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IEA Annex 58: Full-scale Empirical Validation of Detailed Thermal Simulation Programs

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Abstract

As simulation programs become more widely used for building performance assessment and building regulations compliance, there is a need to ensure that there are good quality empirical datasets which can be used to assess the predictive accuracy of these programs. This paper summarises a detailed experiment carried out on two identical full-scale buildings located at the Fraunhofer IBP test site at Holzkirchen in Germany and the associated modelling of the buildings. The work was undertaken as part of IEA ECB Annex 58 "Reliable building energy performance characterization based on full scale dynamic measurements". The test sequence, applied to the side-by-side validation experiment conducted on the multi-roomed Twin Houses, consisted of periods of constant internal temperatures, a period of pseudo-random heat injections and a free-float period. All boundary and internal conditions were comprehensively monitored. Modelling teams were given details of the buildings and the boundary conditions, and over 20 teams submitted their predictions of the internal conditions which were subsequently compared with measurements. The paper focuses on a sensitivity study carried out to assess the overall prediction uncertainty resulting from the uncertainties in the input parameters, as well as identifying those inputs which had the most influence on predictions. An assessment of the measurement uncertainty is also included.

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1. Introduction

As increasingly stringent building energy regulations are implemented in the EU and elsewhere, there is increasing focus on designing and operating low-energy buildings. This has led to more attention paid to modelling the building, usually through the use of simplified methods such as the quasi-steady state methodology in EN ISO 13790 [1] for checking performance against minimum national standards, or detailed simulation programs for analyzing design options and compliance checking of more complex buildings.

As dynamic modelling becomes more widely used in design and compliance, it becomes more important to check that the predictions are correct. This has two aspects. Firstly, proper user training and QA procedures are needed to make sure the models are correctly set up – i.e. correct definitions of internal gains, geometry, construction, heating setpoints etc. Secondly, there need to be well-established checks that there are no internal errors or modelling inadequacies in the programs. It is the second of these, program validation, which is the focus of this paper.

An overall validation methodology is well established and comprises elements of analytical, inter-program comparison and empirical test [2,3]. Inter-program comparative tests are the most commonly applied validation method, with the advantage that they are relatively easy to specify and run, and a large number of parameter variations can be studied. One set of tests in particular, BESTEST, was developed within an International Energy Agency (IEA) project [4]: these tests are commonly used by program developers to test their code, and they have been incorporated into ASHRAE Standard 140 [5]. Although these tests are useful as a diagnostic tool and for providing standard tests for regulation compliance purposes, they do not address the question of whether simulation program predictions reflect actual building performance. Such reassurance is possible through the use of empirical validation studies, but gathering the necessary high quality experimental data is complex, time consuming and expensive. There has been some success in conducting empirical validation experiments within large-scale international (IEA) projects, but these have been at component level or on outdoor test cells (e.g. [6]).

Undertaking empirical validation on full-scale buildings is difficult because of the need to know details of all the heat transfer paths to provide a complete specification, otherwise it will not be possible to identify the cause of mismatches between measurements and predictions, i.e. whether they are a result of program deficiencies or measurement uncertainties. All building details (e.g. dimensions, construction materials, optical glazing properties and heating system) and all the prevailing weather during the test period should be available to the modellers.

This paper outlines details of an empirical validation experiment conducted within IEA ECB Annex 58 "Reliable building energy performance characterization based on full scale dynamic measurements" [7]. The buildings tested were the Twin Houses operated by the Fraunhofer Institute IBP at Holzkirchen in Germany. These are relatively simple houses, but are of realistic dimensions. One important feature of the designed experiment was to use two essentially identical buildings in a side-by-side configuration with slightly different experimental set-ups, so that not only absolute comparisons of measured temperatures and heat fluxes could be made with the predictions but also measured and predicted differences between the two buildings could be compared. The detailed description of the experiment, together with 10-minutely and hourly averaged measured boundary conditions, was circulated to modelling teams, with 21 modelling teams submitting their predictions in advance of the release of the measured internal conditions. This "blind" validation was followed up by re-submissions after the measured data was released, with modelling teams fixing and documenting user errors.

In comparing measurements with predictions and judging the level of agreement, it is important to understand the uncertainties in the experimental data, and in the modelling predictions. This paper focuses on sensitivity studies that have been undertaken to understand the main sources of uncertainty, and uncertainty analysis to evaluate the results.

2. Empirical Validation Specification

2.1. Location and Geometry

The Twin Houses (Figure 1) are two typical German single family detached houses equipped with extensive measurement and control equipment. External walls are insulated according to the German energy code EnEV 2009. Windows are double glazed with glazing with a U-value of 1.2 W/m²K and are equipped with electric external roller blinds. During the measurements all roller blinds in the ground floor were up except for windows in the south façade

– in this case blinds were operated according to different schedules in the two houses. The focus for the validation experiment was the ground floor (7 rooms), with air temperatures in the cellar and the attic measured and supplied to modelling teams as boundary conditions. A constant flow rate mechanical ventilation system was operated.

To be used for side-by-side experiments it is necessary to show that the two houses are essentially identical. They have exactly the same dimensions, room layouts and constructions. Pressurization tests were carried out on the two buildings showing less than 5% difference, within the normal test accuracy of the EN 13829 Standard. A four-day heating test was also carried out with the houses in an identical configuration with the same setpoints: this showed total heating energy consumption of both buildings was within 0.5 %.

Fig. 1. (a) external view; (b) internal view of living room.

2.2. Test schedules

The experiment was divided into four periods, preceded by an initialization phase for a total test period of approximately 2 months during August and September 2013. In the initialisation phase both buildings were heated to a constant temperature of 30 °C to obtain identical and well defined start conditions.

In the first period the room air temperatures were kept constant at a nominal 30 °C with a required heating power controlled by the building management system. The measured temperatures are provided as inputs to the modellers who are then required to predict the required heating power.

In the second period, a Randomly Ordered Logarithmic Binary Sequence (ROLBS) for heat inputs [8] into the living room was enacted, with heat injections of 0 and 500 W. The use of a pseudo-random sequence of heat injections ensures that the solar and heat inputs are uncorrelated, which helps to disaggregate the fabric heat transfer and solar gains in the analysis. The ROLBS sequence was customised to cover the expected time constants of the Twin Houses – large in this case as the houses contain a significant amount of thermal mass. All other rooms were without heating power in this period. The ROLBS sequence of heat inputs was provided to the modellers who then predicted the resulting temperatures in this period.

The third period is a constant temperature period in order to re-initialise the two houses to the same state. The controlled temperature level was set at 25 °C. Again the measured indoor air temperatures are provided to modellers. In the fourth period, the indoor temperatures are free floating with no artificial heat sources, with modellers predicting the internal temperatures.

2.3. Instrumentation

Table 1 lists the sensors inside both Twin Houses calibrated prior to the experiment and the climate sensors from the on-site weather station where the sensors are calibrated regularly as recommended by the manufacturer.

Table 1. Sensors and accuracy.

Parameter	Accuracy
Air temperature in all 7 rooms at a height of 125 cm (radiation shielded)	±0.12 K
Living room air temperatures at a height of 67 cm and 187 cm (radiation shielded)	±0.14 K
Air temperatures in the cellar and attic spaces	±0.14 K
Relative humidity living room	±2.3 %
Fresh, supply and exhaust air temperatures measured in the cellar	±0.02 K
Heating power of the 6 heated rooms	±1.5 %
Supply and exhaust fan power	±1.5 %
Ventilation flow rates	±3.5 m³/h
Heat flux at the west facade	±0.65 W/m²
West wall temperatures: Internal, external and between layers	±0.14 K
Ambient air temperature	±0.10 K
Ambient relative humidity	±2.0 %
Ground temperatures at a depth of 0, 50, 100 and 200 cm	
Wind speed at 10 m height	±0.1 m/s
Wind direction at 10 m height	±1.0 °
Solar radiation: global, diffuse and vertical (north, east, south, west)	±2.0 %
Long wave radiation (horizontal, west)	<34 W/m²

3. Experimental uncertainty

The experimental data uncertainties are small. The individual calibrated shielded temperature sensors have an accuracy of better than 0.15 °C and the heating power accuracy is ±1.5 %. However, some stratification was observed in the living room where the topmost temperature sensor recorded between 1 and 2 °C higher than the middle and lower sensors. Some modellers used the average of the three sensors; others used the middle sensor in order to represent the well-mixed room assumption of all the models used in this exercise. So a reasonable estimate of the room-averaged measured temperature accuracy is in the order of 0.5 to 1.0 °C.

4. Modelling sensitivity and uncertainty analysis

A sensitivity analysis was carried out to determine which parameters have the most influence over the predictions, followed by an overall uncertainty analysis which can be used in comparing measurements with predictions. Results presented here are for one of the Twin Houses, to demonstrate the importance of such analyses in empirical model validation.

A detailed model was built using the dynamic simulation program ESP-r [9] and sensitivity analyses were undertaken independently according to model zone and experimental period, by focusing on the sensible heat loads and the internal temperatures relative to the constant temperature and ROLBS sequences respectively.

Among the several alternatives the Morris Method [10] was chosen for its effectiveness in undertaking parameter screening. This sensitivity technique is generally applied to mono-dimensional model responses, so it was necessary to pre-process the ESP-r outputs. Principal Component Analysis (PCA) [11] was used to decompose the simulation outputs as linear combinations of orthogonal basis vectors. The number of basis vectors sufficient to explain 99% of the simulation set variance was retained. The Morris Method was then applied independently to the coefficients of each basis vector. Finally, the calculated μ^* scores were summed as given in Equation 1. In Equation 1, n is the number of basis vectors and d^2 are the eigenvalues from the PCA. The M_i result is the variance-weighted root of sum of squares of the i-th parameter $\mu^*_{i,j}$ sensitivity indexes (which are effectively the partial derivatives of the model output with respect to each of the model inputs).

$$M_i = \sqrt{\sum_{j=1}^{n} \left(\frac{\mu^*_{i,j} d_j^2}{\sum_{k=1}^{n} d_k^2} \right)} \tag{1}$$

Uncertainties considered in performing the analysis are listed in Table 2, and an example graphical representation of the results for the living room for the constant temperature period is given in Figure 2.

Table 2. Model parameter uncertainties by category.

Parameter	Distribution (with respect to design value)
Conductivity	N(1, 0.35)
Density	N(1, 0.15)
Specific Heat	N(1, 0.3)
Thermal bridges	U(0.9, 1.1)
Infiltration	N(1, 0.33)
Window thermal resistance	N(1, 0.35)
Optical transmission	N(1, 0.33)

The results for the constant temperature period highlighted the most influential parameters as the infiltration and the floor, ceiling and envelope conductivities as expected. Additionally, each zone was found to have different sensitivity characteristics. For example, the living room sensible heat load is highly dependent on the infiltration and ceiling and floor conductivities. Smaller rooms such as kitchen, lobby, bathroom and north bedroom have their heat requirements mostly influenced by parameters responsible for heat fluxes through the openings and external wall conductivities. The south bedroom presented intermediate characteristics, being mostly sensitive to infiltration and external wall material conductivities.

For the ROLBS period, the results for the various rooms were similar. Thermal mass in the floor, ceiling, external walls and internal walls were identified as being important; envelope conductivities were of secondary importance.

Monte Carlo simulations were undertaken in order to compare model and experimental uncertainties, considering only the parameters retained from sensitivity analysis. For the constant temperature period, the uncertainty bands of the measurements overlapped with those of the model predictions. This was not always true for the ROLBS sequence, as shown in Figure 3 for the living room, where the model predictions and measurements overlap consistently at the beginning and at the end of the experimental period, but in the middle of the experiment the model systematically underestimates the internal temperatures. The reasons for this are currently being investigated.

5. Conclusions

A full-scale empirical validation experiment was conducted within IEA ECB Annex 58 based on a side-by-side experiment conducted on the Twin Houses at Fraunhofer IBP, Holzkirchen, Germany. The resulting dataset is useful for program developers to check on their modelling predictions, and to help instil confidence in the ability of simulation programs to accurately predict energy consumption and indoor environmental conditions.

In comparing measurements and prediction in empirical validation, it is necessary to consider uncertainty bands. Some results have been presented to show the use of sensitivity and uncertainty analysis in evaluating the comparisons. The relatively small error bands indicate that the dataset and specification are of high quality.

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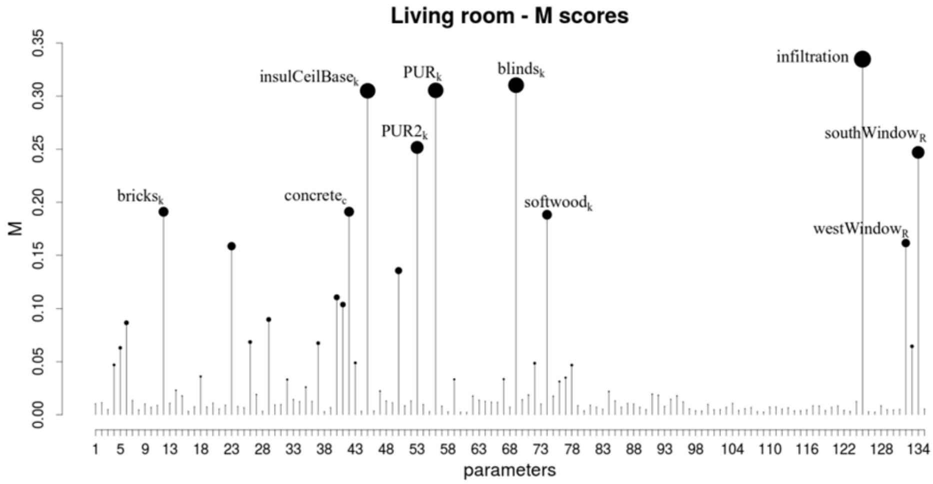

Fig. 2. Mi scores for the living room constant temperature period. R, k and c indicate thermal resistance, conductivity and specific heat

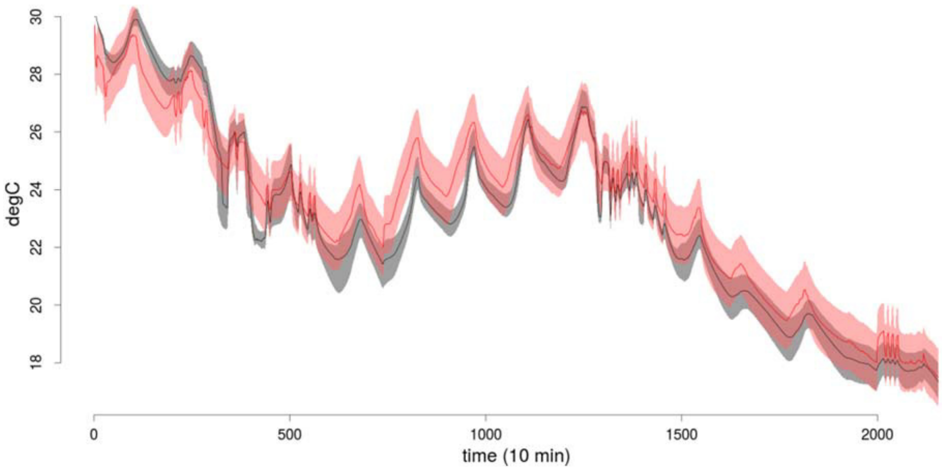

Fig. 3. Mean values and 95% confidence bands for the living room measured (red) and predicted (black) internal temperature: ROLBS

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