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A rigorous physics-based enhanced parameter estimation (EPE) methodology for calibration of building energy simulations

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Buildings rarely perform as designed/simulated and there are numerous tangible benefits if this gap is reconciled. A new scientifically rigorous yet pragmatic methodology for calibrating building energy simulations - called Enhanced Parameter Estimation (EPE) - is proposed that allows physically relevant parameter estimation rather than a blind force-fit to energy use data. Starting with a rapidly created simulation model, calibration is performed in two stages: (a) building shell calibration with the HVAC system replaced by an ideal system that meets the loads (b) HVAC system calibration with the building shell and all internal loads replaced by a box with only process loads. In the first stage, EPE identifies a small number of high-level heat flows in the energy balance, calculates them with specifically tailored individual driving functions, introduces physically significant parameters to best accomplish energy balance, and, estimates the parameters and their uncertainty bounds. Calibration is thus done with corrective heat flows without any arbitrary tuning of input parameters. Calibration accuracy is enhanced by machine learning of the residual errors. The EPE methodology is demonstrated by means of: a synthetic building and an actual 75,000 sq. ft. building in Pennsylvania. Future work needed for widespread application is discussed.

Introduction

Buildings in the United States consume about 40% of total primary energy resulting in a fifth of total greenhouse gas emissions. Energy efficiency in buildings is a climate change imperative and a significant business opportunity. Electric utilities benefit significantly from energy efficiency through deferral of transmission and distribution system infrastructure upgrades. With increasing penetration of renewables, the conventional power generation profile has changed drastically; it now has to deal with increased variability. Buildings can provide flexibility from the demand side to adapt to variability of generation. To take full advantage of greenhouse gas emission reductions as well as grid flexibility arising from building operation and energy conservation measures, one needs to perform simulations of numerous scenarios. Although, for some limited purposes, such as monitoring and verification (M&V), fault detection and simple modifications to building operation, one can use empirical/statistical models, for more comprehensive cases properly reconciled physics-based detailed simulations are essential.

Buildings rarely perform as simulated, even after accounting for design vs as-built differences. Hence the need for reconciliation using monitored data. As noted in Reddy (2006), "Historically, the calibration process has been an art form that inevitably relies on user knowledge, past experience, statistical expertise, engineering judgment, and an abundance of trial and error". This approach hardly informs design or simulation. The building performance gap – the serious discrepancy between modeled and actual energy performance – has often caused frustration Imam, Coley, and Walker (2017), Knapton (2017). In the context of building energy analysis, the term "calibration" is pervasively used to denote any method of reconciling simulations with measured performance. In this paper we identify and distinguish between three terms: *tuning, calibration and parameter estimation*. Most methods fall within the tuning category.

There have been numerous published papers and reports on calibrated simulation and extensive references are

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provided in literature reviews by Reddy (2006) and by Coakley, Raftery, and Keane (2014). An overarching principle is that readily available performance data (Building Energy Management System, interval electric meter, weather station) allows estimation of a small number of parameters, whereas building simulation programs have hundreds if not thousands of inputs. Different calibration techniques handle this problem differently. One approach is by manual, iterative and pragmatic intervention where the analyst changes the simulation inputs based on observed differences between measured and simulated energy use. Another approach Reddy, Maor, and Panjapornpon (2007)) involves a Monte Carlo method of sampling the numerous simulation inputs, identifying and estimating a subset of inputs that gives the best fit to performance data. Subsequently, several researchers have made computational advances, still relying on a variant of Monte Carlo to sample simulation inputs, resulting in the development of Autotune methodology (Chaudhary et al. (2016)) to automate the calibration process. The Autotune methodology also uses a database of building energy profiles, in combination with data mining, to automatically modify the simulation inputs. This approach is intrinsically over-parametrized resulting in a large degree of indeterminacy of the parameters. Therefore, there is little expectation that the reconciled model has captured the right numerical values of the various input parameters.

A novel method proposed in this paper is in the conceptualization and construction of the parameters to be estimated without modifying the simulation input variables. A hierarchy of parameters are defined and as many of them are estimated as the data permits. A two stage process is used: in stage 1 the shell-related parameters are estimated. In stage 2, the HVAC-related parameters are estimated. A comparison of expected and estimated values of the parameters solves the problem of the "scientific" gap between simulations and performance data. This approach also gives an estimate of the errors in the parameters. Note also that in cases where certain flows, e.g., ground heat flow or flow to cooler sky are significant, we can devise specialized simulations to determine the audit heat flows and, introduce and estimate associated parameters.

An earlier attempt at a more statistically sound calibration methodology was made in Sun and Reddy (2006) who proposed a building calibration methodology, along the lines of parameter estimation, that "involves several distinct concepts, namely, sensitivity analysis (to identify a subset of strong influential variables), identifiability analysis (to determine how many parameters of this subset can be tuned mathematically and identifies which ones are the best candidates), numerical optimization (to determine the numerical values of this best subset of parameters), and uncertainty analysis (to deduce the range of variation of these parameters)". Some aspects of this study are adopted in the new methodology for HVAC calibration, but there are important differences as described later.

A true parameter estimation method for reconciling an in-house simulation with actual performance, called PSTAR (Primary and Secondary Terms Analysis and Renormalization) was introduced in Subbarao (1988). PSTAR provides a method for identifying and computing primary and secondary terms in energy balances, and then introduces certain parameters that are estimated from monitored data to enforce energy balance in actual buildings. In conjunction, an experimental procedure called Short-Term Energy Monitoring (STEM) Subbarao et al. (1990) was developed which provides short-term test specifications and analysis to elicit physically relevant parameters. It was applied to a 300,000 sq. ft commercial building (Burch et al. (1990)). PSTAR provides a method for identifying and computing primary and secondary terms in energy balances, and then introduces certain parameters that are estimated from monitored data to enforce energy balance in actual buildings. PSTAR analysis of heat flows provides the conceptual framework for the method described here.

Macro heat flows: A simple case

Working with *macro* heat flows contributing to the overall building energy energy balance is central to our methodology of reconciling simulations with measured data. A typical simulation program, e.g., EnergyPlus NREL et al. (2020), involves *micro* heat flows reaching, for example, the indoor air node from each of the other nodes (as well as any direct input such as convective portion of internal gains). It keeps track of a large number of nodes, and thereby a large number of micro heat flows, but does not distinguish between how much of the heat flow is due to the major external drivers such as indoor temperature, outdoor temperature, solar radiation etc. By contrast, we will consider macro heat flows that can be attributed to a specific driving function, reaching for example the indoor air node. We develop a novel method to obtain these heat flows from specialized EnergyPlus simulations.

Let us start with a simple case. Consider a box with walls (floor included) with nominal conductance $U_{wall,nom}$, area A_{wall}, ceiling with nominal conductance $U_{ceiling,nom}$, area $A_{ceiling}$ and windows with nominal conductance $U_{window,nom}$, and area A_{window}. Assume the heat capacity of all elements to be zero, and neglect solar and internal loads. The box is electrically heated to maintain an inside temperature of $T_{in}(n)$ at time step n, while the ambient temperature is $T_{amb}(n)$. A "simulation" or an expression for the combined energy heat flows gives the heating energy use as

$$\begin{aligned} Q_{sim,nom}(n) = {} & U_{wall,nom}A_{wall}(T_{in}(n)-T_{amb}(n)) \\ & + U_{ceiling,nom}A_{ceiling}(T_{in}(n)-T_{amb}(n)) \\ & + U_{window,nom}A_{window}(T_{in}(n)-T_{amb}(n)) \end{aligned} \quad (1)$$

where the subscript "nom" refers to nominal or first-guess or assumed values.

Compare this with measured heat $Q_{mea}(n)$ (which from physical considerations, under the above-stated assumption of zero heat capacity, will be proportional to $T_{in}(n)-T_{amb}(n)$). It is most likely that the measured heating energy will differ from the simulated heating energy because the assumed input values of $U_{wall,nom}$, $U_{ceiling,nom}$, and

Fig. 1. Schematic to illustrate how a calibration function is used to modify the measured output of a simple device e.g., thermometer. The calibration function is determined initially from known outputs and then used routinely as shown in the flow chart.

$U_{window,nom}$ are estimates and differ from the actual values. We can tune by tweaking individual values to $U_{wall,tune}$, $U_{ceiling,tune}$, and $U_{window,tune}$ such that the resulting $Q_{sim,tune}(n)$ is as close as possible (in the least squares error sense) to $Q_{mea}(n)$. This can be done in an infinite number of ways, and serves to illustrate the concept of over-parametrization as stated earlier. Estimation of the micro parameters $U_{wall,tune}$, $U_{ceiling,tune}$, and $U_{window,tune}$ from measured data usinf the following regression equation

$$\begin{aligned} Q_{mea}(n) \approx\ & U_{wall,tune}A_{wall}(T_{in}(n)-T_{amb}(n)) \\ & + U_{ceiling,tune}A_{ceiling}(T_{in}(n)-T_{amb}(n)) \\ & + U_{window,tune}A_{window}(T_{in}(n)-T_{amb}(n)) \end{aligned} \quad (2)$$

is mathematically undetermined. Only the combined term

$$BLC \triangleq U_{wall,tune}A_{wall} + U_{ceiling,tune}A_{ceiling} + U_{window,tune}A_{window} \quad (3)$$

can be determined. This quantity is called Building Load Coefficient (BLC). This quantity is called Building Load Coefficient (BLC), a terminology previously adopted by ASHRAE and used by several researchers (for e.g., Kissock and Eger (2008), Krarti (2020), Chapter 6). In other words, the regression equation should be modified to

$$Q_{mea}(n) \approx p_{BLC}Q_{sim,nom}(n) \quad (4)$$

where p_{BLC} is the single parameter to be estimated. The deviation of the estimate of p_{BLC} from 1 is a measure of the over or under estimation of BLC. This simple example clearly shows the advantage of working with macro heat flows, in this simple case, $Q_{sim,nom}(n)$.

Eq.(4) can be rewritten as

$$Q_{mea}(n) \approx Q_{sim,nom}(n) + (p_{BLC}-1)Q_{sim,nom}(n) \quad (5)$$

The leads to the important interpretation of the term $(p_{BLC}-1)Q_{sim,nom}(n)$ as a corrective heat flow that makes the simulated heat flow close to (in this simple case, exactly equal to) the actual heat flow.

Consider now the more realistic case when the box elements have varying amount of thermal mass. The energy balance equation is more complex, and will need to consider transient behavior, i.e., past values of temperatures etc. It is no longer clear which specific combination is well-determined. We can surmise that it will involve storage-related quantities such as admittances rather than U-values. Once again, we seek a formulation that handles these dynamic effects implicitly while only exposing a small number of "knobs" to turn that capture the macro heat flow behavior. What these knobs are is considered at length later.

An important element of the full picture is HVAC system. Let us now add an HVAC system to the box. In cases where an overall equipment/system efficiency can realistically capture or account for actual behavior, it is added as an additional knob. For example, the rated COP of a chiller or the full-load efficiency of a boiler. Even for more complex systems, the building envelope parameters estimated above enable us to use the box as a dynamical calorimeter (i.e., an "instrument" that measures the amount of heat introduced or extracted by the HVAC system knowing the driving forces: inside and outside temperatures, solar radiation etc.) to determine heating and cooling provided in each time step. This would then allow us to estimate the HVAC system characteristics.

The PSTAR approach Subbarao (1988) uses building description to compute zonal admittances and resulting heat flows by an in-house simulation program, and then renormalizes (i.e., introduces and estimates parameters such as p_{BLC}) the heat flows to achieve the most accurate energy balance. The patent Subbarao (2000) describes a method to compute heat flows using the simulation program with specialized forcing functions. The method described here represents major improvement over the previous method in the manner in which the heat flows are defined, and how machine learning methods are applied to the residuals, and how a planned approach is adopted to fully incorporating HVAC systems.

Tuning, calibration and parameter estimation

Some discussion on terminology is warranted considering the fact that calibration is loosely used as an umbrella term for any method to reconcile simulation output with performance data. The terms "tuning", "calibration", and "parameter estimation" need to be defined more precisely. *Tuning* is essentially a process involving varying the large number of input parameters either subjectively or based on some expected probability. A set of "best performing inputs" are retained, and an iterative process is followed until the (set of) simulation inputs is deemed satisfactory. Such subjective approaches have intrinsic limitations due to the large number of inputs involved along with the numerous different permutations that can yield equivalent outputs (as illustrated earlier in this paper). Tuning is currently common in both research and professional studies.

Calibration is a well-established term in metrology; it essentially means modifying the raw output of a measuring device with a previously-determined corrective correlation to obtain an improved or more realistic measurement JCGM (2008). The metrology-type calibration process is shown in Figure 1. The figure depicts the process that uses the previously determined calibration function say by comparing the instrument raw readings against those from a more accurate reference standard. During training, the known output is used to determine the calibration function. We can think of a simulator such as EnergyPlus as the measuring device, and, its simulated energy use and indoor temperature time

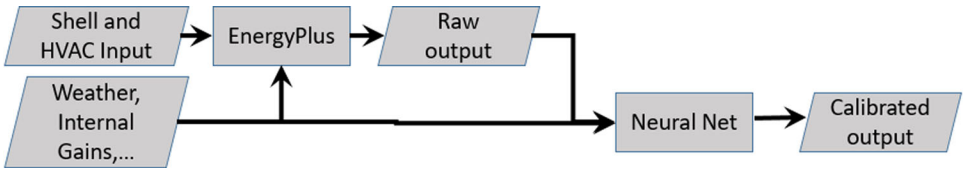

Fig. 2. Schematics of a generalization of the "calibration" process to computer simulations through a black-box approach involving training a neural net. Initially, the neural net is trained from measured data and then used routinely as shown in the flow chart.

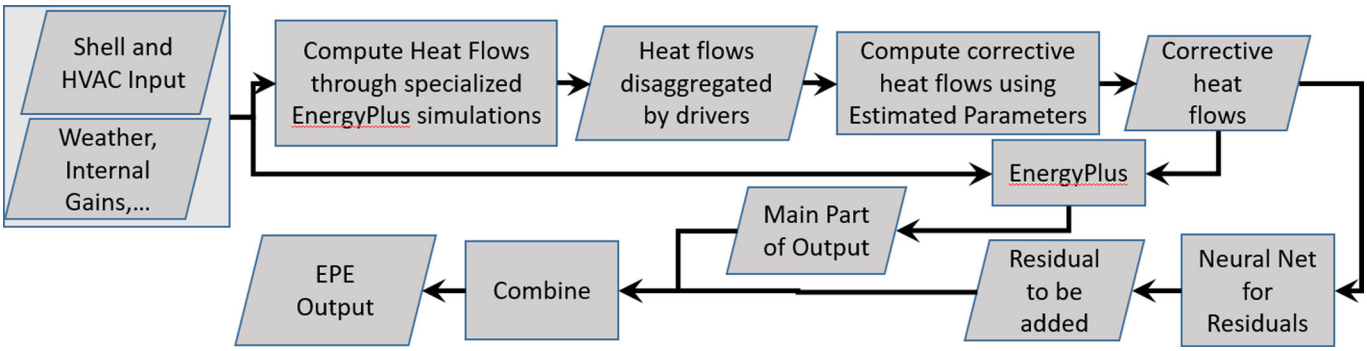

Fig. 3. Schematics of how to deploy the Enhanced Parameter Estimation Method. Initially, the parameters are estimated and a neural net trained from measured data, as described in the text. Note that, as explained in detail below, no modification of shell input parameters of the EnergyPlus model is done. Deviations of simulation inputs from actual are accounted for by corrective heat flows.

series as raw outputs. In this case, there cannot be a simple one-to-one relationship between the raw outputs and calibrated outputs. A generalization is depicted in the Figure 2. EnergyPlus raw output is used as a starting point to empirically obtain improved predictions. For example, using weather and indoor temperature time series as well as energy use time series predicted from a simulation program such as EnergyPlus as inputs, we can train a neural net using measured energy use; this can then be used for improved predictions. This approach must be contrasted with the commonly adopted method of training a neural net with weather and indoor temperature time series as inputs wherein no simulation is involved. A good review of machine learning for building energy estimation is given by Seyedzadeh et al. (2018). The neural network parameters have no direct physical interpretation. We will not pursue this metrology-like calibration approach. What we propose and formulate in detail is an enhanced parameter estimation approach we call EPE (Figure 3). The term "calibration" is ubiquitous for any reconciliation method; we will use that term loosely.

Enhanced parameter estimation (EPE)

This section describes the various elements of EPE: the mathematical formulation of the method, the multiple specially tailored EnergyPlus simulations needed, the manner in which some key parameters are to be estimated, and, finally the use using of a machine learning approach to the residuals to improve the predictive ability of the simulated model. Results of applying this methodology to a synthetic building and to a real building are described.

Formulation of the method

A simulator such as EnergyPlus performs an energy balance at a number of nodes, in particular at each surface node and each zone air node. Measured performance data on buildings does not permit modeling each of these nodes. Let us examine the energy balance at each of the zone air nodes. A typical simulator computes only the net heat flow at each node without separating the contributions from each of the drivers - indoor air temperature, outdoor air temperatures, solar radiation etc. We take a different approach of determining the contribution to the heat flow at the zone air node from each of the drivers separately but aggregated over all building components (all the walls, windows, etc). This method of disaggregation implies certain linearity assumptions and so corrections due to nonlinearities are handled separately. There are only a relatively small number of such heat flows to deal with and calibration can now be done by correcting these heat flows. If the overall shape of a heat flow is close to the actual, its magnitude can be corrected by a simple multiplicative factor, to be estimated from performance data. A more complex correction is to introduce a first order transfer function whose additional parameters are to be estimated from performance data. We should introduce just enough parameters such that they can be estimated with acceptable uncertainty, and no more. This is the overall PSTAR concept Subbarao (1988). In the original article, the heat flows were computed from a building description through in-house software. In Subbarao (2000) the heat flows were computed from specialized runs of DOE-2 simulator. In the present article, the individual heat flows are identified in a slightly different manner and system nonlinearities are incorporated

through a machine learning model of residuals. Application to HVAC systems is further refined. In the implementation of the basic method, certain issues need to be addressed. If tracer gas measurements of infiltration are available, infiltration heat flow should be treated as known. It may be best in some cases to compute ground heat flow (through specialized simulations) and treat it as a separate heat flow. Usually, the ground heat flow in commercial buildings is small compared to other major heat flows and its correction may not be warranted. If seasonal differences in solar shading as well as cloud cover are important, the seasons should be treated separately. Some of these issues are addressed in the real building application presented in this article. Only sensible heat flow is considered in this study even though the approach can be extended to include latent heat flow. We will now discuss specifics of defining and determining various heat flows.

Consider a one-zone building first. The energy balance equation can be written as

$$Q_{load}(t) + Q_{HC}(t) = 0 \tag{6}$$

where $Q_{HC}(t)$ denotes the heating/cooling delivered to the air node by the HVAC system and $Q_{load}(t)$ denotes the heat loss/gain by the zone air node from all mechanisms. Typically, a simulation computes $Q_{load}(t)$ and uses Eq.(6) to determine $Q_{HC}(t)$ (subject to thermostatic constraints). Simulations also typically compute explicitly $Q_{infiltration/ventilation}(t)$ and $Q_{ground}(t)$ (whose meanings are self-evident) that contribute to $Q_{load}(t)$. LEP represents lights, equipment and people. $Q_{LEP,\,convection}(t)$ is the convective part of the internal gains from LEP; the radiative part goes through the nodes. We can thus write

$$Q_{load}(t) = Q_{all_{surface}nodes}(t) + Q_{infiltration/ventilation}(t) + Q_{ground}(t) + Q_{LEP,\,convection}(t) \tag{7}$$

The term $Q_{all_{surface}nodes}(t)$ represents the heat gain by zone air from all the surface nodes.

For an actual building with performance data, the term $Q_{infiltration/ventilation}(t)$ can come from tracer gas and/or airflow measurements. If such measurements are not available, we have only models to rely on and in this case calibration should address these models. It is not feasible to determine from measurements the rest of the terms in Eq.(7). (The heat output from lights, equipment and people can be obtained from measurements, but it is generally not feasible to directly measure the convective portion).

Restricting for the moment to building shell only, consider the case when the term $Q_{HC}(t)$ comes from measurements (for example from thermal energy flow meters). The term $Q_{load}(t)$ of Eq.(7) comes from models (the infiltration/ventilation term possibly coming from measurements). These two terms will not, in general, satisfy Eq.(6); hence the need for calibration.

Let us focus on the term $Q_{all_{surface}nodes}(t)$. Temperatures (indoor and outdoor, sky), solar radiation, and internal gains contribute to this heat flow. Linearity assumption allows us to consider one of these at a time, and add them at the end; nonlinearities are addressed later.

Consider first the heat flow due to temperatures. The heat flow at time t due to current and past indoor and outdoor temperatures $T_{in}(t')$ and $T_{out}(t')$ can be written as (with the convention that a positive value implies heat gain by the air node) a convolution integral (see LBL and LANL (1982)):

$$\int_{-\infty}^{t} dt' \ \left[-V(t-t')T_{in}(t') + W(t-t')T_{out}(t')\right] \tag{8}$$

This can be rewritten as a sum of two heat flows $Q_{in}(t)$ and $Q_{BLC}(t)$

$$Q_{in}(t) = -\int_{-\infty}^{t} dt' \ V(t-t')T_{in}(t') + LT_{in}(t) \tag{9}$$

$$L = \int_{0}^{\infty} dtV(t) = \int_{0}^{\infty} dtW(t) \tag{10}$$

$$Q_{BLC}(t) = -L\left[T_{in}(t) - T_{out}^{eff}(t)\right] \tag{11}$$

$$T_{out}^{eff}(t) \triangleq \int_{-\infty}^{t} dt' \ \frac{W(t-t')}{L} T_{out}(t') \tag{12}$$

The quantities $V(t-t')$ and $W(t-t')$ are the appropriate transfer functions, which automatically obey the constraint in Eq.(10). They can be computed from a building description (see Subbarao (1988)). We do not need to explicitly compute them because we use simulation outputs to generate disaggregated heat flows. If all exterior walls are massless, W is proportional to the Dirac delta function, $W(t-t') = L\delta(t-t')$ and the effective outside temperature is equal to the actual instantaneous outside temperature. As the walls become more massive, the effective outside temperature is a weighted average of current and past temperatures, with the weights depending on the wall characteristics. For a lightweight wall, the weights decrease rapidly unlike for a heavyweight wall. Sky temperature effects can easily be included by modifying Eq.(8) to a form as follows:

$$\int_{-\infty}^{t} dt' \ \left[-V(t-t')T_{in}(t') + W(t-t')T_{out}(t') + W_{sky}(t-t')T_{sky}(t')\right] \tag{13}$$

Sky view factors are incorporated in the transfer function. Note that a continuous time formulation is used. It is straightforward to switch between continuous and discrete formulation as convenient.

We will now add $Q_{sun}(t)$ to account for solar gains, and $Q_{LEP}(t)$ to account for gains from light, equipment and people that appear as heat gain at the indoor-air node. Note in particular that the term $Q_{LEP}(t)$ is the heat gain by the air node after accounting for the delayed release of the gains and any loss through the walls without appearing as gains at the air node. Additional energy flow terms such as infiltration, ventilation and ground flow will have to be included when necessary. For the time being, for pedagogical simplicity, we have set them to zero. The heating/cooling load at the zone air node can be written as:

$$Q_{load}(t) \triangleq Q_{BLC}(t) + Q_{in}(t) + Q_{sun}(t) + Q_{LEP}(t) \quad (14)$$

Let us denote by $Q_{HC}(t)$ the heating/cooling delivered to the air node by the HVAC system. Finally, the energy balance equation for the air node is (same as Eq.(6) in the earlier context):

$$Q_{load}(t) + Q_{HC}(t) = 0 \quad (15)$$

The building load $Q_{HC}(t)$ is met by energy $E(t)$ (electricity and/or gas collectively) that is a function of $Q_{HC}(t)$, weather variables such as outdoor temperature collectively denoted by Weather(t), and a set of system parameters such as COP, part load efficiency etc. collectively denoted by $\{\alpha\}$:

$$E(t) = Function(Q_{HC}(t), Weather(t), \{\alpha\}) \quad (16)$$

The energy use $E(t)$ is an output of the simulation. Our main problem is how best to reconcile simulated values of $E(t)$ with the measured values.

The basic methodology is best explained through a step-by-step process for a one zone building. Variations can be addressed as needed.

We start with:

- An EnergyPlus simulation model, called audit model, that is the one to be reconciled with performance data. Our calibration can compensate for (certain types) of input errors and so a rough reasonable model is a good start.
- The available performance data consists of time series of
  - Indoor temperature $T_{in,measured}(t)$
  - Weather (outdoor temperature, solar radiation, …) collectively denoted by $Weather(t)$
  - Heat input from lights, equipment and people $LEP(t)$
  - Energy Use (electricity, gas) collectively denoted by $E(t)$
  - Additionally, short-term data for the actual heat input $Q_{HC}^{mea}(t)$ (may be negative) possibly through flow ΔT type measurements

The analysis consists of two stages. In Stage 1, the building shell related parameters are estimated; HVAC system is replaced by an ideal system that simply delivers the required heating/cooling. In Stage 2, the HVAC related parameters are estimated with the building shell replaced by a box with only process loads.

Stage 1: Building Shell parameters

- Perform an EnergyPlus simulation of the audit building, for the period for which $Q_{measured}(t)$ is available using actual $Weather(t)$, measured $LEP(t)$ with $T_{in,measured}(t)$ as the set-points. Denote the resulting load by $Q_1(t)$. If the audit building shell accurately represents the real building shell (and the simulator is accurate), $Q_1(t)$ would be equal to $Q_{measured}(t)$. We do not expect this to be the case and now need to reconcile simulated and actual performances.
- Perform a second EnergyPlus run, this time with the solar radiation set to 0, and obtain the simulation output $Q_2(t)$. The heat flow

$$Q_{sun}(t) \triangleq Q_2(t) - Q_1(t) \quad (17)$$

can then be identified as the heat input to the indoor air node due to solar radiation after accounting for any delayed release.

- Perform a third EnergyPlus run, this time with the indoor temperature fixed at a constant value $T_{in,fixed1}$ and the solar radiation set to 0, to obtain the simulation output $Q_3(t)$.
- Perform a fourth EnergyPlus run, this time with the indoor temperature fixed at a constant value $T_{in,fixed2}$ and the solar radiation set to 0, to obtain the required input $Q_4(t)$.
- Perform a fifth EnergyPlus run, this time with the indoor temperature fixed at a constant value $T_{in,fixed1}$ and the solar radiation as well as Light, Equipment and People heat input set to 0, to obtain the simulation output $Q_5(t)$.
- Compute the following hourly heat flows:

$$Q_{in}(t) \triangleq -Q_2(t) + Q_3(t)\frac{T_{in,measured}(t) - T_{in,fixed2}}{T_{in,fixed1} - T_{in,fixed2}} + Q_4(t)\frac{T_{in,fixed1} - T_{in,measured}(t)}{T_{in,fixed1} - T_{in,fixed2}} \quad (18)$$

$$Q_{BLC}(t) \triangleq -Q_2(t) + Q_3(t) - Q_5(t) - Q_{in}(t) \quad (19)$$

$$Q_{LEP}(t) \triangleq -Q_3(t) + Q_5(t) \quad (20)$$

Note that $Q_{LEP}(t)$ is the effect of $LEP(t)$ after accounting for any time delays and losses. The term $Q_{in}(t)$ is the heat flow to the air node based on the history of indoor temperatures. $Q_{BLC}(t)$ is the heat flow to the air node based on the current indoor temperature and an effective outdoor temperature that is based on the history of outdoor temperatures (including contributions from the history of sky temperature depression)

- Introduce parameters to be estimated so as to best satisfy the following equation:

$$Q_{BLC}(t) + Q_{in}(t) + Q_{sun}(t) + Q_{LEP}(t) + Q_1(t) = 0 \quad (21)$$

We now bring in $Q_{HC}^{mea}(t)$, and require that Eq.21 be satisfied with $Q_{HC}^{mea}(t)$, not $Q_1(t)$. We modify the rest of the heat flows by introducing parameters and estimate them to satisfy the equation in the least squares error sense. The simplest modification is:

$$p_{BLC}Q_{BLC}(t) + p_{in}Q_{in}(t) + p_{sun}Q_{sun}(t)) + p_{LEP}Q_{LEP}(t) + Q_{HC}^{mea}(t) \approx 0 \quad (22)$$

The parameters can be determined by simple regression. These parameters change only the scale of a heat flow but not the shape. To change the shape we have to introduce additional parameters. A heat flow, e.g., $Q_{sun}(t)$ is further modified through a transfer function as follows:

$$Q_{sun}^{mod} = p_{sun}Q_{sun}(t)) + Q_{sun}^{TF}(t) \quad (23)$$

where

$$Q^{TF}_{sun}(t) = \alpha_{sun} Q^{TF}_{sun}(t-1) + \beta_{sun}(Q_{sun}(t) - Q_{sun}(t-1)) \quad (24)$$

Eq.(22) is modified into the following energy balance equation

$$p_{BLC}Q_{BLC}(t) + p_{in}Q_{in}(t) + p_{sun}Q_{sun}(t) + p_{LEP}Q_{LEP}(t) + Q_{TF,sun}(t) + Q^{mea}_{HC}(t) \approx 0 \quad (25)$$

Note that this formulation has resulted in two additional parameters for the solar heat flow α_{sun}, β_{sun}. Similar parameters can be introduced to the other heat flows. We have to be judicious in introducing additional parameters through an error analysis to ensure that the data supports their estimation. We now have a nonlinear regression problem. It can be solved using Levenberg-Marquardt method (Press et al. (2007)). It is obvious that the simulated building would behave closely to the real building if we add the following process load to the simulated building:

$$Q_{correction}(t) \triangleq (p_{BLC}-1)Q_{BLC}(t) + (p_{in}-1)Q_{in}(t) + (p_{sun}-1)Q_{sun}(t)) + (p_{LEP}-1)Q_{LEP}(t) + Q^{TF}_{sun}(t) \quad (26)$$

Similar modifications are needed to accommodate transfer functions for any of the heat flows. One can create any number of corrective heat flows. The EnergyPlus simulation we started with is modified by adding $Q_{correction}(t)$ as a process heat. The resulting output is EPE's calibrated output. EPE accomplishes shell calibration without any modification of the simulation inputs (as noted in the Introduction section, data does not support any systematic modification of the vastly undetermined problem); the deviation of the simulated building from the actual is corrected by introducing corrective heat flows.

- Examine the parameters in light of their physical significance
- The deviation of, for example, p_{BLC} from 1 is a measure of the extent to which the initial audit-based estimate of BLC is over or under the measurement-based estimate. The simulation input file can be reexamined in light of such deviations, but there is no systematic way to assign the correction to individual walls, windows etc. (Large deviations may point to possible bugs in inputs; such erroneous inputs should obviously be fixed.) Similarly all the other parameters should be examined.
- Develop a neural net for the residuals
- With the various heat flows as inputs and residuals as output, a neural net is trained. When a new set of inputs are presented, the resulting output is an additional (although generally small) corrective heat flow. This corrective heat flow will capture the small non-linear behavior and other perturbations and improve the predictive ability for the calibration process.

Stage 2: HVAC System

- Replace the building shell by a process load whose time series behavior is given by:

$$Q_{reconciled}(t) \triangleq -Q^{mod}_{BLC}(t) - Q^{mod}_{in}(t) - Q^{mod}_{sun}(t) - Q^{mod}_{LEP}(t) + Q_{residual}(t) \quad (27)$$

Specialized simulations are done to obtain the heat flows which are then modified to obtain the process load. (We can, of course, use $Q_{measured}(t)$ directly for the periods when it is available)

- Perform an EnergyPlus simulation with the audit HVAC system and the process load to determine the simulated energy use time series $E_{sim}(t)$.
- If the audit description of the HVAC system is accurate, then $E_{sim}(t)$ will be close to $E_{measured}(t)$. This is generally not expected.
- Identify the parameters to be estimated and estimate them
- In some ways this is similar to the shell problem but in many ways, there are important differences. First of all, each time step is essentially independent of the previous time steps (unless one is considering minute-by-minute control sequence, or storage elements as part of the HVAC system). There are, as for the shell, a large number of parameters and not all can be determined with whole building data.

It is important to ensure that the data and the parameters to be estimated are well-matched and the resulting calibrated simulation is applicable for the intended use. In calibrating hourly simulation with monthly data there is a mismatch (highly overparametrized and so a large number of diverse input variable sets will yield very good fits to utility bills). Unfortunately, this is quite common. In Chaudhary et al. (2016), the authors calibrate an EnergyPlus simulation model using hourly data, but do not consider variations in indoor zone temperatures. The thermal mass behavior in response to indoor temperature variations is important in terms of the relative magnitude of heat flows and neglecting this is unlikely to yield proper calibrated models. The EPE method avoids such mismatch. One should still be cognizant of the limitations. For example, evaluation of a component retrofit requires additional component level data.

Synthetic building example

In this section, we will demonstrate the multi-stage methodology for a synthetic building i.e., a software model of a building from which we generate simulated data and use it as the "real" data. The "real" building is then taken to be the one simulated in EnergyPlus to give hourly time series of indoor temperatures and delivered heating and cooling energy in step 1 and electrical consumption by HVAC system in step 2. In this section, the terms "measured" and "real" refer to this building.

In Section "Actual building in Philadelphia", we consider an actual building with actual measured data. Table 1 clarifies the terminology in the context of synthetic and actual building cases.

For this study, the "real" building is the 53,600 sq. ft. building with normal construction which corresponds to the medium office building prototype selected by USDOE for work related to ASHRAE 90.1 standard development. The audit building has been intentionally modified so as to have different insulation, mass and solar characteristics; more

Table 1. Terminology for synthetic and real building cases.

	Synthetic Building Case	Real Building Case
Actual Building	Represented by a simulation input file	The physical building
Measured performance data	Comes from EnergyPlus simulation with above input file	Comes from Building Management System and weather station measurements
Audit Building	Represented by the above file with alterations that represent the deviations of the audit building from the actual	Represented by a simulation input file derived from audit
Calibrated Building	After calibration, represented by the same audit input file except corrective heat flows are included as process loads, and audit HVAC parameters are replaced by estimated parameters. Neural net for the residuals introduces additional modifications as explained in the text.	After calibration, represented by the same audit input file except corrective heat flows are included as process loads, and audit HVAC parameters are replaced by estimated parameters. Neural net for the residuals introduces additional modifications

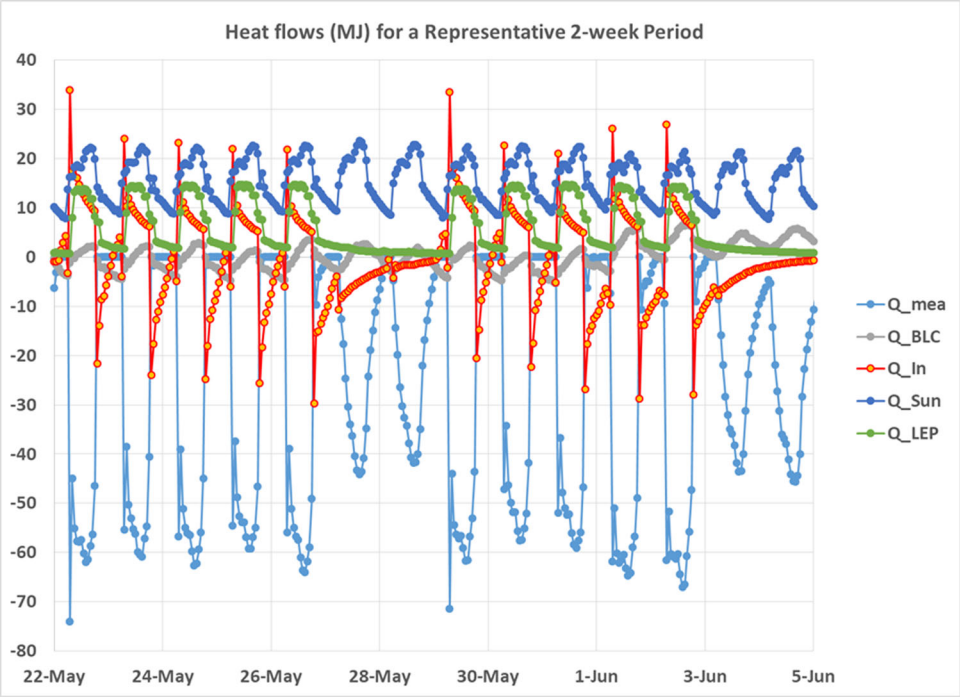

Fig. 4. Heat Flows (MJ/hr) for the Synthetic Building: $Q_{mea}(t)$ is "measured" and the rest computed following the EPE methodology for a representative 2-week period.

specifically it has more insulation, more mass (added concrete wall layer) and smaller solar heat gain coefficient. Two locations were selected for analyzing such a building: Phoenix, AZ and Philadelphia, PA. A more detailed study was done for the Phoenix location.

Note that evaluation with a synthetic building allows us to vary the inputs at will and evaluate the accuracy of the Enhanced Parameter Estimation (EPE) process with more certainty. Step 1: Obtain the measured (hourly) values of indoor temperature $T_{in}(t)$ and delivered heating/cooling $Q_{HC}^{mea}(t)$ for the "real" building Step 2: Run the five EnergyPlus simulations of the audit building as specified (recall in particular, that in the first two simulations, the measured zone temperature time series are used as set-points) and determine the four heat flows $Q_{BLC}(t)$, $Q_{in}(t)$, $Q_{sun}(t)$, $Q_{LEP}(t)$.

These and the "measured" heating/cooling energy delivered are shown in Figure 4; the corresponding driving functions are shown in Figure 5. The period of analysis covered two months: May-June. For clarity, only a representative 2-week period is shown in the figure. If the audit building were identical to the real building (and if EnergyPlus is a fully accurate simulator) the five heat flows would add up to 0, or

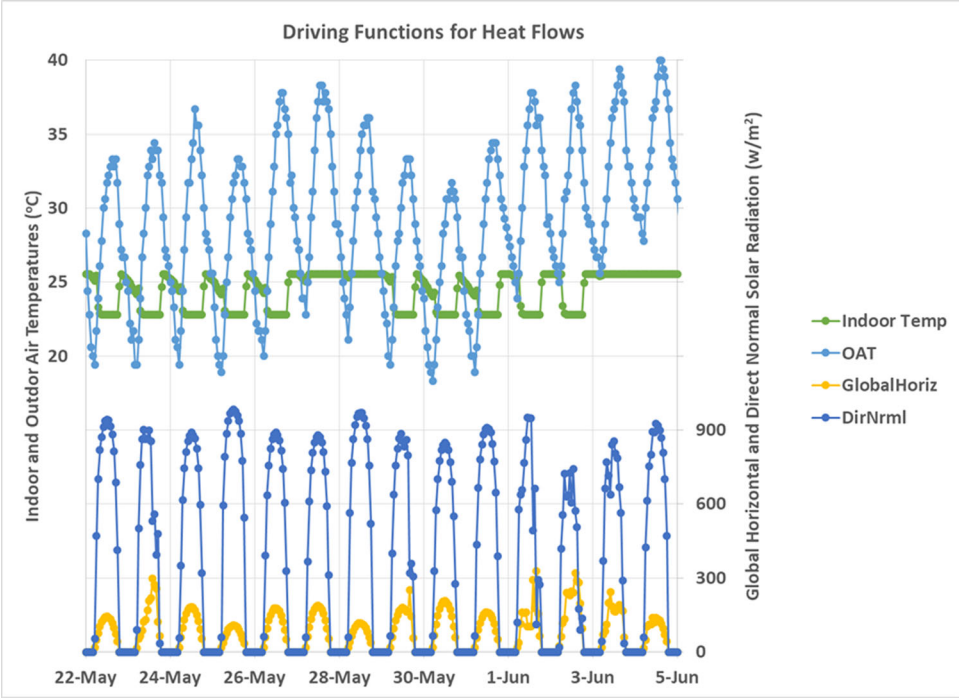

Fig. 5. The driving functions - Indoor and outdoor temperatures and solar radiation that result in the heat flows - corresponding to the period shown in Figure 4.

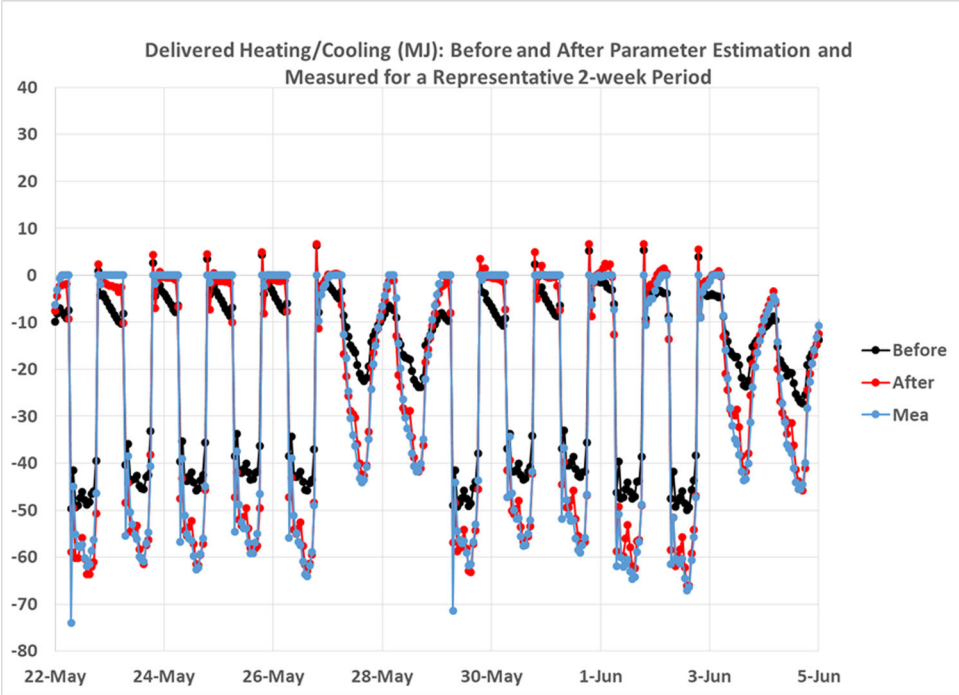

Fig. 6. The delivered heating/cooling energy (MJ/hr) flows (equal to the negative sum of the four heat flows) before and after the best fit, compared to measured values for the synthetic building for the same representative 2-week period.

equivalently the negative of the sum of the four computed flows would equal the delivered heating/cooling energy amounts.

This hourly sequence of negative values of the sum is labeled "Before" in Figure 6.

Step 3: Perform a non-linear least squares best fit. The negative sum after the best fit is also shown in Figure 6. Note the improvement. The "After" plot is much closer to the "mea" and captures peaks and valleys better. The parameters from the best fit are shown in Table 2. The one

standard deviation errors quoted are purely statistical. (To avoid collinearity, p_{LEP} was set to 1 and not estimated in these runs. Such correlations can often be avoided by choosing suitable data windows. This issue needs further study).

Step 4: Identify a neural net model for the residuals of the best fit least squares model. To avoid confusion, let us call this PE_Residuals (for Parameter Estimation Residuals). With the usual caveats, we proceed to improve the estimate by using neural nets. The PE_residuals show some residual pattern not captured by the parameter estimation process. With the six heat flows $Q_{BLC}(t)$, $Q_{in}(t)$, $Q_{sun}(t)$, $Q_{LEP}(t)$, $Q_{TF,in}(t)$, $Q_{TF,sun}(t)$ as inputs and PE_Residuals as output with 9 hidden nodes, a multilayer perceptron network was trained on the PE_Residuals from the May-June data. The fitted PE_Residuals are now added to the delivered heating/cooling from the parameter estimation step to improve the estimate. The improvement is significant as can be seen from a scatter plot, Figure 7, of the three heat flows vs measured flow: The "audit" heat flows are quite far from the "measured". When the corrective heat flows are included as given by parameter estimation, the agreement improves significantly. It is further improved by the enhancement from the additional corrective heat flow given by the neural net.

The mean bias error and root mean square (RMS) errors are shown in Table 3. Note that after the parameter estimation step, the mean bias error is essentially zero after calibration while the RMSE value has been reduced three-fold. The RMSE is further reduced (from 3.23 MJ to 2.47 MJ) after the neural net fitting procedure is applied.

One of the thorny problems in applying neural networks to time series is handling past values of driving functions. In our case, this is a non-issue since the inputs are heat flows that already incorporate the history of driving functions. Thus, each row is treated independently. The time series problem has been reduced to a problem where each hour is treated independently!

Table 2. The Estimated parameters (May–June data).

p_{BLC}	1.48 ± 0.02
p_{in}	0.63 ± 0.05
p_{sun}	1.29 ± 0.01
p_{LEP}	1
$p_{in,phase}$	0.43 ± 0.04
$p_{TF,in}$	0.94 ± 0.01
$p_{sun,phase}$	1.35 ± 0.02
$p_{TF,sun}$	0.988 ± 0.002

Physical significance of the parameters

The parameters have physical significance which helps us better understand the performance of the building. The parameter p_{BLC} was estimated to be 1.48. This implies that the building load coefficient of the actual building is roughly 48% higher than that of the audit building. We cannot go beyond this to determine which components (walls or windows etc.) are causing this discrepancy; reasonable conjectures would be circumstance specific. Since the "real" building is synthetic, we know the actual numerical values of the parameters. The differences between the actual and the audit building were such that the load coefficient of the

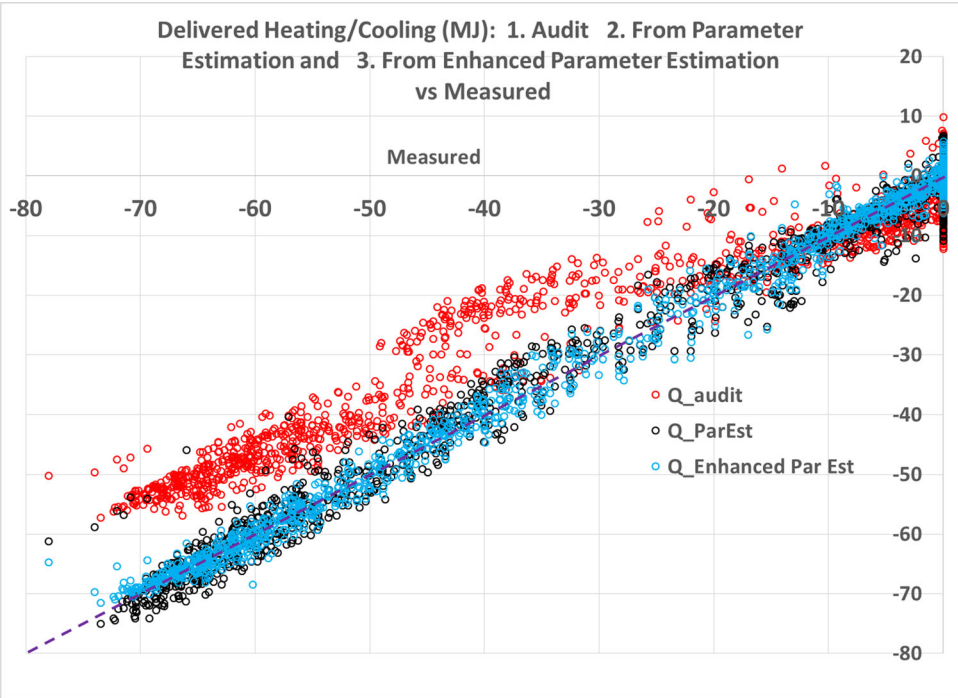

Fig. 7. Scatter plot showing the extent to which the EPE process improves the agreement with measured data (May-June data for the synthetic building in Phoenix). Delivered Heating/Cooling (MJ/hr): Audit, From Parameter Estimation and From Enhanced Parameter Estimation vs Measured.

Table 3. Goodness-of-fit statistics of the EPE process for the synthetic building for the period May–June.

	Audit Building	After Parameter Estimation	After Parameter Estimation and Residual Neural Net (Enhanced Parameter Estimation)
Mean Bias Error	5.13 MJ	−0.02 MJ	−0.05 MJ
Root Mean Square Error	10.33 MJ	3.23 MJ	2.47 MJ

actual building is roughly 40% higher; this is in good agreement with our parameter estimation (see Table 3). The value of the load coefficient is somewhat dependent on the treatment of convection and radiation at the interior and exterior surfaces and this must be resolved if the differences are to be reconciled further. Similarly, $p_{sun} = 1.29$ implies that the actual building has roughly 29% higher solar gains. The solar heat gain coefficient of the windows of the actual building was about 47% higher; we need to also consider opaque gains. Similarly $p_{in} = 0.63$ means that the actual building has less effective thermal mass; this is consistent with the differences between audit and actual building inputs to EnergyPlus. The other parameters modify the delay characteristics of solar gains and of heat flows due to indoor fluctuations beyond what is in the audit description.

HVAC system

So far, we have used May-June data with hourly delivered heating/cooling data available to us. This enabled us to estimate envelope parameters as well as train a neural net to address the envelope characteristics. We will now use the EPE methodology to predict loads on the mechanical systems, and thereby perform HVAC reconciliation. If the delivered heating/cooling data is available, for example, through a thermal meter, we can simply use that data to analyze the HVAC system; in particular, we could estimate certain HVAC parameters. We can visualize a use-case situation where the needed instrumentation is installed temporarily and then removed to reduce operating costs, while being able to keep monitoring the HVAC performance continuously. The proposed procedure involving enhanced parameter estimation would permit using the building envelope as a calorimeter, essentially as a substitute for flow-ΔT type instrumentation. We will discuss this aspect next. Suppose we have July-August data with indoor temperatures and HVAC electricity use. We can use the indoor temperature data in EnergyPlus to compute the four heat flows as described in the previous section: $Q_{BLC}(t)$, $Q_{in}(t)$, $Q_{sun}(t)$, $Q_{LEP}(t)$ for the period July-August. From the previously estimated $p_{TF,in}$ and $p_{TF,sun}$ parameters, we can determine the two additional flows $Q_{TF,in}(t)$, $Q_{TF,sun}(t)$. We can now apply Eq. 25 and include the hourly residual time series data from the neural net to get the best estimate of delivered cooling:

$$\begin{aligned} Q_{HVAC}^{estimate}(t) = {} & p_{BLC}Q_{BLC}(t) + p_{in}Q_{in}(t) + p_{sun}Q_{sun}(t) \\ & + p_{LEP}Q_{LEP}(t) + p_{TF,sun2}Q_{TF,sun}(p_{TF,sun1}, Q_{sun}(t)) \\ & + p_{TF,in2}Q_{TF,in}(p_{TF,in1}, Q_{in}(t)) + NN_{Res} \end{aligned} \tag{28}$$

The term NN_{Res} represents the residual time series estimated from the neural net.

We can now run an EnergyPlus simulation with the estimated loads as process load inputs to an isolated box; the building envelope is replaced by this isolated box for this simulation. Energy Plus takes the load time series and outputs electricity use time series using the user-specified input for the HVAC parameters - COP under rated conditions, and part load, and off-rated performance. We can now perform a non-linear least squares estimation of the HVAC parameters. To do this using software packages requires repeated calls to EnergyPlus. It is important to recognize that the data permits estimating a very small number of HVAC parameters, and these should be chosen judiciously.

To illustrate the general approach, we assume that the only parameter to be estimated is the COP under rated conditions and leave part-load and off-rated corrections at their default values. We can run EnergyPlus for a range of values of COP. We compute the RMS error as a function of rated COP and identify the value at the minimum error; this is a manual process for accomplishing the nonlinear estimation. This process of searching for a COP values which results in minimum RMSE is shown in Figure 8.

The rated COP that minimizes the error turned out to be 3.625. Because the real building is in fact synthetic, we know the real COP value was 3.5. The difference is due, in addition to uncertainties of the methodology, mainly to an artifact of EnergyPlus. For the building we can deduce the electricity time series from EnergyPlus in two ways: One is via the normal simulation. The second is to first get the cooling loads (with the right indoor temperatures specified) and introduce them to another simulation with the shell replaced by an isolated box. The two are expected to be essentially identical; however, we found a 2% increase for the isolated box. This suggests that for some unidentified reason (to be investigated), EnergyPlus increases the load by 2% while simulating the box. To match the normal electricity with a 2% higher load use requires about a 2% increase in COP.

How repeatable are the parameter estimates

To evaluate whether the parameter estimates are impacted by climate, we have repeated the analyses for the same months (May-June) in two different climates: Philadelphia and Phoenix. The results are shown in Table 4. The agreement is generally satisfactory considering we do not expect them to be identical. As is to be expected from physical considerations, differences in sky temperature, ground

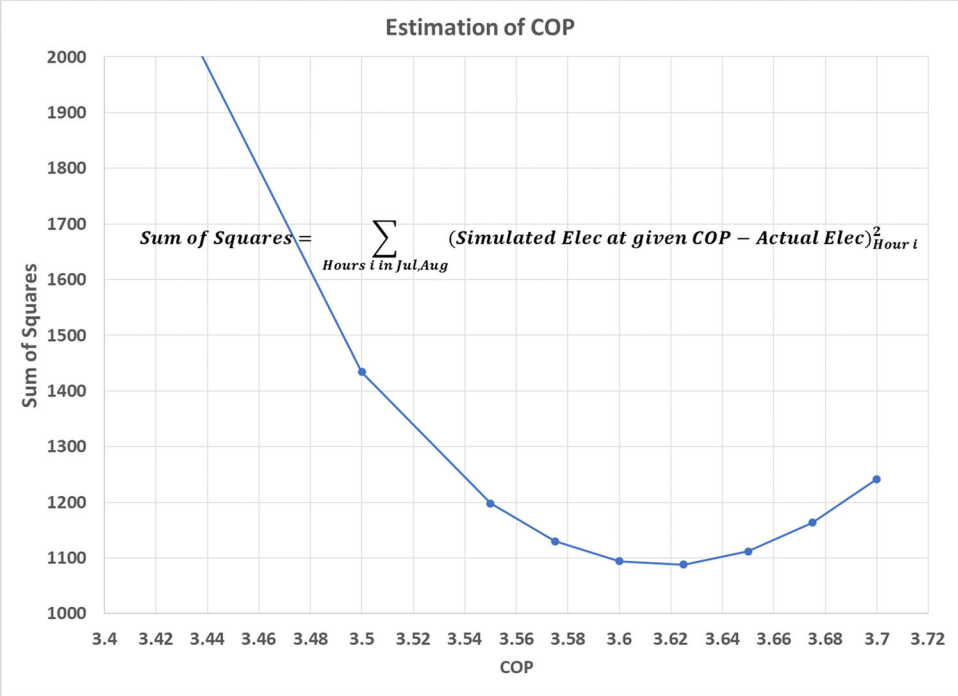

Fig. 8. Search process to determine the best estimate of cooling system COP that minimizes Mean Square Error $(MJ/hr)^2$.

Table 4. Estimated parameters in two different climates along with uncertainty values.

	Philadelphia	Phoenix
p_{BLC}	1.57 ± 0.03	1.48 ± 0.02
p_{in}	0.69 ± 0.02	0.63 ± 0.05
p_{sun}	1.42 ± 0.01	1.29 ± 0.01
p_{LEP}	1	1
$p_{in,phase}$	0.45 ± 0.02	0.43 ± 0.04
$p_{TF,in}$	0.70 ± 0.02	0.94 ± 0.01
$p_{sun,phase}$	1.37 ± 0.03	1.35 ± 0.02
$p_{TF,sun}$	0.954 ± 0.002	0.988 ± 0.002

reflectivity between the two cities are likely to affect the parameter estimates.

Actual building in Philadelphia

In order to evaluate our EPE methodology in an actual building, we identified a building, located in the Philadelphia Navy Yard, for which an EnergyPlus simulation input model was also developed from a previous study. Building 101 was initially built in 1911 as a marine barrack with the gross building floor area about 75,000 ft^2. This was a brick building with double-pane windows and underwent a major HVAC system renovation in 1999. The building had 3 above grade floors and one Basement floor which primarily served as mechanical and storage rooms. The HVAC system in the building comprised of three variable-air-volume (VAV) air handling units (AHUs) with total design airflow of 53,240 CFM. The terminal units have hydraulic reheat coils to meet the heat/reheat loads which are served by a 1,632 MBH gas-fired boiler. The AHUs are served by DX cooling coils. The boiler supplies 180 °F hot water to AHU heating coils, Terminal Box reheat coils, and hot water radiators. The attic spaces are heated by hot water unit heaters. Further details can be found in Xu (2012). For our study, we had access to the 2016 end-use energy data for each minute, which included lighting electric, AHU fans electric, DX Coils electric, pumps electric, total building electric and miscellaneous equipment electric energy as residual. Gas consumption data by the boilers were also available for each minute. We carried out the analysis at an hourly level. The weather file for this location, for the year 2016, was obtained from a vendor.

Real buildings, unlike synthetic buildings, present unique challenges; the EPE methodology should be adapted to meet the challenges. Such inevitable complexities in dealing with real buildings should not detract from the methodology itself.

The building has 7-zones. Multizone buildings require additional issues to be addressed: (a) do available data may neatly align with the zones, (b) are the energy flows (e.g., delivered HVAC energy, internal gains, ventilation) in any given zone available with acceptable accuracy to perform parameter estimation at the zone level. In this article, we will start with energy balance for each zone and then sum over the zones to obtain energy balance for the whole building.

The measured data is shown, for representative winter and summer periods, in Figures 9 and 10 respectively. For

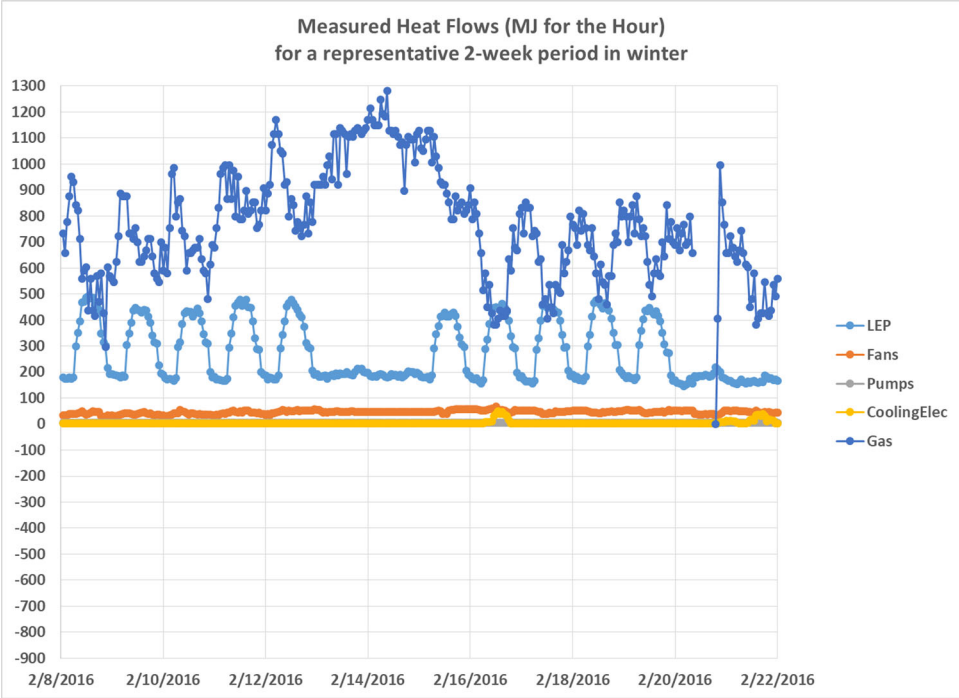

Fig. 9. Measured Heat Flows (MJ/hr) for a representative 2-week period in winter for the actual building.

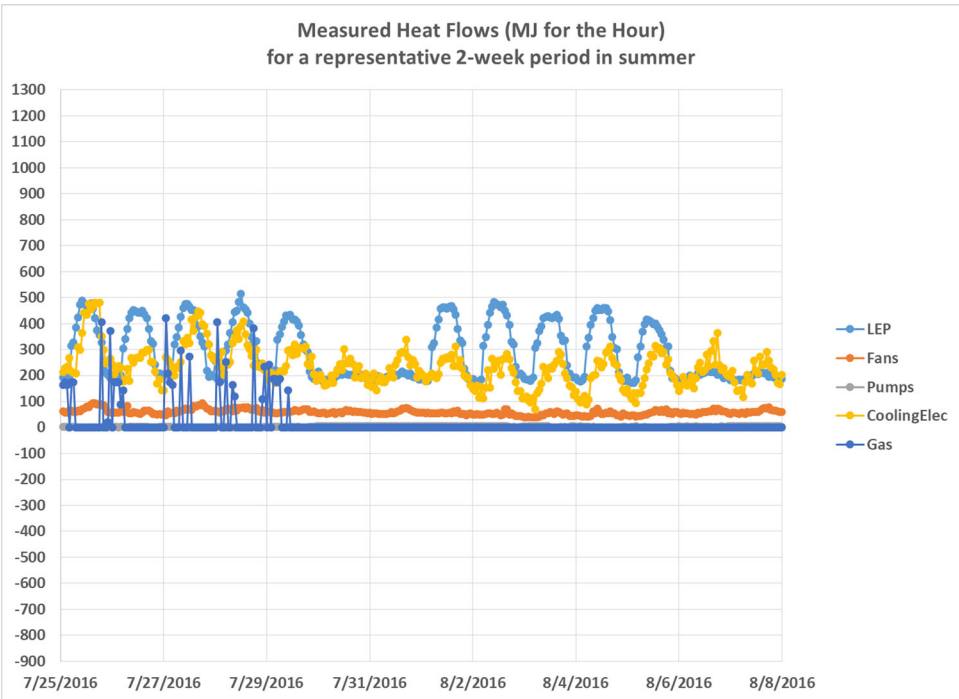

Fig. 10. Measured Heat Flows (MJ/hr) for a representative 2-week period in summer for the actual building.

ease of comparing magnitudes of various heat flows, which is a crucial step, a common scale is used in the graphs. Although some data channels are available for each zone or for each air handler, for the purposes of this graph the sum is presented. LEP represents the energy due to lights, equipment and people. Delayed release of this energy, loss of some energy incident radiatively on exterior walls etc. are considered later during analysis. Similarly, measured gas input to the boiler and electrical energy input to the HVAC systems are shown. Efficiency considerations are also done later during the analysis.

We can generalize Eqs (6) - (15) for each zone. We now have to include interzone heat flow through the common walls and interzone air flows in addition to $Q_{BLC}(t)$,

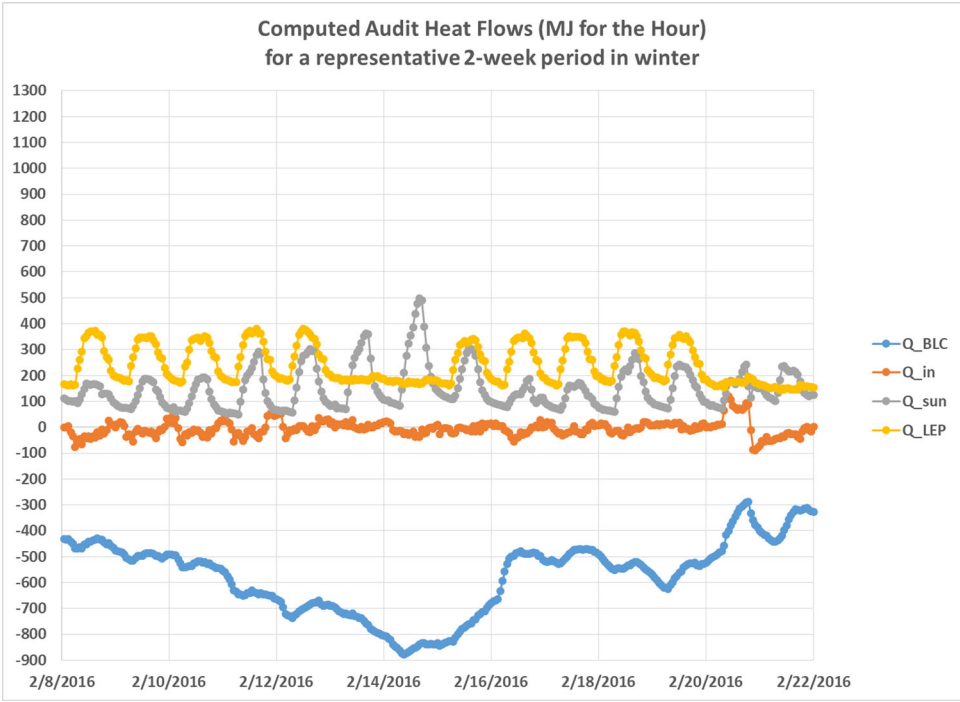

Fig. 11. Some computed pre-calibration Heat Flows (MJ/hr) for the actual building (shown for the representative 2-week period in winter).

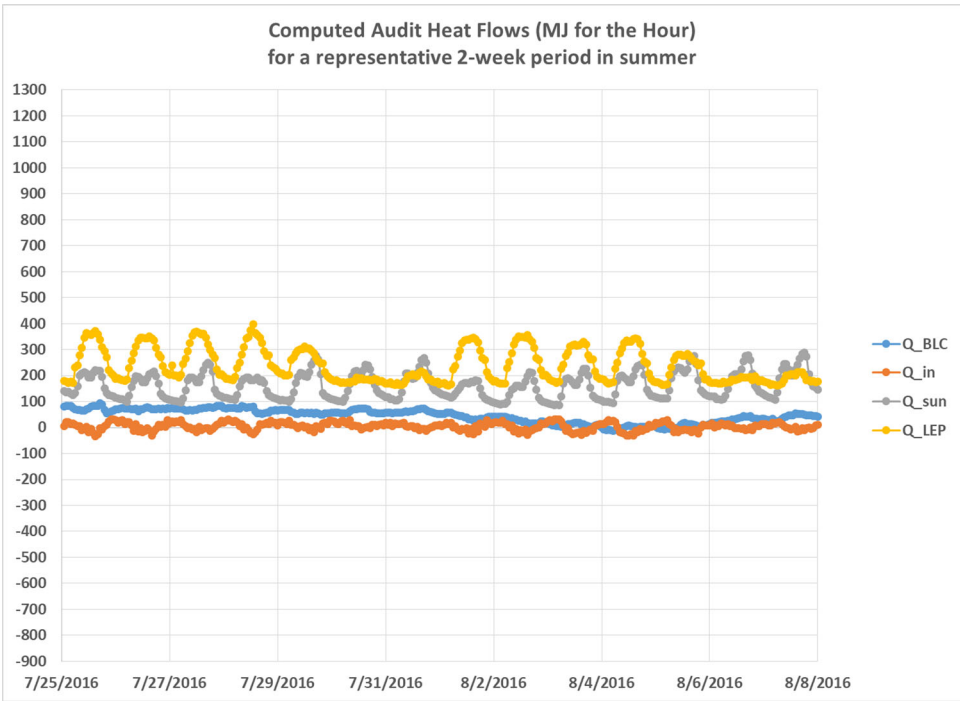

Fig. 12. Some computed pre-calibration Heat Flows (MJ/hr) for the actual building (shown for the representative 2-week period in summer).

$Q_{in}(t)$, $Q_{sun}(t)$, $Q_{LEP}(t)$ for each zone. When we eventually sum over the zones, the interzonal terms add to zero

From the 7-zone input file, the four audit heat flows $Q_{BLC}(t)$, $Q_{in}(t)$, $Q_{sun}(t)$, $Q_{LEP}(t)$ are computed for each zone as explained before. In these computations, each zone is scheduled to maintain its measured temperature at each hour; also, for computational convenience we can disable ground heat flow and air flows in the specialized simulations. The

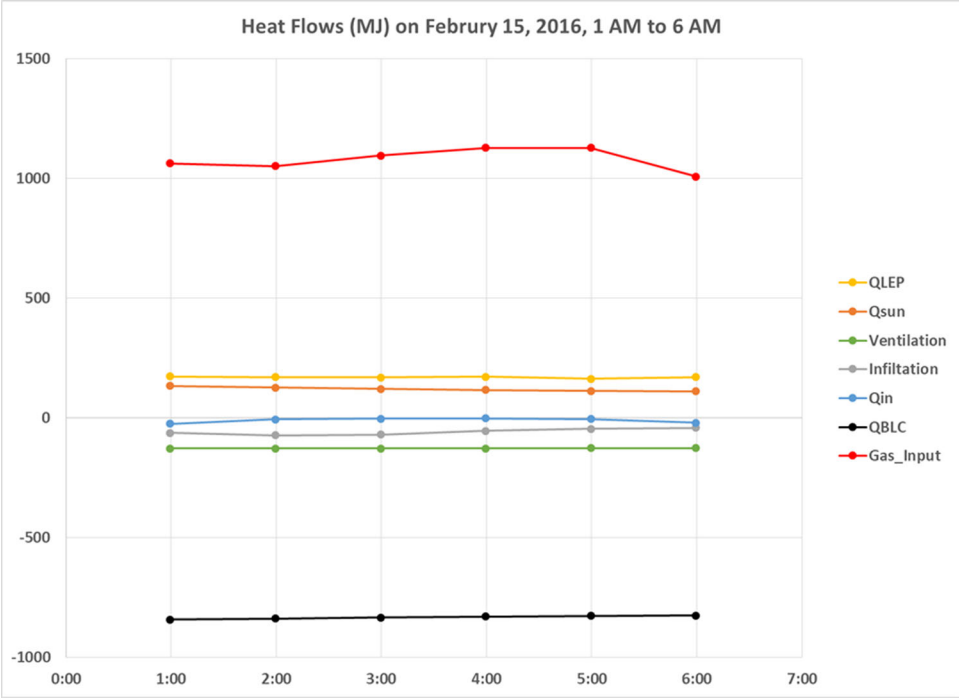

Fig. 13. Gas, and electricity use and pre-calibration heat flows (MJ/hr) for a 6-hour period 1 AM to 6 AM on February 15, 2016 for the actual building.

computed heat flows for the audit building are shown in Figure 11 for 2 weeks in winter and in Figure 12 for the 2 weeks in summer. The varying magnitudes of the individual heat flows both diurnally as well as seasonally are noteworthy.

Additionally, ventilation is estimated from each of the fan flows and associated return, outdoor and mixed air temperatures. Infiltration is modeled following Ng, Persily, and Emmerich (2015). Modeled ground heat flow was small and is incorporated without further correction.

The next step of parameter estimation requires great care.

- One can attempt to perform energy balance for each zone and estimate parameters at individual zone level. Given the uncertainties in delivered heating/cooling for each zone and interzonal heat transfer and airflow, this was deemed too problematic. We concluded that one should first perform the energy balance by summing over zones, even though certain flows are calculated at the zone level.
- If we have a known (i.e. measured) heat flow (not just gas input or electrical input to a HVAC system), whose magnitude was large enough for at least for some portion of the data period, the parameter estimation would be more robust. Otherwise, only combinations of parameters can be estimated. For our building, delivered heating/cooling energy use was not available. (Recall that we do have electricity and gas use time series. The HVAC system converts this into delivered heating/cooling; in the past, in some buildings, we have obtained this from temperature and water flow measurements, but not in this building). Inspection of the graphs (at least during the plotted period) shows no suitable period with a large enough known heat flow, even if we were to treat Q_{LEP} as known. (Note: Q_{LEP} is the heat released to the air node after accounting for delayed release, loss through exterior walls etc. It is not equal to *LEP* input; even the total Q_{LEP} is less than *LEP* by an amount that depends on the details of radiative couplings as can be seen from the data in the graphs. So Q_{LEP}, the actual heat input to the air node, is close to the known electricity consumption by lights and equipment plus heat attributed to people; that is as far as this can be estimated. One can, as an approximation, treat Q_{LEP} as a known heat flow. This is tantamount to accepting that the simulation correctly handles delays and losses of *LEP*. We can then filter on periods when it has large numerical values.)
- As proof of concept, we filtered for periods when Q_{BLC} is high and Q_{LEP},Q_{sun},Q_{in} are low, and found 6 contiguous hours from midnight to 6 am on February 15 to be suitable. The heat flows for that period are shown in Figure 13. The energy balance equation for each hour in this period is

$$p_{BLC}Q_{BLC}(t) + p_{BoilerEff}Q_{gas}(t) + Q_{LEP}(t) + Q_{sun}(t) + Q_{in}(t) + Q_{ventilation}(t) + Q_{infiltration}(t) \approx 0 \quad (29)$$

Because of the relatively low magnitude of Q_{LEP}, Q_{sun}, Q_{in} in the early morning hours, they are secondary terms and we are justified in not associating parameters with them. We can thereby determine a relationship between p_{BLC}, $p_{BoilerEff}$. Knowing one parameter would allow the other to be determined. As we vary p_{BLC}, the corresponding value of $p_{BoilerEff}$ can be determined by least squares fit. The resulting relationship is shown in Figure 14.

To summarize, the dominant heat flow is $p_{BLC}Q_{BLC}$ for the time period selected. The terms Q_{LEP}, Q_{sun}, Q_{in} are small but nevertheless contributed to improve the accuracy of p_{BLC}

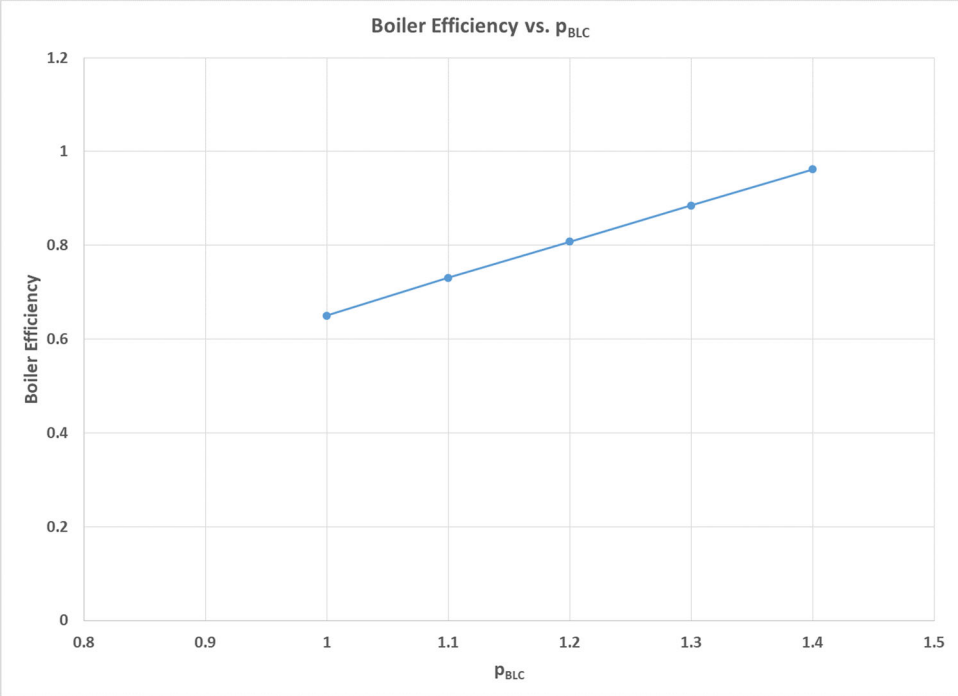

Fig. 14. Boiler Efficiency as a function of p_{BLC}.

estimate. These heat flows constitute a net heat loss that is compensated by the heat introduced by the boiler with the measured gas input. For any given boiler efficiency (with default part-load and off-rated curves) we can determine the heat introduced by the boiler. This relationship is shown in Figure 14. If we assume the boiler efficiency to be in the 80% to 90% range, p_{BLC}, will be in the 1.2 to 1.3 range, implying that the envelope is 20% to 30% more lossy than implied by the EnergyPlus input file.

Estimating the full set of parameters including p_{in} and p_{sun} as well as training a neural net for the residuals, requires additional data that was not available. Also, a detailed analysis of data windows to elicit specific parameters in specific windows is necessary and is left for future study. Preliminary analysis indicated p_{in} to be substantially smaller than 1, indicating that the building is thermally less massive than that implied by the audit simulation input file.

Summary and future work

The Enhanced parameter Estimation (EPE) methodology described in this paper is significantly different from conventional approaches to calibration. It allows one to systematically and objectively reconcile building energy simulations with actual performance data based on sound scientific and heat transfer principles. In summary, EPE consists of the following steps:

- Various sources of zone level heat flows are defined and computed using a set of specially formulated EnergyPlus simulation runs
- Least Squares fit to the model of the energy balance is accomplished by introducing and estimating parameters with physical significance. This aspect has been demonstrated in both synthetic and real buildings
- A two-stage calibration method is developed: (i) for analyzing the building shell, the HVAC system is replaced by an ideal system; and (ii) for analyzing the HVAC system, the building shell is replaced by a box with only process loads.
- Improved model prediction accuracy is achieved by training a neural net to the time series of residuals remaining after the least squares parameter estimation.
- Inputs to the neural net are computed heat flows that automatically incorporate the history of temperatures, solar radiation, internal gains, etc., thus simplifying a time series problem into one in which each hour is independent as far as the neural net is concerned.
- The entire EPE process can be automated but would require further software and interface development.

Future work should address (a) incorporation of the parameters into EnergyPlus simulation with thermostatic constraints, (b) refinements to multizone buildings, (c) automatic determination of data windows in which different parameters are best elicited through classification methods, (d) advanced HVAC parameter estimation (e) refining the methodology with data from additional actual buildings, and (f) demonstration of the efficacy of this methodology to different types of buildings in different climate zones under different control and operation strategies.

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