(2b) is called linear Gaussian measurement equation because the probability density function of the v is Gaussian distribution. With this augmented state vector form (Eq.2), both x and w can be estimated using the standard Kalman filter (Simon 2006). This state augmentation technique was applied to our study to estimate the dynamic parameter (or state) of the internal aggregated load.

It should be noted that Eq.(2) gives the augmented state equation but it is not the recursive equations of the filter (i.e. time update and measurement update). In addtion, the details of the propagetion of the error covariance were omitted in this paper for want of space.

RESEARCH HYPOTHESIS

In this study, it was assumed that the internal aggregated load can be represented by the movement of a simple random walk. The random walk is a mathematical formalization of a path that consists of a succession of random steps. For example, the path traced by a molecule as it travels in a liquid or a gas, the search path of a foraging animal, the price of a fluctuating stock and the financial status of a gambler can all be modeled as random walks (Eq.1).

In this study, the internal aggregated load (q_L) is defined as the sum of instantaneous loads except for the load caused by envelopes (opaque, transparent) and systems (e.g., outdoor air intake, supply air). The expression is as follows.

$$q_L = q_p + q_e + q_l + q_{iv} + q_{mix} \tag{3}$$

where, q_p is heat gain from people [W], q_e is heat gain from equipment [W], q_l is heat gain from lighting [W], q_{iv} is heat gain/loss from infiltration and ventilation by occupants (e.g. opening/closing windows) [W], q_{mix} is heat gain from air movement between zones [W].

Interestingly, the internal aggregated load (Eq. 3) depends on the characteristics of occupants' behavior. Hence, it is very difficult to quantify by any deterministic physical relationship. As mentioned above, the heat gain from people depends on their age, sex, and activities, while the heat gains from lightings and equipment depend on how and when people operate those (Duska et al. 2007). Likewise, infiltration and ventilation depend on how and when people open and operate windows and systems. Currently, there are divergent opinions about the modeling possibility of human behavior (Pierce et al. 2010; Lu et al. 2010a, 2010b; Clinton et al. 2011; Rachlin, 2012). In addition, under uncertain weather conditions, airflows in buildings are irregular (or random), can be regarded as the random walk (or Brownian motion process). With what has been mentioned above being considered, the internal aggregated load is assumed as the random walk (Eq.4)

$$q_L(i+1) = q_L(i) + w'(i) \qquad (4)$$

The 'random walk hypothesis' implies that the internal aggregated load is colored noise. In other words, it can be modeled as the random walk, and therefore estimated by the state augmentation technique using a standard Kalman filter. Finally, the estimation performance of Kalman filter was investigated through the virtual experiment and mini test-bed experiment in the following sections.

VIRTUAL EXPERIMENT

Virtual experiment, or building simulation allows direct control of all boundary conditions and error parameters, and it generates the values of observable as well as non-observable parameters as well as state variables of our interest. In this study, the noise-free aggregated load was obtained from an EnergyPlus simulation run.

Three experiments were designed to test the performance of the Kalman filter (Table 1). The purpose of the first experiment is to verify the performance under an unrealistic internal load condition. In case of experiment #2, the load was generated like a sinusoidal wave. In the third experiment, noise (random load) was added to the load generated in experiment #2 to reflect a more realistic condition. An overview of the virtual experiment was shown in Figure 1 and Table 1.

Table 1. Experiments description

NO.	DESCRIPTION
1	The internal load increases and decreases sharply three times (unrealistic internal load condition).
2	The internal load varies like a sinusoidal shape to reflect a more realistic condition.
3	The same load from exp#2 is combined with random noise at every 10 minutes. This is a case as close to a real-life as possible.

Simulation model

For this study, a simulation model was developed as shown in Figure 2. The model room was a rectangular space with 3m (H) x 3m (W) x 3m (D), that of a small office unit. The window, south facing, 1m (W)×1m (H), consists of a double glazing (6 mm clear + 12 mm air cavity + 6 mm clear). Only the south envelope has contact with outdoor, others are set to be adiabatic. In this study, the medium-weight type of construction was chosen according to ASHRAE (2009).

The object 'ideal HVAC system' in EnergyPlus was used to control the room air temperature. The ideal HVAC system is an ideal unit that mixes air at the zone return with a specified amount of outdoor air, and then adds or removes heat and moisture at '100% efficiency' in order to produce a supply air stream at specified conditions. The simulation run was conducted under clear sky conditions using EPW file (location: Seoul, Korea, summer: Jul. 1st).

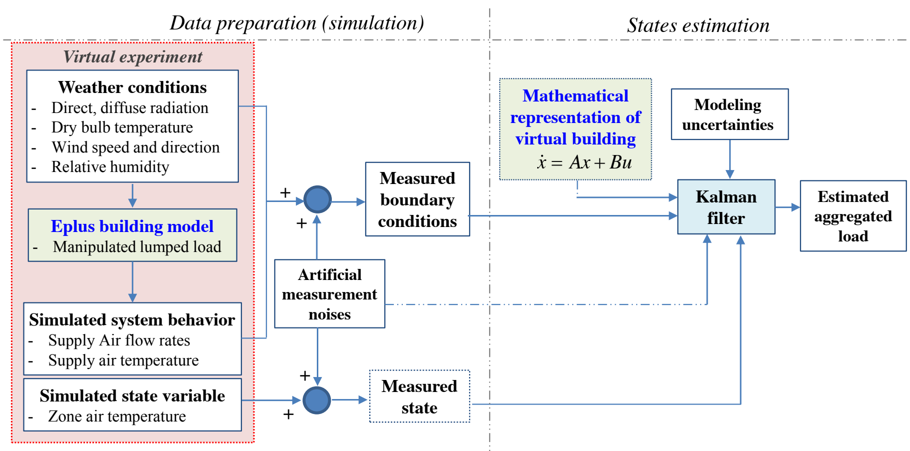


Figure 1. Overview of the virtual experiments

Artificial noises were added to the simulated data from EnergyPlus to imitate real measured data. The measured data and quantity of the noise are shown in Table 2. Examples of the noisy measurements (outside dry bulb temperature and wind speed, global solar radiation) are shown in Figure 3.

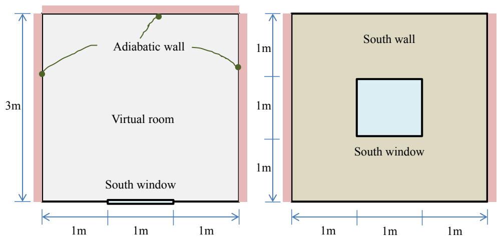
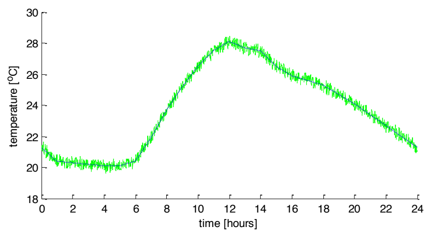


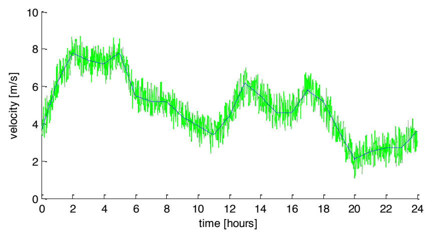
Figure 2. Simulation model
(left: floor plan, right: elevation)

Table 2. Noise of measured data

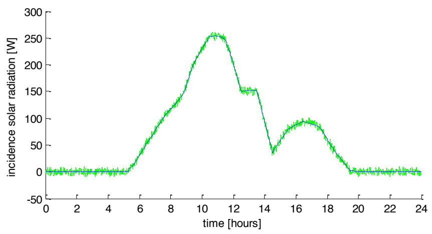
LIST	NOISE (sensitivity)	DIM.	REFERENCE
Outdoor air temperature	±0.5	[ºC]	HOBO Weather station (H21-001)
Outdoor wind speed	±1.2	[m/s]	Gill inc. (WindSonic 1405)
Solar radiation	±10	[W/m²]	LI-COR (LI-200SA)
Indoor air temperature	±0.5	[ºC]	General T-type thermocouple
Supply airflow rate	± 0.1	[m/s]	Testo vane probe (0635 9335)
Supply air temperature	±0.5	[ºC]	General T-type thermocouple



(a) outdoor air temperature



(b) outdoor wind speed

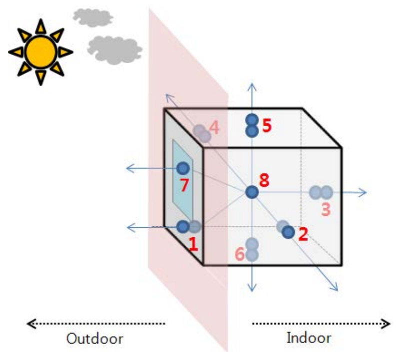


(c) global solar radiation on the south vertical wall

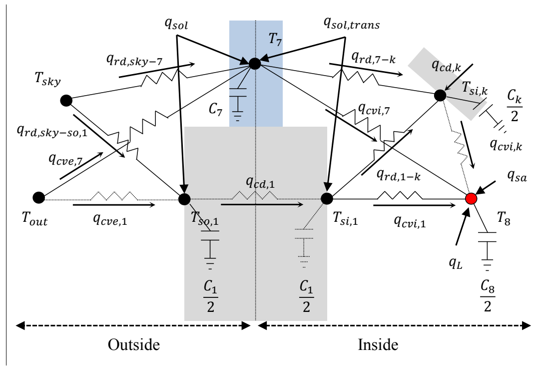
Figure 3. Examples of the measured data (green line) and simulated (or true) value (blue dotted line)

Mathematical modeling of the virtual building

The virtual building (Figure 2) was modeled as a simple RC network as shown in Figure 4. In this modeling approach, the walls, ceiling and floor were simplified as two nodes, and the window was simplified as a lumped node. The heat balance equation at each node for nodes #1 through #8 in Figure 4(a) was based on textbooks (Clarke 2001; Duffie and Beckman, 2006; Incropera et al. 2008; ASHRAE 2009). The details were omitted in this paper for want of space. It should be noted that the simplified RC model (state-space model) was made purposefully different from the EnergyPlus model considering a real-life situation (Table 3).



(a) nodes configuration
(1,2,3,4: wall nodes, 5: roof node, 6: floor node, 7: window node, 8: zone air node)



(b) RC-network details of the south envelope

Figure 4. State-space model used in Kalman filter.
(T=temperature [ºC], C=capacity [J/K], q=heat gain [W]; Subscript notation: sky=sky or ground, si=inside surface, so=outside surface, k=node index (1,2,3,4,5,6,7,8), out=outside, sa=supply air, L=internal aggregated load, sol,trans=transmitted solar radiation, cvi=convection on the interior surface, cve=convection on the exterior surface, rd=radiation , cd=conduction)

Table 3. Comparisons of applied heat transfer method in EnergyPlus and the state-space model. The words in italic mean the name of heat transfer algorithms in EnergyPlus (DOE 2011)

HEAT TRANSFER	ENERGYPLUS	STATE-SPACE MODEL
Wall cond.	*ConductionFiniteDifference*	*ConductionFiniteDifference :simplified*
Wall conv. (inside)	*FohannoPolidoriVerticalWall*	*ASHRAE model*
Wall conv. (outside)	*MoWiTT*	*SimpleCombined model*
Ceiling conv.	*AlamdariHammondStableHorizontal*	*ASHRAE model*
Floor conv.	*AlamdariHammondUnstableHorizontal*	*ASHRAE model*
Window conv. (inside)	*ISO15099Windows*	*ASHRAE model*
Window conv. (outside)	*NaturalASHRAEVerticalWall*	*SimpleCombined model*
Transmitted direct solar	*FullInteriorAndExterior*: beam radiation reaches each surface in the zone by projecting the sun's rays through the exterior windows.	All beam solar radiation entering the zone is assumed to be diffused on all surfaces
Long-wave heat exchange (inside)	a grey interchange model based on the *ScriptF*	Surface radiosity balance equation

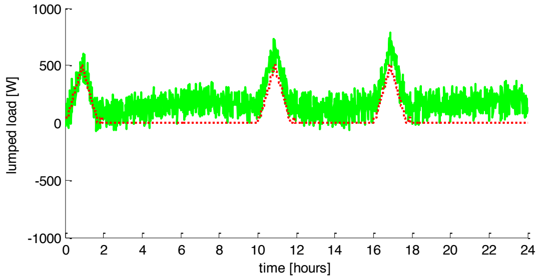
Results of the virtual experiment

The initial guesses of the Kalman filter are regarded as design variables and usually determined by the subjective judgment of users. Proper initial guesses are important for reliable estimation and fast convergence. It is strongly advised to be elaborate on the reasoning of the initial guess. The authors' choices and reasoning are summarized in Table 4.

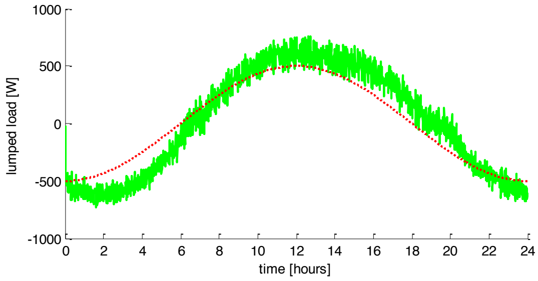
Table 4. Initial value setting of the virtual experiment (SYM in subscript parenthesis refers to address of the element in matrix)*

PARAM.		SYM.*	VAL.	DIM.	REASONS
State vector	Air temp.	$x_{(1,1)}$	25	[°C]	General room temperature
	Wall in/ex temp.	$x_{(i,1)}$ (i=2,...,13)	25	[°C]	Similar to general room temperature
	Window temp.	$x_{(14,1)}$	25	[°C]	Similar to general room temperature
	Aggregated load	$x_{(15,1)}$	0	[W]	No heat input at initial stage
Covariance matrix		$P_{(j,j)}$ (j=1,...,14)	10^2	[°C^2]	Confidence on guess of initial temperature would be ±10°C
		$P_{(15,15)}$	439^2	[W^2]	Confidence on initial guess of the aggregated load is calculated as follows: - Calculate internal heat gain of medium office building under normal condition (lighting: 10W/m², equipment: 10.8W/m², people: 140/5=28W/m², floor area: 9 m²) - Total heat gain is 439 W - Confidence range would be ±439W
Measurement matrix		$H_{(1,1)}$	1	[-]	Only air temp. is measured
		$H_{(1,n)}$ (n=2,...,15)	0	[-]	Not measured
Model noise covariance matrix		$Q_{(m,m)}$ (m=1,...,14)	0.5^2	[°C^2]	Modeling error would be ±0.5°C
		$Q_{(15,15)}$	439^2	[W^2]	Modeling error would be the same as $P_{(15,15)}$
Measurement noise covariance matrix		R	0.5^2	[°C^2]	Measurement error would be ±0.5°C (see Table 2)

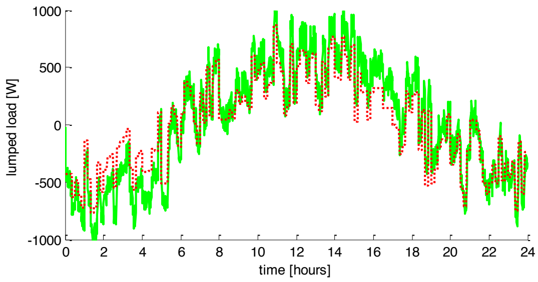
Figure 5 shows manipulated (true) internal aggregated load in EnergyPlus (in red) and estimated load (in green). The estimation performance was assessed using three factors including RMSE (root-mean-square error), NRMSE (normalized root-mean-square error), R-square (coefficient of determination) (Table 5).



(a) Experiment #1



(b) Experiment #2



(c) Experiment #3

Figure 5. Comparison between estimated aggregated load and true value (green line: estimated value, red dotted line: true value)

Table 5. Comparisons of estimation performances

Exp.	RMSE [W]	NRMSE [-]	R^2 [-]
1	163.47	0.326	-0.820
2	157.89	0.157	0.800
3	166.12	0.101	0.820

In the case of experiment #1, the Kalman filter was not divergent and appropriately good to estimate the load despite factitiously manipulated trend. The performance is relatively good with RMSE of 163.47[W], NRMSE of 0.389, and R-square of -0.82.

The negative sign of the R-square, defined as (1-SSE/SS_{yy}), means that the sum of square of residual (SSE) (estimation error) is greater than the total sum of squares of data (SS_{yy}). If the variance of the observed values is small (around 0W), the total sum of squares of data is accordingly small and this will give a negative value of R-square regardless of the estimates being acceptable. In this case, it is better to look at the RMSE (NRMSE) as a performance statistic, which is good enough.

In the case of experiment #2, the Kalman filter kept track of the true value that has sinusoidal shape (Figure 5(b)). Overall performance is acceptable: the performance statistic shows an RMSE of 157.89W, NRMSE of 0.157, and R-square of 0.80. Considering the estimated range (from -500 to 500 W), the estimation performance is significantly improved compared to experiment #1, the Kalman filtering can be regarded as a good estimation method for this sinusoidal load pattern. However, there is slight deviation at hours 2-4 (low) and hours 16-18 (high) from the true value (Figure 5(b)).

In experiment #3, random loads (cause by external effects) were added to the sinusoidal load at every 10 minutes. This is obviously most random condition, such as a real-life, but the results validate accurate performance; the performance statistic RMSE, NRMSE, and R-square are 166.12W, 0.101, and 0.820 respectively. This signifies that the Kalman filter would be a suitable approach to achieve good estimations of load patterns in real-life cases.

MINI TEST-BED EXPERIMENT

To complement the 'virtual' experiment, a small-scale 'real' experiment was conducted for a proof-of-the-concept. The mini test-bed reported in Kim et al (2012) was used in our study. A brief summary of the mini test-bed (Figure 6) is as follows: it is rectangular and made of Expanded Polystyrene (EPS). It contains a heating cable inside which emulates a convective heating system. Electric consumption of the heating cable is measured by a wattmeter, and air and surface temperatures of the EPS box are measured by t-type thermocouples. NI Compact DAQ 9174 is utilized for data acquisition.

The experiments were conducted twice (10/28/2012 and 10/29/2012) with 10W and 30W heating cables for 160 minutes with a sampling time of 1 sec. During the experiments, the heating cable was randomly turned on/off.

It should be noted that in contrast to the virtual experiment, the true value of convective heat emission (or instantaneous load) from the heating cable is unknown under this mini test-bed experiment. Therefore, the measured electric power was used to validate the experiment. An overall concept of the mini test-bed experiment is shown in Figure 7.

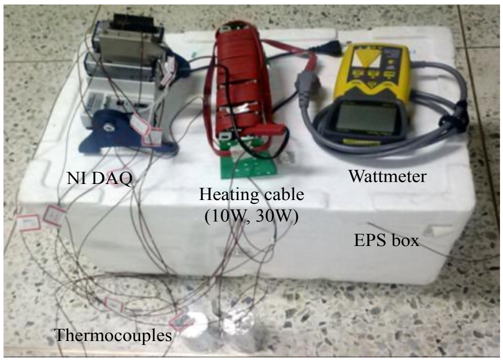


Figure 6. Configuration of the mini test-bed

The modeling approach is the same as that of the virtual experiment. The heat balance equation at each node (Figure 8) is based on the same textbooks (as mentioned previously) and the detailed explanation is omitted. It should be noted that the mini test-bed is designed with the purpose of indoor testing; hence exterior environmental effects (wind and solar radiation, etc.) are not considered.

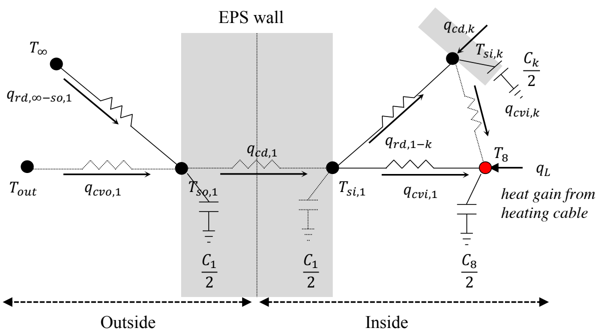


Figure 8. RC-network details of the EPS box

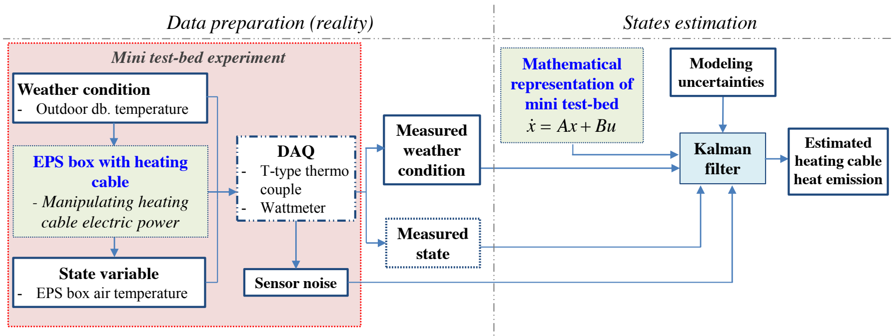


Figure 7. Overview of the mini test-bed experiment

Result of the mini test-bed experiment

Initial value setting of the state vector is similar to that of the virtual experiment (Table 4). In this experiment, the covariance and the model noise of the aggregated load were modified to take the nominal power of the heating cable into consideration. Customized initial setting of the Kalman filter is shown in Table 6. The dimensions of the vector and matrix were reduced from 15 to 14 due to absence of the window node in the mini test-bed (compared to Table 4 and Figure 4).

Table 6. Initial value setting of the mini test-bed experiment

PARAM.		SYM.	VAL.	DIM.	REASONS
State vector	Air temp.	$x_{(1,1)}$	25	[°C]	General room temperature
	Wall in/ex temp.	$x_{(i,1)}$ (i=2,...,13)	25	[°C]	Similar to general room temperature
	Aggregated load	$x_{(14,1)}$	0	[W]	No heat input at initial stage
Covariance matrix		$P_{(j,j)}$ (j=1,...,13)	10^2	[°C²]	Confidence on guess of initial temperature would be ±10°C
		$P_{(14,14)}$	30^2	[W²]	Maximum nominal heating cable power is 30W. Confidence range would be ±30W
Measurement matrix		$H_{(1,1)}$	1	[-]	Only air temp. is measured
		$H_{(1,n)}$ (n=2,...,14)	0	[-]	Not measured
Model noise covariance matrix		$Q_{(m,m)}$ (m=1,...,13)	0.5^2	[°C²]	Modeling error would be ±0.5°C
		$Q_{(14,14)}$	5^2	[W²]	Modeling error would be ±5W
Measurement noise covariance matrix		R	0.5^2	[°C²]	Estimation error would be ±0.5°C (see Table 2)

During the experiment, the 10W heating cable was turned on and off four times, and the 30W cable three times (Figure 9). Because the true convective heat emission from the heating cable is unknown, the result is compared to the electric power consumption. The estimation errors are roughly 3W and 5W for the 10W heating cable and 30W heating cable respectively.

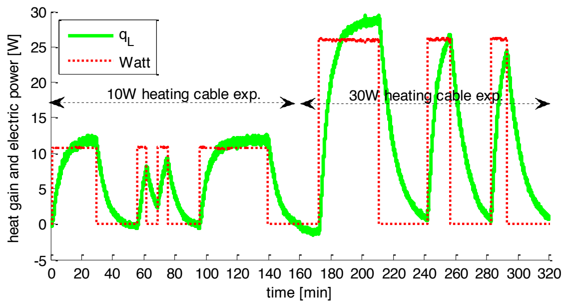


Figure 9. Comparison between estimated heat gain and electric power of 10W and 30W heating cables (q_L: estimated aggregated load, Watt: electric power)

Meanwhile, the pattern of the convective heat emission from the heating cable can be guessed by comparing the pattern of the measured air temperature shown in Figure 10, because there is only one source (convective heat emission) that heats air temperature. A closer look at Figures 9 and 10 reveal that both show a similar pattern. It can be concluded that the heat gain is reasonably estimated by the Kalman filter.

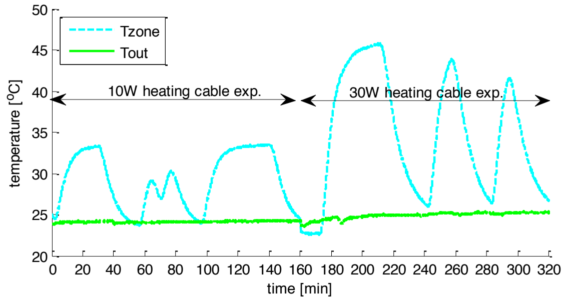


Figure 10. Measured EPS box air temperatures (T_{zone}) shown with outdoor air temperatures (T_{out})

CONCLUSION

This paper has examined the estimation performance of the Kalman filter in estimating the time-varying parameter, internal aggregated load. This paper presents a challenge to quantify the internal aggregated load, which is difficult to handle in energy modeling of existing buildings. As a proof-of-concept, the virtual and real experiments were conducted, producing promising results.

It should be noted that the residual error is inevitable because the estimation performance is impacted by the uncertainty (or noise) of the mathematical model ("epistemic uncertainty") and measurement ("aleatory uncertainty"). As addressed in (Incropera et al. 2008; Kim and Park 2011; Hugo 2012; Booth et al. 2013), heat transfer phenomena in real-life is complex and uncertain. Moreover, there is no crystal-clear way to measure such parameters or variables.

This leaves us no option except to some extent seeking a compromise with regard to uncertainty. In spite of many unknowns and the incomplete model, this study shows that accurate estimates can be achieved by making the best use of existing knowledge. The following aspects will be explored for further study:

- *Hypothesis testing* of the Gaussian random walk of the internal aggregated load.
- *Reduced-order Kalman filtering*. A high order state-space model is prone to error. Probably, a reduced-order model would relieve this problem, but the appropriate level of accuracy must be guaranteed.
- *Enhanced experiments*. Large scale experiments should be conducted for testing the approach presented in this paper.

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