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Calibration and uncertainty analysis for computer models – A meta-model based approach for integrated building energy simulation

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HIGHLIGHTS

- ▶ We monitor and model an office building before, during and after an energy retrofit.
- ▶ We describe the advantages and the drawbacks of different calibration strategies.
- ▶ Piece-wise regression, Gaussian processes regression and model fitting techniques are used.
- ▶ We cross-validate the calibration comparing indicators obtained with different techniques.
- ▶ We present the calibrated prediction values for a reference meteorological year.

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ABSTRACT

In energy and environment field models are constructed, in general, based on well-defined physical phenomena and properties. Calibration and uncertainty analysis hold a particular interest because models represent a simplification of reality and, therefore, it is necessary to quantify to what degree they are imperfect before employing them in design, prediction and decision making processes. Integrated building energy models attempt to describe the effect of various internal and external actions (weather, occupancy, appliances, etc.) through physical relations (both algebraic and differential) and they are being widely used to design and operate high performance buildings, which are an essential component of a global energy strategy to reduce carbon emission and fossil sources depletion. An approach oriented to systems and able to integrate effectively field measured data and computer simulations for calibration in the modeling process has the potential to revolutionize the way buildings are designed and operated, and to stimulate also the development of new technologies and solutions in the field. The research presented in this paper aims to represent an initial step towards this integrated approach.

1. Introduction

The importance of uncertainty in energy modeling is often undervalued. A model represents a simplification of reality and therefore it is important to quantify to what degree it is imperfect before using it in design, prediction and decision-making processes. All these activities can receive a benefit from a meaningful and affordable representation of uncertainty. In energy and environment field, models are constructed based on well-defined physical phenomena and properties (e.g. energy balance, mass balance, conductivity, etc.).

At present, building energy performance simulation is a mature field and the growing level of detail of the available tools [1] results in a huge amount of parameters, all of which are uncertain to some degree. Although uncertainty can be easily estimated for many parameters, it is difficult to deal with it at the system level (aggregated effect of all uncertainties), in particular in building design process (design optimization performed before construction and commissioning) [2–13] and operational optimization (model predictive control and event detection in real time) [14–23].

High-performance buildings (both new and retrofitted) are an essential part of a global energy strategy to reduce carbon emission, fossil sources depletion and more in general, to obtain a reduced environmental impact in a cost-effective way. In order to achieve these results, it is required to rely heavily on validated models, both in the design and operational phase [1,20,24,25]. Far, since efficient buildings have to become a normal practice in a reduced time frame, due to the criticality of the global goals, it is necessary to foster the increase of field knowledge by focusing on the previously mentioned aspects. In other words, a "learning from performance" approach must be adopted to critically analyze the result of different design strategies and technologies.

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Nomenclature

Variables, parameters and statistical quantities

c	specific heat
d	observed/experimental data
E	electricity demand
f	weighting coefficient for intermittent operation
F	fuel demand
H	heat transfer coefficient
HC, CC	heating and cooling coefficient of the building
HS, CS	slope of temperature dependent heating and cooling energy demand
m	number of input variables, dimensionality of the input
n	number of experimental observations of the response, number of training points
Q	heat demand
T	temperature
x	input variables
X	input variables dataset
y	response variables
Y	response variables dataset
ε	random variable describing difference between predictions and observations
η	efficiency, gain utilization factor, losses utilization factor
θ	calibration inputs to the simulator, weight coefficients in the regression model
μ	mean value of variables
ρ	density
σ	standard deviation, hyperparameter
Σ	covariance matrix

Functions and operators

$G(\cdot)$	simulation model operator
$E(\cdot)$	expected value, conditional expectation
$cov(\cdot)$	covariance function
$f(\cdot)$	probability density and distribution function, function of likelihood
$g(\cdot)$	probability distribution for prior in Bayesian modeling
$h(\cdot)$	regression function
$k(\cdot,\cdot)$	kernel function (basis function)
$K(\cdot,\cdot)$	covariance function
$L(\cdot)$	likelihood function
$l(\cdot)$	log-likelihood function
$m(\cdot)$	mean function
$p(\cdot)$	probability density function

Subscripts and superscripts

$^{-}$	average value of variable
*	test dataset
a	air
adj	adjusted
c	change-point
C	cooling
d	day
ext	external air temperature
f	weighting coefficient
gn	gains
H	heating
i, k	training value indexes
ind	temperature independent demand
ls	losses
n	noise (error)
set	set-point
sys	system
t	duration of the analysis period
tr	transmission
ve	ventilation

Modeling correctly uncertainty is time-consuming and requires an additional effort in the overall design and operational optimization phase but, on the other hand, can provide more robust design solutions [26–28] and decision-making processes [29,30].

For example, it is possible to obtain not only a deterministic solution to a problem but rather a probabilistic solution (probability distribution), thus helping to gain greater confidence in the results with respect to the propagation of errors and underlying complex interactions among factors.

As a matter of facts, accuracy of energy and environmental modeling is not the only problem involved in the process of creating high-performance buildings. Actually, other factors such as economy viability [31,32] and impact of climate change [33,34] are other problems that strongly influence the success or the failure of an investment [35–38] and, therefore, the repeatability of the related technical solution or design strategy within a certain context.

Building energy models attempt to describe through physical relations (both algebraic and differential) the effect of various internal and external actions (weather, occupancy, appliances, etc.). All these relations require the use of a large number of parameters and despite the fact that the results for each single component or sub-system can be easily validated, overall system simulation output can be far from the measured value [39] in real word applications. As a consequence, it is necessary to perform an uncertainty analysis procedure, in order to quantify properly how uncertainties in input reflect on output. This can be done, in general, by assigning appropriate statistical distribution to inputs, running several models (employing a sampling strategy) [24,36,40,41] and analyzing relevant statistics for selected outputs.

However, not all the aspects modeled have the same level of importance and not all the inputs give the same contribution to error propagation [42–44]. As a consequence, uncertainty analysis must be coupled with sensitivity analysis to attribute a measure to the relative importance of the different input parameters [2,41,45].

Further, a profound knowledge of the component (or process, or sub-system) level behaviour is itself fundamental but not sufficient, because it is also crucial to analyze, interpret and model complex interactions based on continuously updated field data [20,21,46], for example, in dynamic commissioning and monitoring of buildings [47], which require a multi-scale system analysis.

A modeling approach oriented to systems and able to integrate effectively field measured data, computer simulations and to address multiple scales and periods under uncertainty [48] has the potential to revolutionize the way buildings are designed and operated, and to stimulate also the development of new technologies and solutions. Improvement in building energy modeling can involve, in particular:

1. integration between model driven and data driven multi-objective design optimization;
2. characterization of the dynamics of multi-scale, multi-period energy systems;
3. control, prediction and event detection for energy systems.