

Integrating physics-based models with sensor data:

An inverse modeling approach

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Abstract

Physics-based building energy models (e.g., EnergyPlus) rely on some unknown input parameters (e.g., zone air infiltration) that are hard to measure, leading to uncertainty in simulation results especially for existing buildings with varying operating conditions. With the increasing deployment of smart thermostats, zone air temperature data are readily available, posing a new opportunity for building energy modeling if such data can be harnessed. This study presents a novel inverse modeling approach which inverts the zone air heat balance equation and uses the measured zone air temperature to analytically calculate the zone air infiltration rate and zone internal thermal mass (e.g., furniture, interior partitions), which are two important model parameters with great variability and difficult to measure. This paper introduces the technical concept and algorithms of the inverse models, their implementation in EnergyPlus, and verification using EnergyPlus simulated building performance data. The inverse modeling approach provides new opportunities for integrating data from massive IoT sensors and devices to enhance the accuracy of simulation results which are used to inform decision making on energy retrofits and efficiency improvements of existing buildings.

Keywords: Inverse model; EnergyPlus; building performance simulation; internal thermal mass; infiltration; sensor data

1. Introduction

Building energy retrofit is a cost-effective means of reducing greenhouse gas emissions by improving energy efficiency. The global energy efficiency market in the building sector was predicted to grow from \$68.2 billion in 2014 to \$127.5 billion in 2023 [1]. Building energy retrofit projects often rely on using building energy simulation to quantify energy savings of energy conservation measures (ECMs), which serve as the basis for project financial analysis to prioritize investment. However, energy simulation applications require some input parameters that are highly unknown and hard to measure, leading to large uncertainty in energy saving estimates and thus increased financial risk. Gaps and limitations on building energy retrofit analysis are mainly caused by the issues of ease of use and accuracy of simulation engines which require many input parameters [2,3].

Retrofit projects typically use calibrated energy models to ensure that baseline building systems are properly modeled. There are challenges in calibrating energy models for measurement and verification of energy savings. First, it needs to select parameters that significantly influence the simulated energy use. Heo and Zhao introduced technical approaches to select the most influencing parameters for energy model calibration [4,5]. Calibrations are typically done using: (1) manual processes with expert's rule of thumb or evidence-based [6,7], and (2) the recent automated methods backed by mathematical algorithms considering uncertainties [8–11]. For example, ExCalibBEM calibrates energy models through optimization of key parameters [12]. The challenge in the expert's calibration is that energy models are typically complex and have far more input parameters that can be manually analyzed by users, thereby it needs significant domain expertise. On the other hand, automated calibrations typically employ optimization-based or pattern-driven methods to identify parameters with predefined

variation ranges. The automated calibrated energy model may correspond to an unrealistic building configuration as multiple possible models can meet the calibration criteria [13] which are usually based on monthly or hourly whole-building electricity, and other fuel uses rather than more detailed sub-metered energy uses of individual building systems.

There are two common approaches to energy modeling: data-driven aka *black-box* models, and physics-based aka *white-box* models [14]. The data-driven approach uses measured data and various statistical techniques to develop models that take arbitrary collections of input variables [15]. Data-driven models tend to be both application specific and building specific, with some applications requiring a significant amount of measured data for training purposes [16,17]. These characteristics make data-driven models difficult to apply to different buildings or buildings without measured data. In recent years, data-driven energy models are getting attention as they provide discovery of models from large volumes of data. Also, data-driven models can be applied to replicate building stock energy consumption using energy consumption survey data with inference methods [18]. However, data collection is a tedious process, and some input parameters are difficult to estimate. In practice, a long- or short-term monitoring is usually conducted to train the model for estimating parameters, which helps enhance the calculation for existing buildings [19,20].

On the other hand, physics-based first principle approach covers a wide spectrum of complexity from low-fidelity reduced order and steady-state models [21–23] to high-fidelity dynamic models [24–26]. Decades of research have brought the development of various energy modeling methods and reviews of them [27–29], offering many calculation tools [30]. The physics-based models (also called forward modeling approach) take the physical parameters that describe the building as input, which can include building location, local weather conditions,

geometry, envelope construction materials, operational schedule, HVAC systems, and configurations. The physics-based models are typically used in the design phase to support building designers evaluate the energy performance of various design choices. Their drawback is that they require a significant number of building parameters as input and some of them are difficult to obtain in practice.

Zone internal thermal mass and zone air infiltration rate are two important yet uncertain user input parameters in physics-based models, contributing to the uncertainty of simulated results which pose challenges to an accurate estimate of energy savings from the retrofit of existing buildings. These two parameters are difficult to measure in practice even though possible in theory. Internal thermal mass refers to non-structural elements with thermal capacitance such as changeable partitions, furniture, and books. Although internal thermal mass has substantial influence on zone thermal dynamics, it has not been well studied in building energy simulation practice because it is both difficult to measure in compact form (e.g., a thermal mass constant for a zone) and time-consuming to characterize in more granular form (e.g., mass and thermal properties of furniture and books) [31,32]. Zone air infiltration rate has significant impacts on building energy use and indoor air quality. The air infiltration rate changes in time and dynamically influenced by indoor and outdoor climatic conditions. Infiltration is difficult to measure and characterize. Blower door testing is usually applied to residential buildings while hard for commercial buildings. Specifying the sizes and distribution of cracks in the building envelope, the permeability of the envelope, the airflow to the building, and the pressure distribution in and around the building is impractical [33].

This study focuses on the development and application of a novel inverse modeling approach to calculate two unknown and hard to measure input parameters, the zone air infiltration rate and

the zone internal thermal mass, using the measured zone air temperature. Zone air temperature data are easily available nowadays due to the wide adoption of smart and low-cost thermostats or portable temperature data loggers. Therefore, the inverse models have application potentials. Remaining sections of the paper cover the concept of the inverse model, the model algorithm development, and verification of the inverse model using simulated data.

2. Concept and Algorithm of the Inverse Models

2.1 Concept of the inverse models

Solving building energy and environmental problems inversely using measured data gets more attention as more sensor and meter data become available nowadays. Inverse modeling is a discipline that applies mathematical techniques to combine measurements and models. Inverse modeling can provide solutions when direct measurements of model parameters are not available or possible, rendering the use of numerical techniques [20]. It is used widely in the field of data assimilation where it serves as a method for estimating the state of a system and for determining optimal values of uncertain model parameters [34,35]. Many inverse modeling techniques are explored in building physics research to estimate the target parameters of complex problems, and the importance of the optimal use of data and algorithms was addressed when solving inverse problems [36]. Zhang et al. [37] addressed the limitations of physics-based thermodynamics and heat transfer in understanding building systems and environmental problems and introduced inverse modeling approaches to solve uncertain or unknown parameters using measured data. Moftakharia et al. [38] investigated the estimation of unknown thermal design parameters in building systems using numerical simulation and inverse modeling methods. Kuate et al. [39] proposed algorithms to reconstruct parameters of a building energy prediction model coupled with mathematical equations at a reduced scale single zone. Another study compared inverse

modeling approaches in predicting building energy performance [20]. An inverse modeling approach was also employed at a building stock scale to estimate building parameters, using energy consumption data and a reduced order energy model with statistical procedures, for a building stock model [18].

2.2 Zone air heat balance equation

Our approach begins with the fundamental physics-based zone air heat balance algorithm shown in Equation 1. The inverse models are built upon reformulating the zone air heat balance equation using the zone air temperature from measurements as a known input parameter to calculate the zone internal thermal mass or zone air infiltration rate as an unknown output parameter. The energy stored in the zone is represented as the product of zone air temperature T_z change rate and the zone heat capacitance C_z , which equals the sum of zone loads and the energy provided by the HVAC system Q_{sys} . C_z includes both the zone air thermal capacity and the effective capacitance of zone internal thermal mass (e.g., furniture, books, and changeable partitions), which is assumed to be in thermal equilibrium with the zone air. \dot{m}_{inf} is the zone infiltration mass flow rate. The multiplier, C_T in Equation 2, represents the equivalent adjustment to the zone air thermal capacitance.

$$C_z \frac{dT_z}{dt} = \sum Q_{int} + \sum h_s A_s (T_s - T_z) + \sum \dot{m}_{iz} C_p (T_{iz} - T_z) + \dot{m}_{inf} C_p (T_o - T_z) + Q_{sys} \quad (1)$$

$$C_z = V \rho_{air} C_p C_T \quad (2)$$

The concept of effective zone air thermal capacitance is used in the zone air heat balance calculations in the building performance simulation tools EnergyPlus [40] and DeST [41] as one way to consider the impact of partition walls and furniture on zone thermal dynamics. In EnergyPlus, the term is called the multiplier of zone air thermal capacitance; In DeST, the term is called the furniture coefficient.

EnergyPlus [40] was used for the demonstration of the inverse model development. EnergyPlus is an open source building energy simulation engine that can model ventilation, cooling, lighting, water use, renewable energy generation and other building energy flows. EnergyPlus is managed by DOE for new releases every six months for new modeling features and bug fixes. EnergyPlus enables testing new features [42], which makes it ideal for the implementation and verification of the inverse models. It should be noted that the proposed inverse models are generic and can be adopted by other building energy simulation applications. EnergyPlus has two zone air heat balance solution algorithms: *3rd order backward difference* and *analytical*. The *3rd backward difference* method provides stability without requiring a prohibitively small time step, but has truncation errors and requires a fixed time step length for the previous three time steps. Therefore, different time step lengths may result in invalid temperature coefficients. The *analytical* method is an integrated approach that can obtain solutions without truncation errors. It only requires the zone air temperature at the previous time step and is thus independent of time step length [26].

2.3 The algorithm to solve zone internal thermal mass

Thermal mass plays an important role in energy models to predict the transient cooling or heating loads and in strategizing heating, ventilation, and air conditioning (HVAC) system controls. There has been numerous research on energy efficient design and reducing peak cooling demand using thermal mass [43–47]. Building envelope takes a significant amount of thermal mass, and their physical properties such as density, volume, and specific heat capacity can be determined per construction documents. However, the internal thermal mass has not been paid adequate attention in most building energy simulation practices.

2.3.1 Representation of zone internal thermal mass

Components such as furniture and partitions with thermal capacitance cannot be ignored in the dynamic thermal models. Although the internal thermal mass has a substantial influence on the prediction of peak cooling demand, it is very difficult to obtain detailed physical properties as required inputs to the current simulation tools [31,32]. This is one key factor leading to high uncertainty for energy performance analysis and simulations results. There have been efforts in exploring ways to estimate the thermal mass of zones. Braun et al. provided thermal mass control strategies, including internal thermal mass estimates that optimize the heating and cooling energy cost savings [19,48]. They developed a simplified heat balance equation, and derived an inverse model, using short-term measured data to identify control strategies for shifting and reducing peak cooling loads. Their studies provide background on the concept and solve the problem of optimizing zone temperature set-points. Wang et al. provided a method to estimate the building internal thermal mass, using a thermal network structure of lumped thermal masses and operational data to estimate the lumped parameters [32]. A genetic algorithm was used to estimate the lumped internal thermal parameters.

Antonopoulos and Koronaki [49, 50, 51] studied zone thermal mass and quantified its influence on zone thermal dynamics. They used two terms, apparent and effective thermal capacitance, with the former term represents the simple sum of all physical thermal capacitance of building envelopes (walls, roofs, floors), interior partitions, and furniture. While the latter term represents the equivalent thermal capacitance, which is calculated in their study by forcing the solution of a lumped-system differential equation to follow the experimentally validated, finite-difference solution of a rigorous set of coupled differential equations describing the heat transport and energy balance in buildings. They found that for typical fully-insulated, one-story,

detached houses, the envelope, interior partitions and furnishings effective heat capacitances are 78.1%, 14.5% and 7.4%, respectively, of the total effective thermal capacitance.

National Renewable Energy Laboratory (NREL) studied details of the U.S. Department of Energy (DOE) reference models to represent the internal thermal mass in U.S. commercial buildings [52]. These DOE reference building models use representative inputs for internal mass with assumptions of standard wood, medium smooth interior furnishing conditions.

There are two approaches to model internal thermal mass in EnergyPlus. One approach is to use the InternalMass object to define construction specifications of internal furnishing materials, and the other is to use the temperature capacitance multipliers. The multiplier approach increases the zone air capacity equivalently to represent the effective storage capacity of the zone internal thermal mass [26]. The InternalMass object specifies construction materials and surface areas of internal thermal mass objects. InternalMass objects participate in the zone air heat balance and the long-wave radiant exchange, and exchange energy through its both surfaces by convection. The geometry of InternalMass objects is greatly simplified. They do not directly interact with solar heat gain calculations because they do not have a specific location in space. The proper modeling of furniture (internal mass object) is an area that needs further research in EnergyPlus. There are complicating factors in finding the direct view factors of the internal mass object for long-wave radiation calculation since the location of surfaces such as thermal mass representing furniture and partitions are not known. Another limiting factor is the exact calculation of direct view factors is computationally very intensive even if the positions of all surfaces are known [26]. The ZoneCapacitanceMultiplier:ResearchSpecial object is an alternative compact specification that sidesteps challenges in determining volumes and thermal properties of individual internal thermal mass objects. Shown in Equation 2, the capacitance multiplier C_T

scales the heat capacity of the air in the zone. A value of 1.0 indicates the capacitance comes only from the zone air – a case representing an empty zone without furniture etc.

The zone capacitance multiplier only corrects the zone air heat capacity reflecting heat stored in the internal mass. Assumptions are not different from the approach used in the InternalMass object, which ignores the geometry construction of the internal mass, and assumes no reception of solar heat gains through windows. EnergyPlus version 8.6 and older assume a single constant multiplier for all zones in a building. Although users can set this multiplier, it is not easy to determine a reasonable value for a typical or specific room furniture configuration. We enhanced EnergyPlus to allow zone-specific multipliers.

We compared EnergyPlus simulation results of the two approaches under diverse internal thermal mass and climate conditions, using the DOE reference small office model which is composed of five zones (one core zone and four surrounding perimeter zones) [52]. Table 1 shows the specifications of the two internal thermal mass modeling approaches. The InternalMass object modeling approach used an internal furnishing construction with six-inch wooden material. The interior furnishing surface area is double of the zone floor area. The multiplier approach used the ZoneCapacitanceMultiplier:ResearchSpecial object to assign the temperature capacity multiplier for all zones in the building. The multiplier is 1.0 assuming a zone has no internal mass and has a value greater than 1.0 if a zone is furnished. To determine the best multipliers for different simulation settings, we conducted parametric runs varying the multiplier from 1 to 20.

Table 1 Simulation setup to compare two approaches representing zone internal mass

Two Approaches		Specification
EnergyPlus Object	Field	

InternalMass	<ul style="list-style-type: none"> - Construction - Surface Area 	<ul style="list-style-type: none"> - Construction name: Interior Furnishings - Material: Standard 6 inch wood - Surface area: Two times of the zone floor area - Properties: <ul style="list-style-type: none"> • Thickness: 0.15 m • Conductivity: 0.12 W/m-K • Density: 540 kg/m³ • Specific heat: 1210 J/kg-K
ZoneCapacitanceMultiplier: ResearchSpecial	Temperature Capacity Multiplier	Parametric runs with multiplier from 1 to 20

The simulation results of the zone mean air temperature were compared using the Normalized Mean Bias Error (NMBE) and Coefficient of Variance of Root Mean Square Error (CVRMSE). NMBE and CVRMSE are commonly used to determine the goodness of fit between two sets of data from energy simulation results [13]. If NMBE and CVRMSE of two sets of results are no greater than 10% and 30% for hourly data comparison, they are deemed to agree with each other. It was found that a multiplier of eight provided the best fit between two results sets based on the NMBE (less than 4%) and CVRMSE (less than 5%). This comparison study confirms that the internal thermal mass modeling approach using the InternalMass object with construction specifications can be alternatively represented with the temperature capacity multiplier modeling approach. The multiplier of eight can be used to represent the internal thermal mass in this case.

2.3.2 Calculating the zone thermal capacitance multiplier

The zone internal thermal mass including furniture, books, and changeable partitions is assumed to be in thermal equilibrium with the zone air. Thus internal thermal mass can be added to the zone heat capacitance, C_z according to Equation 2. The internal mass is represented as a capacitance multiplier, C_T indicating the capacitance as part of the air in the volume of the specified zone. The default value is given as 1.0 corresponding to the total capacitance of the

zone's volume of air at current zone conditions. The proposed inverse model derives the capacitance multiplier that indicates the internal thermal mass heat capacitance added to the zone air. Equation 3 calculates the time-series zone air temperature, T_z by reformulating Equation 1 using the *analytical* solution method of the zone air heat balance.

$$T_z^t = (T_z^{t-\delta t} - X) \times e^{\left(-\frac{\sum h_s A_s + \sum \dot{m}_{iz} C_p + \dot{m}_{inf} C_p + \dot{m}_{sys} C_p}{C_z^t} \delta t\right)} + X \quad (3)$$

$$\text{Where } X = \frac{\sum Q_{int} + \sum h_s A_s T_s + \sum \dot{m}_{iz} C_p T_{iz} + \dot{m}_{inf} C_p T_o + \dot{m}_{sys} C_p T_{sup}^t}{\sum h_s A_s + \sum \dot{m}_{iz} C_p + \dot{m}_{inf} C_p + \dot{m}_{sys} C_p} \quad (4)$$

Equation 5 inverts Equation 3 to calculate the zone heat capacity C_z^t using the zone air temperature at the current time step T_z^t and the previous time step $T_z^{t-\delta t}$.

$$C_z^t = -\frac{(\sum h_s A_s + \sum \dot{m}_{iz} C_p + \dot{m}_{inf} C_p + \dot{m}_{sys} C_p) \delta t}{\ln \left[\frac{T_z^t - X}{T_z^{t-\delta t} - X} \right]} \quad (5)$$

Equation 5 can be solved when the HVAC system is off ($\dot{m}_{sys} = 0$) or on (requiring to measure \dot{m}_{sys}). When the temperature difference between T_z^t and $T_z^{t-\delta t}$ is small or even zero, for example when the HVAC system is on to maintain zone temperature close to the thermostat setpoint, or when the HVAC system is off and external thermal disturbances are constant, the denominator of Equation 5 can become close to zero, which leads to unstable C_z^t calculations. Zone heat capacity is an important component for buildings as it stabilizes interior temperatures. The temperature capacity multiplier, i.e., the internal mass multiplier C_z^t is calculated for each time step using Equation 6.

$$C_T^t = \frac{C_z^t}{V\rho_{air}C_p} \quad (6)$$

An underlying assumption of the inverse model is that the zone heat capacity is treated as constant for the equilibrium of the inversed zone air heat balance model. However, in a mathematical point of view, the calculated C_z^t will vary with the actual dynamic conditions, leading to the varying internal mass multiplier C_T^t . The inverse model determines a time span when $|T_z^t - T_z^{t-\delta t}| > 0.05^\circ\text{C}$ that provides a more stable condition to calculate C_z^t . The internal mass multiplier calculations are only done when the zone air temperature difference between two adjacent time steps meets this criteria, to avoid the anomaly or overflow results from incorrect use of the inverse model.

2.4 The algorithm to solve zone air infiltration rate

Infiltration is represented as a volumetric or mass flow rate of outside air into a building. Infiltration is an uncontrolled outside air flow depending on the air-tightness of the building envelope and indoor and outdoor climate conditions. A large percentage of the total energy loss of a building can occur through envelope leakage, resulting in excessive heating and cooling loads. The infiltration air flowrate is inherently dynamic and difficult to measure, making it a highly uncertain parameter in building energy models.

2.4.1 Representation of zone infiltration rate

The infiltration modeling is relatively simplified in energy simulation because of difficulties in providing detailed inputs of the envelope crack size and distribution, the air permeability, and the pressure distribution in and around the building. The infiltration airflow model captures a function of the infiltration design airflow considering building's construction quality and local

weather conditions. Wind speed and temperature at the zone height – both are sensitive to elevation and height from the ground - are driving factors which affect pressure difference between the outside and the inside of the building. The simple infiltration modeling approach has an empirical correlation that modifies the base infiltration rate as a function of wind speed and temperature difference across the envelope [33]. Equation 7 shows the infiltration rate calculation used in EnergyPlus. The EnergyPlus object ZoneInfiltration:DesignFlowRate defines a design infiltration air flowrate with correcting coefficients.

$$q_{inf} = q_{inf_design} F_{schedule} [A + B|T_z - T_o| + C \times v_{wind} + D \times (v_{wind})^2] \quad (7)$$

The difficulty in using this approach is the determination of the design flowrate and the reasonable values of the coefficients. The DOE reference energy models provide representative design infiltration rates for different building types, construction types, and built years [52]. Table 2 shows examples of design infiltration volumetric flowrates and their air change per hour (ACH) for the reference office models.

Table 2 Infiltration flowrates in DOE reference office building models

Vintage	Building type	Infiltration ACH in perimeter zones	Assumptions of infiltration design flowrate for perimeter zones
Pre-1980	Small office	2.46	0.001133 m3/s/m2 (0.22 cfm/ft2) per exterior surface area at 4 Pa pressure difference.
	Medium office	1.03	
	Large office	0.98	
Post-1980	Small office	2.46	
	Medium office	1.03	
	Large office	0.98	
New-2004	Small office	0.66	0.000302 m3/s/m2 (0.06 cfm/ft2) per exterior surface area at 4 Pa pressure difference.
	Medium office	0.28	
	Large office	0.26	

2.4.2 Solving the zone infiltration rate

The proposed inverse model derives the infiltration air flowrate at each timestep of the simulation using the measured zone air temperature. Equation 8 shows the heat balance equation that calculates the time series zone air temperature using the *3rd order backward difference* method.

$$T_z^t = \frac{\sum Q_{int} + \sum h_s A_s T_s + \sum \dot{m}_{iz} C_p T_{iz} + \dot{m}_{inf} C_p T_o + \dot{m}_{sys} C_p T_{sup} - \left(\frac{C_z}{\delta t}\right) (-3T_z^{t-\delta t} + \frac{3}{2}T_z^{t-2\delta t} - \frac{1}{3}T_z^{t-3\delta t})}{\left(\frac{11}{6}\right) \frac{C_z}{\delta t} + \sum h_s A_s + \sum \dot{m}_{iz} C_p + \dot{m}_{inf} C_p + \dot{m}_{sys} C_p} \quad (8)$$

Equation 9 inverts Equation 8 to derive the zone infiltration mass flow rate using the zone air temperature.

$$\dot{m}_{inf} = \frac{\sum Q_{int} + \sum h_s A_s T_s + \sum \dot{m}_{iz} C_p T_{iz} + \dot{m}_{sys} C_p T_{sup} - \left(\frac{C_z}{\delta t}\right) (-3T_z^{t-\delta t} + \frac{3}{2}T_z^{t-2\delta t} - \frac{1}{3}T_z^{t-3\delta t}) - T_z^t \left(\left(\frac{11}{6}\right) \frac{C_z}{\delta t} + \sum h_s A_s + \sum \dot{m}_{iz} C_p + \dot{m}_{sys} C_p\right)}{C_p (T_z^t - T_o)} \quad (9)$$

The infiltration volume flowrate q_{inf} is then calculated from the derived infiltration mass flowrate using Equation 10.

$$q_{inf} = \frac{\dot{m}_{inf}}{\rho_{air}} \quad (10)$$

The inverse equation derives more reliable infiltration flowrates for time steps when the difference between the indoor zone air and outdoor air temperature, a denominator term in Equation 9, is greater than 5 °C, i.e., $|T_z^t - T_o^t| > 5.0 \text{ }^\circ\text{C}$.

3 Implementation of the Inverse Models in EnergyPlus

The implementation in EnergyPlus involves several steps: (1) revising the existing object *ZoneCapacitanceMultiplier:ResearchSpecial* to enable a flexible representation of a zone air temperature capacitance multiplier, i.e., different internal mass multipliers can be input and used for different zones, (2) creating a new object *HybridModel:Zone* incorporating new inputs for the

inverse models, and (3) coding the inverse models in the zone air heat balance calculation module.

3.1 Changes in the existing object to enable different capacitance multipliers for individual zones

The existing EnergyPlus object *ZoneCapacitanceMultiplier:ResearchSpecial* allows a capacitance multiplier input to specify the effective thermal capacity of the zone air. The capacitance multiplier of 1.0 indicates the capacitance of the zone air only. The multiplier can be greater than 1.0 when considering the thermal storage capacity of zone internal thermal mass including furniture, books, and partitions in the zone. EnergyPlus versions 8.6 and older were limited to have a single multiplier for all zones of a building, which is specified by the field, *Temperature Capacity Multiplier* in the EnergyPlus object, *ZoneCapacitanceMultiplier:ResearchSpecial* [26]. A new field, *Zone* or *ZoneList Name* was added to enable specifying a different multiplier for a specific zone or zone list/group, which allows internal mass levels to be treated differently for individual zones as needed.

3.2 An energyplus new object for the inverse models feature

A new object *HybridModel:Zone* was created in EnergyPlus Input Data Dictionary (IDD) to define user inputs for the inverse models. The inverse model feature uses a new simulation flag triggered by user-specified object(s) *HybridModel:Zone*. The object specifies calculation options, measured temperature data, and the temperature measurement period. These are defined at the per-zone basis.

HybridModel:Zone,

A1, \field Name

A2, \field Zone Name

A3, \field Calculate Zone Internal Thermal Mass (Yes or No)

A4, \field Calculate Zone Air Infiltration Rate (Yes or No)

A5, \field Zone Measured Air Temperature Schedule Name

N1, \field Begin Month

N2, \field Begin Day of Month

N3, \field End Month

N4; \field End Day of Month

This new object triggers the inverse modeling simulation that calculates the zone temperature capacitance multipliers or infiltration rate depending on user's input. The zone air temperature inputs are designed to be a time schedule using the *Schedule:File* object with values stored in an external Comma Separate Value (CSV) file. The inverse zone heat balance equations are added to the EnergyPlus code module *ZoneTempPredictorCorrector*. The inverse models allow individual zones to have different temperature measurement periods, and some zones can have measured temperature data while others do not.

4 Verification of Results from the Inverse Models in EnergyPlus

This section presents the verification of the inverse models implemented in EnergyPlus using simulation results of the DOE reference small-office models. The small office building has a single story with five zones: four perimeter ones and one core. The simulation setup includes three typical climate locations: Miami (Florida), Chicago (Illinois), and Fairbanks (Alaska) representing hot climate, hot-summer and cold-winter, and cold climate, as well as two vintages: pre-1980 and 2004 conditions. DOE reference energy model development report provides details of the small-office model [52].

4.1 Verification of the zone internal thermal capacitance multiplier

Figure 1 illustrates the process of verifying the calculation of the capacitance multipliers for individual zones. The verification workflow is as follows:

- 1) Create five instances of the *ZoneCapacitanceMultiplier:ResearchSpecial* object, one for each zone. Then enter the *Temperature Capacity Multiplier* field of each object as follows:

- Core zone_ZN: 2.0
- Perimeter_ZN1: 5.0
- Perimeter_ZN2: 10.0
- Perimeter_ZN3: 15.0
- Perimeter_ZN4: 20.0

Different values were used for different zones to test their diversity and sensitivity.

- 2) Run EnergyPlus simulation in a normal mode (rather than the inverse mode) to calculate and generate an output of *Zone Mean Temperature* for each zone with a timestep of ten minutes.
- 3) Create a CSV file for the *Schedule:File* object using the simulated zone air temperature for each zone.
- 4) Create inputs in *HybridModel:Zone* object for each zone with the following settings:
 - *Calculate Zone Internal Thermal Mass*: YES
 - *Calculate Zone Air Infiltration Rate*: NO
 - *Zone Measured Air Temperature Schedule Name*: use the schedule name in the *Schedule:File* object
 - *Begin Month*: 1
 - *Begin Day of Month*: 1
 - *End Month*: 12
 - *End Day of Month*: 31
- 5) Run EnergyPlus simulation in the inverse model mode to calculate multipliers for each zone.
- 6) Obtain zone capacitance multipliers from the zone summary table of EnergyPlus' tabular reports.

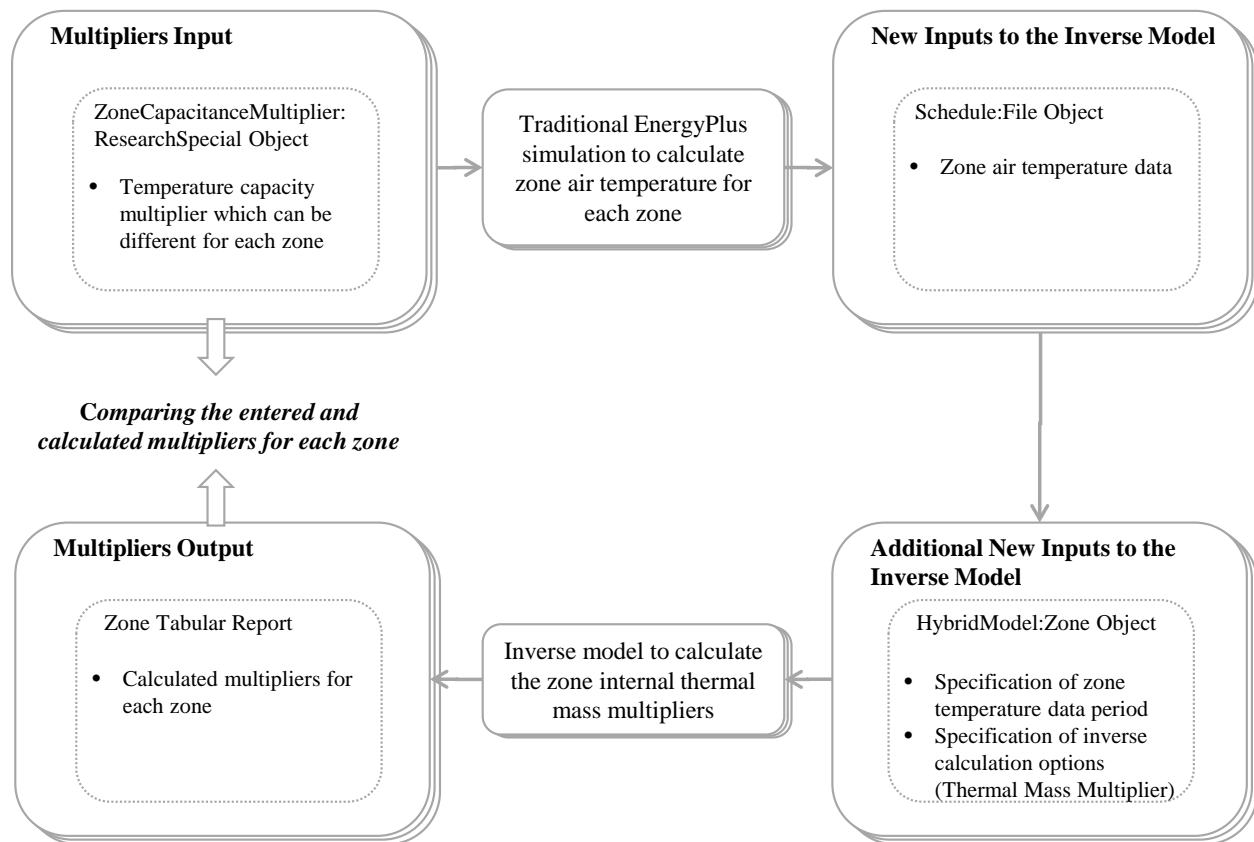


Figure 1 Verification workflow of the inverse model of zone internal thermal mass in EnergyPlus

Table 3 shows the verification results, which confirm the zone capacity multipliers calculated using the inverse model in EnergyPlus are almost the same as the entered multiplier values that were used to calculate the zone air temperature. This verifies that the inverse model of the zone internal thermal mass is correctly implemented in EnergyPlus. Some minor differences are caused by the normalization of temperature data when transforming the heat balance equation and numerical rounding in processing parameter values.

Table 3 Inverse model results for verification of the zone capacity multiplier calculation

Building	Location	Vintage	Multiplier Input				
			2	5	10	15	20
Multiplier Inverse Model Results							

			Core zone	Perimeter zone 1	Perimeter zone 2	Perimeter zone 3	Perimeter zone 4
Small Office	Miami	1980	2.00	5.00	10.00	15.00	20.00
Small Office	Miami	2004	2.00	5.00	10.00	15.00	20.00
Small Office	Chicago	1980	2.00	5.00	10.00	15.00	20.00
Small Office	Chicago	2004	2.00	5.00	10.00	15.00	19.99
Small Office	Fairbanks	1980	2.02	5.00	10.00	15.00	20.00
Small Office	Fairbanks	2004	2.00	5.00	10.00	15.00	20.00

4.2 Verification of the zone infiltration rate

To verify the inverse model of zone air infiltration rate implemented in EnergyPlus, the same small-office building model was used. The verification workflow (Figure 2) is similar to the previous one. First, a complete year of EnergyPlus simulations with HVAC systems off (free floating mode) were run in normal mode, covering a range of combinations of zone infiltration rates (1, 2, and 3 air change per hour) and zone internal capacity multipliers (1, 5, and 10) listed in Table 4, to generate the zone air temperatures. The simulated zone air temperatures were then compiled as schedules to drive the inverse mode EnergyPlus simulations to calculate the zone air infiltration at each ten-minute time step. Finally, the entered and calculated zone air infiltration rates were compared to verify the inverse model.

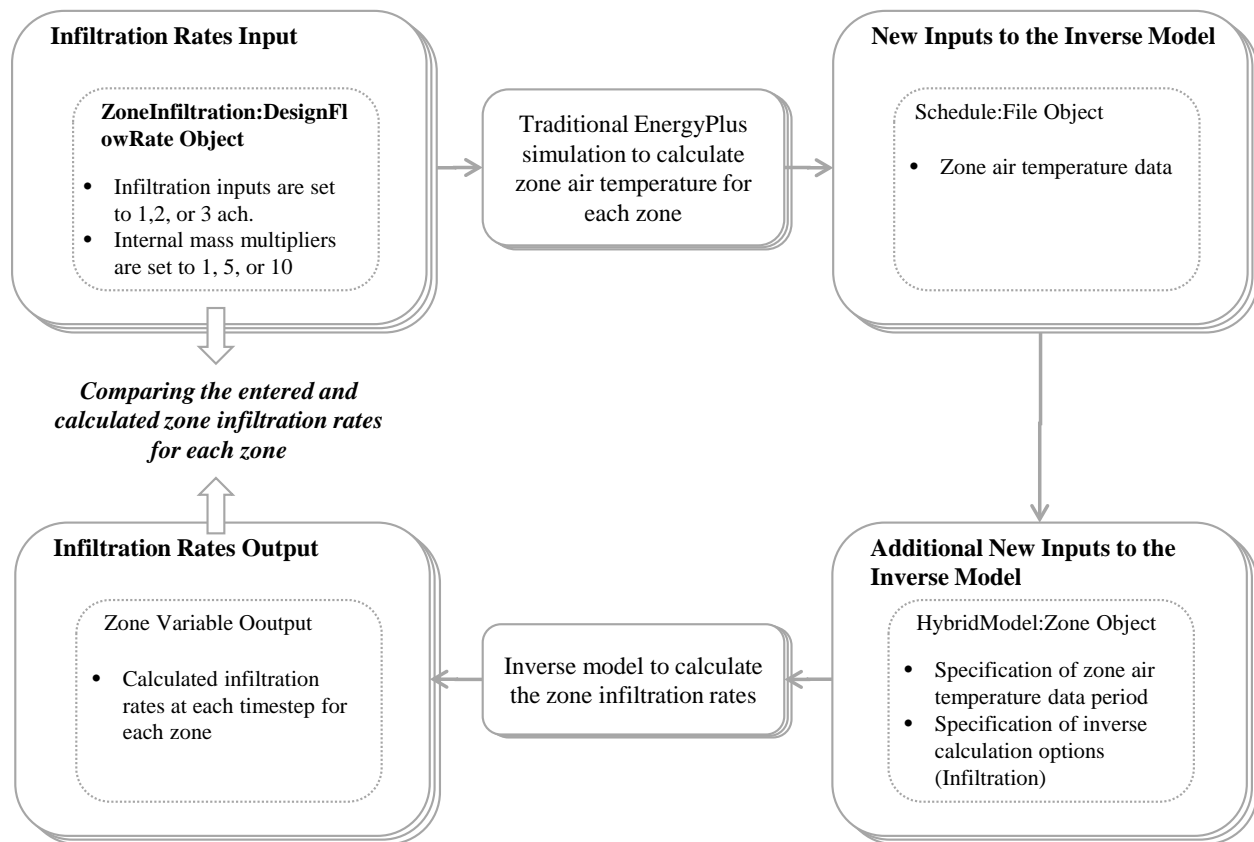


Figure 2 Verification workflow of the inverse model of zone infiltration rate in EnergyPlus

Table 4 shows the simulated results of the annual averaged infiltration rates calculated from the inverse models, which agree with the input infiltration rates very well (relative errors range from -1% to 9%). This verifies that the inverse model of zone air infiltration rate is correctly implemented in EnergyPlus. Some minor differences are caused by the normalization of temperature data when transforming the heat balance equation and numerical rounding in processing parameter values.

Table 4 Inverse model results for verification of the zone air infiltration rate calculation

Building	Location	Inputs	Infiltration simulation result
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		Infiltration design flow rate input (ACH)	Internal mass multiplier	Core zone	Perimeter zone 1	Perimeter zone 2	Perimeter zone 3	Perimeter zone 4
Small Office - pre1980	Miami	1	1	1.00	1.00	0.99	1.00	1.00
		1	5	1.00	1.00	0.99	1.00	1.00
		1	10	1.04	1.09	1.07	1.05	1.07
		2	1	2.00	2.00	2.00	2.00	2.00
		3	1	3.00	3.00	3.00	3.00	3.00
	Chicago	1	1	1.01	1.02	1.02	1.01	1.02
		1	5	1.05	1.07	1.05	1.05	1.06
		1	10	1.07	1.09	1.08	1.07	1.08
		2	1	2.01	2.01	2.01	2.01	2.01
		3	1	3.00	3.00	3.00	3.00	3.00
	Fairbanks	1	1	1.01	1.02	1.01	1.01	1.01
		1	5	1.04	1.06	1.04	1.04	1.05
		1	10	1.05	1.07	1.05	1.05	1.05
		2	1	2.01	2.01	2.01	2.01	2.01
		3	1	3.00	3.00	3.00	3.00	3.00

5 Discussion

When both the zone infiltration and internal mass parameters are unknown, the inverse models cannot solve both unknown parameters at the same time. The problem can be formulated as an optimization problem that can be solved iteratively. For example, the infiltration rate can be solved inversely first by assuming a default internal mass multiplier (we recommend 3 to 6 for lightly furnished offices, 6 to 10 for typical offices, and 10 to 15 for heavily furnished offices) representing a typical office furnishing configuration. Then the calculated infiltration rates can be used to adjust the internal mass multiplier using the inverse model. This iterative process ends when satisfied solutions are achieved.

Wider use of sensors to meet the need for better controls in existing buildings enables a new paradigm of research in building energy simulation. Zone internal thermal mass and infiltration are common uncertain parameters that hinder the accuracy of energy simulation. Typical energy modelers do not have enough knowledge on these parameters, and even experienced ones often rely on default values provided by tools or values used in reference models, which do not reflect real building conditions. The inverse modeling approach aims to solve these uncertain parameters in energy modeling for existing buildings, which can be integrated into the traditional energy model calibration workflow to speed up the process.

The mathematical expressions of the cause-effect relationships for physical systems are often a bottleneck when solving problems in complex built environments. When such mathematical expressions are representing physical systems, the correlations among various factors are intertwined with each other. The inverse models have limitations in exploring the uncertainties of other model parameters, which causes all uncertainties are reflected in the two zone parameters (internal thermal mass and infiltration), and this can lead to overfitting. The impact of the uncertainty of zone air temperature data should also be studied as the temperature sensor may lack needed routine calibration for accurate measurement, or the zone air temperature is not measured at the right location.

This study examines the internal thermal mass multiplier approach to capture the abstract of the physical characteristics of the internal thermal mass. The multiplier approach has not been widely used for inputs to represent the internal thermal mass in typical energy modeling practices. The DOE reference models show that the typical internal mass objects can be represented as a multiplier of eight. Thus, it is recommended that energy modelers use the multiplier of eight as a starting point for typical office internal mass configurations. A smaller

multiplier for light furnishing environments and a greater multiplier for heavy thermal mass offices can be considered.

The current implementation of the inverse models applies to periods when HVAC systems are off, i.e., zones are in free-floating mode. However, this is not a limitation of the inverse models but rather based on the assumption that measured energy delivered by HVAC systems is not easily available. The inverse models will be expanded in future to cover periods when HVAC systems are operating, which will require the measurement data of the supply air temperature and supply air volume as input parameters to the inverse models.

6 Conclusions

This study presents a novel approach to formulating and solving inverse problems of using the zone air temperature in the zone air heat balance equation to calculate the zone internal thermal mass multiplier and infiltration rate, when a zone is in the free-floating mode (i.e., the heating and cooling system is off). The inverse models were implemented in EnergyPlus version 8.7 and later. However, the models are generic and can be adopted by other building simulation programs. Verification results, using the simulated data from the DOE reference small-office building models, demonstrate the correct implementation of the inverse models in EnergyPlus. The inverse models provide a new way of applying sensor data in building performance simulation, which can improve the simulation accuracy and thus help address challenges in estimating energy savings from retrofitting of existing buildings.

Future efforts include expanding the inverse approach for zones with HVAC system in operation, which requires the measured delivered energy from HVAC system as an input to the inverse model. A follow-up paper will provide details of the validation method, process and results of the inverse models using measured data collected from controlled experiments

conducted at the Facility for Low Energy eXperiment (FLEXLab) in Lawrence Berkeley National Laboratory (LBNL) [53].

Nomenclatures

Q_{int}	Internal heat gains from occupants, lights and plug-in equipment
h_s	Convective heat transfer coefficient
A_s	Zone surface area
T_s	Zone surface temperature
T_z	Zone air temperature
T_{iz}	Interzone air temperature
T_o	Outdoor air temperature
T_{sup}	HVAC system supply air temperature
q_{inf}	Infiltration air flow rate
\dot{m}_{inf}	Infiltration air mass flow rate
\dot{m}_{iz}	Interzone air mass flow rate
\dot{m}_{sys}	HVAC system air mass flow rate
V	Zone air volume
ρ_{air}	Air density
C_z	Heat capacity of zone air and internal thermal mass
C_p	Zone air specific heat
C_T	Heat capacity multiplier
A	Constant coefficient
B	Temperature coefficient
C	Velocity coefficient
D	Velocity squared coefficient
v_{wind}	Wind velocity
$F_{schedule}$	Infiltration schedule value between 0 and 1

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