Geo-referenced Imaging and Co-simulation for Continuous Monitoring of Built Environment

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Abstract

The building sector, accounting for roughly one third of total energy use in OECD countries, provides huge and well-known potentials for energy savings which may be reached technically by highly efficient insulation systems and HVAC systems. Assessing and optimizing the energy performance in practice, however, needs a holistic approach covering the entire life cycle and focusing on the interactions within the building and between its natural and urban environments. An integral planning process requires information technology support based above all on the building information model (BIM) and building performance simulation models.

This paper describes a new technology for verifying the performance of existing buildings by continued design simulation in the use phase. Infrared thermography localized in six degrees of freedom with concurrent numerical simulation is proposed for parameter calibration. In this way, the model keeps track of the current building condition. Forward simulation and inverse parameter estimation together provide for the quantitative interpretation of thermal images which is lacking in building thermography today. Preliminary simulation examples will motivate the approach.

1. Introduction

Sparing use of energy resources or high energy efficiency (EE) is not an end in itself but a means for a building to impart productivity and utility to its occupants while reducing the carbon footprint. Quantitative performance metrics can assess how well it meets that purpose. Assistance by simulation tools during design is customary at least for commercial and public buildings (schools, hospitals, offices). Figure 1 illustrates the design and use phases in the building lifecycle, advocating continuous performance assessment [8] to test actual performance against the design baselines and to explain and understand deviations. The term ‘building sector’ is used as a synonym for all economic activities in the building lifecycle, with an emphasis here on occupancy.

1.1. Building Lifecycle

While lifecycle analysis proper covers all pre-chains and post-chains (fabricating components, providing end energy, demolition, and recycling), this paper focuses on the design and use phases.

The design work proper can be divided into conceptual, preliminary, and final design [15]. In the design phase already are interdependent and often conflicting decisions made. Consequently, a globally optimal combination is difficult to obtain. Early design choices such as orienting the building, roughly shaping its envelope and roof, composing the façade and glazing, assigning room shapes and sizes, designing principal air flows and paths of daylight have the greatest impact on the overall EE, and curtail options that are available later on. These decisions are long-lasting and hardly change and, as they shape the building character and its visual appearance, they are made by architects. Later on in the design, engineering choices of heating, ventilation, and air-conditioning systems (HVAC), building services and materials will follow.

The use phase comprises the construction completed by initial commissioning and the occupancy phase proper. Discrepancies may be detected between design intents and details of the current
building construction, between statistical and actual occupancy schedules or between predicted and actual modes of HVAC operation, possibly due to prevailing weather conditions. Efforts known as continuous commissioning are being made to adjust and optimize building operation [9, 11]. In the course of a building life, the envelope condition degrades and diverges from specifications, causing reduced airtightness, traces of moisture, compaction of insulation material, delamination, heat-structure interactions, or UV fading of coatings [12]. Rash and possibly inadvertent changes in HVAC control settings or unnoticed component failure may jeopardize the energy-saving or commissioning benefits achieved in the past. Informed decision-making is needed for planning retrofits, to balance benefits, costs, and impairments to tenants. The building stock will not benefit from major formalized design efforts anyway, but contribute much to the actual energy performance in the building sector.

**Figure 1: Towards lifelong performance simulation, adapted from [7]**

### 1.2. Tools and Deficiencies

While simple tools perform demand calculations under stationary conditions, e.g. according to DIN V 18599, in terms of heating, cooling, air, and daylight, whole-building performance simulators (BPS) also predict transient building response under realistic load and assess components in their unique building context using comprehensive criteria. There is empirical evidence of BPS indeed resulting in a significant reduction of the emission of greenhouse gases and substantially improving comfort levels [5]. Yet simulation is put aside in the use phase because calibration and validation are admittedly difficult and under-determined, and the high effort hardly pays off [15].

Monitoring, taking regular measurements of mostly energy consumption is performed for an operational rating during continuous commissioning [11] but casts a narrow perspective on performance and provides little diagnostic value. Complementary diagnostic aids, such as building thermography for damage inspection, require human expertise for interpretation. Often, the precise measurement context (environment) is lacking, and so are the quantitative impact and significance of findings. There are few exceptions, e.g. Asdrubali et al. [2] who presented a quantitative evaluation method for thermal bridges in buildings under steady-state conditions by calculating temperature differences between the zone air and the inner walls weighted by area. Specialized procedures for non-destructive testing (NDT), e.g. Active Thermography or ‘Lock-in- Thermography’, provide deeper insight by estimating quantitative parameters of an operational component model characterizing a defect or damage. However, they focus on components, only.
The new concept of *quantitative geo-referenced thermography* (QGT) aims at preserving the advantages of qualitative thermography for fast, non-intrusive thermal mapping. Using geo-referenced (mobile) IR camera images to estimate energy-related model parameters extends the NDT principle to cover *whole buildings*. Inspecting in-situ (indoor and outdoor) under natural weather and occupant influences greatly generalize the context of a part fixed in a mock-up and subjected to sinusoidal heating. Of course, relaxing the NDT assumptions goes at the expense of higher disturbances and inaccuracies (section 4). By predicting the impact of estimated parameter values on overall performance, BPS is integrated into the use phase of the building life cycle.

### 2. Whole-building Performance Simulation

Building simulators accept as raw input time series of building load (local weather data, occupancy, and user actions / commands) and produce time series of the energy supply required (fuels, electricity) and the zone temperatures. From these, the performance measures are calculated (figure 2).

Significant results are obtained by statistical aggregation. First, a probability density function (pdf) of load curves (e.g. Markov processes of typical weather at the building site) is specified. Next, the simulator is fed with random samples from the load pdf, preferably in a way covering the probability space evenly and efficiently, to collect performance values. Finally, the frequency distribution of performance is accumulated and moments (mean, variance, and extremes) are extracted.

![Figure 2: Building performance criteria and calculation, adapted from [7]](image)

One advantage of simulating existing building is its ability to calculate complex performance criteria that cannot be measured directly by sensors. These criteria serve as a yardstick throughout the lifecycle. For instance, thermal comfort is readily calculated from the percentage of people dissatisfied, ascertained once and in a standardized fashion (e.g. by the Fanger metric, see Figure 2).

Model solution complexity ranges from stationary heat balance equations (demand calculations) to transient thermodynamic solutions of ordinary differential equations (ODE) to computational fluid dynamics solving partial differential equations (PDE) for transport of air and moisture.

A web site maintained by the U.S. Department of Energy ([Building Energy Software Tools Directory](http://www.eere.energy.gov/buildings/tools), DOE 2011) provides a long list of available BPS tools and vendors. A survey by Crawley et al. [3] updated since 2005 as a live document compares the capabilities of twenty major BPS in terms of practitioners’ needs. Most BPS programs evolved as standalone packages (e.g. EnergyPlus, ESP-r, TRNSYS, IES-VE), while others rest upon numerical frameworks or simulation...
languages (such as HamLab on Matlab / Simulink, or Modelica). The second class better supports component-based development and creation of novel interfaces for mobile sensors. Another aspect important to our project is interoperability between BPS and BIM (using IFC, gbXML or CityGML as exchange standards). This goal may be operationalized by automatic export of geometry and material for simulation [4]. Alternatively, BPS may run inside an integrated BIM runtime environment; see [7, 13].

3. Concept and Architecture

This paper focuses on IR thermography as the main sensor for condition estimation. Figure 3 provides a survey of sensor and software components and data flows between them. Before applying thermography, the building model should be pre-calibrated to reasonably predict the actual building’s energy use [7] recorded by heat quantity meters.

Which parameters can be estimated typically? There are, for example, thermal conductivities and capacities of composite slabs, façades, and insulation material; thermo-optical properties of glazing (reflectance, transmittance, and absorbance); air exchange rates of zones and openings; effective thermal resistance and operating coefficients such as load or utilization factors of HVAC facilities. Built-in sensors such as flow meters may be combined with mobile remote sensor measurements.

The primary purpose of estimation is detecting deviations of actual parameter values from design expectations (documentation versus reality) or values drifting by operational wear. Estimation via an inverse model maximizes the likelihood of measurements given their prediction as a function of parameters. Predictions are based on the numerical (iterative, temporally evolving) solution of the governing equations; an analytical one is not available in closed form, in general. The final goal is to quantitatively assess how the estimated parameter changes impact the performance indicators.

The following key assumptions must be met:

- Parameters must be observable from the thermal building response (an image sequence). I.e., the system will respond differently for different parameter values under otherwise identical conditions.
- Camera position and orientation must be determined in six degrees of freedom for each image or must be continuously tracked to generate corresponding predictions.
- Initial and boundary values as well as the load acting on the building during inspection must be measured and be imposed on the model execution. Furthermore, the model bias, i.e., the discrepancy between modelled and real building, must be identified independently [7].

The building information model (BIM, shaded in gray in fig. 3) forms the backbone of the model and a starting point for the dynamic state equations. It determines the paths of heat transfer (conduction, convection, and radiation) and the flows of air and moisture through geometry and topology (shapes, sizes, and relationships). The building materials attached specify the dynamic thermophysical properties of heat and mass transfer. Graphically, the BIM represents the part hierarchy of the entire building, possibly embedded in its neighborhood, as a 3-D scene graph. The BIM serves as the main link between the simulator predicting the behavior by solving the state equations and the inspection system localizing itself with respect to the coordinate frame of the BIM.

The core simulation model consists of an ODE system of purely thermal state components (state $T$ in fig. 3) and may be assumed to be linear and time-invariant (LTI) in simple cases. System matrix coefficients are functions of the parameters $p$ changing at a slower rate than states (e.g., specified by an aging function). Parameters may be state-dependent on their part; e.g., conductivity is temperature-dependent, making the ODE time-dependent and nonlinear. Parameters change also in discrete events during the building lifetime when components break down or are replaced. PDE of fluid dynamics combining heat, air mass, velocity, and moisture content become ‘ODE’ after spatial discretization.
Figure 3: Data flow diagram of quantitative geo-referenced thermography (QGT) identifying the building condition. Directed arrows symbolize the flow of information between data repositories and processing instances. Real-world sensor measurements are shown by blue arrows.

The inspection and localization system consists of a mobile IR camera (hand-held or mounted on a vehicle) and auxiliary sensors and software to estimate its position and orientation.

For prediction, the camera view pose (coordinate frame) acts as an ‘index’ into the BIM scene graph to find the components that the IR camera should ‘see’, i.e. from which it receives thermal radiation directly or by reflection. The simulation model is queried for the thermal state values of these components at the time of image capture. Disturbing radiation from the sun or the night sky and reflections from background objects are present, depending on the viewing geometry, and are accounted for. An essential part of prediction is the IR camera model [1] converting thermal radiance into a virtual IR image according to the detector’s spectral response function. However, not a rendered image but its explicit functional dependency on the parameters is the main purpose of all calculations, yielding a mobile measurement or error function.

The inverse model attempts to estimate only few parameters at a time as free variables, the ones associated with parts seen in the camera field of view, in order to make estimation ‘less under-determined’ [7]. Several different images in space and time may be combined in one error function; the final function shape appears at inspection time, only. Main tasks of the inverse model for a maximum-likelihood problem statement are to calculate the Fisher information matrix expressing how sensitive measurements are to parameters, to minimize the error (nonlinear regression) including regularization terms, and to estimate the uncertainty (covariance) of the minimizing parameters by assuming a known uncertainty of the imaging process.

Unlike continuous estimation e.g. by means of an Extended Kalman Filter, QGT identification takes place in discrete inspection campaigns. The building state at campaign start must be measured to set up the simulation with correct initial and boundary values. Quickly changing weather data, e.g. solar radiation and wind speed, and occupant actions such as entering or leaving, opening windows, and changing HVAC settings, should be recorded during a campaign, translated, and imposed on the co-simulation. These are the sometimes complex tasks of campaign control.

With a well-designed and detailed model and identical starting values, the parameter values explaining the thermal images best reveal some aspects of the true building condition. The scope of a parameter may be an entire zone, e.g. the infiltration rate, or a small region, such as a thermal
bridge or a moist patch on a wall with locally deviating heat capacity or conductivity. The information gained is the difference from prior values or other parts. Impact analysis has to translate this into a difference in global performance, like expected energy cost per year or loss in thermal comfort. Therefore, the forward simulation model is run and compared under large sets of identical building loads outnumbering by far the load conditions during inspection and identification.

4. Scientific Challenges
This concept gives rise to serious scientific questions for which we have no final answers yet:

Localization: GPS and compass based positioning known from mobile city guides (smart phone app) does not work reliably indoors, and its orientation accuracy is limited. In contrast, efficient and inexpensive *range* cameras like *MS Kinect* may be overcharged outdoors or in large buildings due to their short range. Geo-referenced thermography (without thermodynamic co-simulation) was implemented and analyzed by Still and Hoegner [14] with two IR cameras mounted on a street vehicle. They applied GPS for coarse absolute localization and feature matching for fine registration using a 3-D CityGML street map of an urban district. Registration results served to map the thermal images onto building surfaces. One problem of thermal images for localization is the disparity of features: Thermal edges in IR images versus geometric edges in CityGML models. A localization system for *ThermoTracer TH 7800* including a stereo camera and vehicle sensors (GPS, inertial measurement unit, compass) was recently designed in a diploma’s thesis [10].

Error Function: As an executable function, its coefficients depend on the *iterative solution* code, the *simulation time*, and the *camera view pose*. Differentiating the error function at run-time may require symbolic processing and automatic differentiation. Though the state vector components ‘viewed’ by the camera are found efficiently by GPU (graphical processing unit) rendering, the corresponding finite-volume elements may disagree with the original design geometry referred to as the BIM and assumed as scene graph. Transformations and refinements, e.g. due to gridding algorithms, are opaque to simulation users and to external tools. Identification with mobile cameras and co-simulation therefore requires novel interfaces providing deep access to the simulator code. Most building simulation packages are not prepared for this. These challenges persist notwithstanding the formulation of the error function as a deterministic prediction or Bayesian likelihood (pdf).

Observability: Active thermography for non-destructive testing utilizes a *periodic* heating source and admits identification methods in the *frequency* domain. In QGT, image responses contain many frequencies apart from the typical diurnal and weekly cycles. Furthermore, the errors by far exceed the ones encountered in NDT applications, as discussed in [7], section 4.2. Identification therefore needs methods in the time domain or fully Bayesian inversion. Two error sources dominate: Firstly, inaccurate capture of starting values and input trajectories acting on the building, and secondly, model bias or mismatch or discrepancy, see Kennedy and O’Hagan’s seminal paper [6]. Model bias lets the estimation abuse parameters as ‘tuners’ or ‘tweaks’ rather than indicators of the true equipment condition unless the bias is identified separately from the correct parameter values.

5. Preliminary Examples
A simple transient simulation of a single-zone cuboid building (thermal-only, in Matlab) was performed to answer basic questions: Are different operating conditions (thermo-physical parameters) distinguished by the thermal responses of the building? The building has a flat roof, a massive adiabatic floor slab, a large south-exposed window, and a heating and cooling control algorithm. Walls and ceilings are composed of different materials. The weather interface accounts for internal solar gains. A stochastic weather generator for a climate similar to Karlsruhe was invoked for 10 days in winter with identically repeated trials. The following thermo-physical building conditions represented by parameters are clearly observable from the curves and can be quantified:
1. Rate of infiltration / natural ventilation
2. HVAC: Thermal resistance of the heat exchange between zone air and circulating fluid
3. Envelope heat coefficients (conductivity and diffusivity of slabs / façade)
4. Thermo-optical window performance parameters (transmittance of glazing, shading Y/N?).

A few examples are shown in figure 4. Due to the coarse model, the potential of thermography measuring spatially highly resolved temperature fields has not yet been traded on; one average value per building slab and zone air is insufficient, in general, to detect and explain deficiencies.

6. Concluding Remarks

Cautious readers may notice that building simulation is just one application example – perhaps not the most rewarding one - of remote identification of transport models using mobile camera networks. This evolving computational discipline opens up many applications, for example:

- Efficient remote validation / calibration of urban climate or energy simulation models;
- Efficient condition-based maintenance of petrochemical plants or district heat infrastructure;
- Remote identification of process plants after an accident or disaster causing destruction of built-in sensors.

Figure 4a: Thermal responses for an envelope of high thermal diffusivity (left) and low diffusivity (right). Slab temperatures on the left stay closely together and show a marked diurnal oscillation; on the right, they are independent with little oscillation and converge to a joint mean in the long run.

Figure 4b: More and less efficient heat transfer between heating / cooling medium and zone air. Left: Small total resistance $R_{\text{exch}} \approx 0.01 \, [\text{K/W}] \Rightarrow$ tightly corresponding air and water temperatures and a moderate amplitude of air temperature ([19°C, 26°C]). Right: Larger resistance $R_{\text{exch}} \approx 0.1 \, [\text{K/W}] \Rightarrow$ high water return temperature and higher amplitude of air temperature ([17°C, 28°C]).
Figure 4c: Window glazing of high solar transmittance ($\tau = 0.7$) and no blinds (left) compared with ultra-low-transmittance ($\tau = 0.3$) glazing and shading device (right). On the left, frequent overheating and subsequent under-cooling periods occur, while the air temperature curve on the right is smooth.

References


