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CALIBRATING SYMPHONIES

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Abstract
In this paper we address the general topic of calibrating initial Building Energy Performance Simulation models, iBEPS. We build upon a recently published paper entitled "Narrowing the Gap - A Framework for Connecting and Auto-Tuning a Design BPS Model to a Physical Building" to outline a methodology for calibrating iBEPS models. We highlight common trends and pitfalls encountered in iBEPS calibration studies, and propose strategies and a methodology for overcoming these obstacles. The methodology is implemented and tested on IEA Annex 58 single housing model.

1. Introduction

Commissioning of buildings is becoming a necessity and a legal requirement in construction, as well as in building certification programs; thus bridging the gap between designed models and as-built systems. With monitoring periods of up to two years, commissioning provides a means of assessment, and feedback for early stage design.

This has led to a surge of automated and software-assisted tools aimed at helping the building modeller calibrate iBEPS models, as well as guidelines to standardize the evaluation of the final calibrated building model ([1, 2]). However there has been a general lack of discussion concerning the nature of the calibration problem itself. We would like to shed light in this study on the calibration problem of an iBEPS model, hoping to better define its boundaries and assumptions. To do this we need to start with models.

1.1 What is it that we are calibrating?

Models generally fall into two categories, that of the physical, and that which is mathematical. *Whilst all physical-based models are mathematical, the converse does not hold true, not all mathematical models can be described as physical.* In fact, to qualify as a physical-based model, the latter should be formulated as a system of physically meaningful equations. That is to say, a system of equations with parameters reflecting

physical quantities. This in itself is an important classification to make. For though both physical-based and mathematical models tend to benefit us, by revealing accurate predictions of how a physical system behaves, only a physical-based model can reveal the inner characteristics of the physical system which caused that specific behaviour. Inducing physical characteristics from a purely mathematical model requires a high degree of complexity, and will not be addressed within the scope of this paper.

A building can in fact be modelled as a mathematical and/or physical-based model. A multi-layered artificial neural network, ANN, has been shown to predict with high level of accuracy the behaviour of a building([3]). Meanwhile physical-based models of buildings have undergone rigorous simulation validation tests, and can be just as accurate([4]). If we were to compare these two types of modelling, the unstructured formulation of the multi-layered artificial neural network, meant that it was restricted to the allocated boundary conditions. That is to say if any physical property in the building were to change, for instance installation of new windows, the ANN has to relearn and modify it's structure to accommodate this change. This limits mathematical models in their analytical uses, making them ill equipped for what-if scenarios, retrofitting analysis, as well as diagnostic and fault detection features. In the commissioning phase of a building, the main purpose of a calibration is to understand the physical characteristics of the building, in hope of rectifying any irregularities. The calibration of an iBEPS model serves as a diagnostic tool for the energy modeller.

1.2 What are we able to calibrated in an iBEPS model?

In fact, most iBEPS models contain both physical-based and mathematical models within their description. For even though most iBEPS model can be described in terms of physically meaningful set of equations, some parts elude this due to their complexity. An apparent example would be a heat pump model. Heat pumps incorporate several dynamic behaviours, such as the interaction between the evaporator and its environment, and another between the condenser and its environment, and as such is often described as a mathematical model with parameters that are optimized to fit the manufacturer's data. Hence we can conclude here our first limitation in calibrating an iBEPS model. *We can not calibrate all parts of an iBEPS model in a physically meaningful manner, and therefore we should aim to calibrate an iBEPS model not as a whole, but as the sum of it's parts*.

This becomes more evident once we consider how an iBEPS model is constructed. With a building envelope, zones, plant, air handling units, internal gains, control schemes, and distribution network models, all simulated in unison to predict the actual behaviour of a building, the problem of calibrating all parts together becomes increasingly a hopelessly undetermined one. To further illustrate this point, and future points, we would like to introduce a metaphor that will make it easier for us to understand the nature of the problem at hand. One would like to imagine calibrating a building's performance, as one calibrating a symphony orchestra. Both consist of different acting elements, which

have to be conducted in collaboration to deliver a performance.

And so if we would like to tune any one of the string instruments, there is no way around having to start tuning the first string, and only then move on to tune the rest of the strings in reference to the first. Similarly in a building, in order to calibrate the ventilation rate of any specific zone, first we need to make sure that the air handling unit is itself calibrated and in good working order, and the duct network losses are all accounted for. *Hence any form of iBEPS calibration is preferred to be a sequential one.* In the commissioning phase of a building one has access to excite, and turn off systems while monitoring them, allowing us to perform calibration in a sequential manner.

1.3 Which parameters to calibrate?

And so the question renders itself, which parameters should we consider when we can not consider all? Two camps emerge, one relying on an expert's knowledge and experience in building physics, the other on sensitivity analysis. Here is why sensitivity analysis is an inappropriate tool to rely on in our case. Imagine trying to calibrate our symphony by selecting the most influential instruments. Sensitivity analysis yields the most influential parameters with respect to our selected output. This can performed by varying each parameter at a time, or any combination of parameters to include correlation effects. Regardless of which method is used, the output is a list of the most influential parameters. If we were to conduct this on our orchestra, most likely the drummer along with the loudest of instruments will be on top, leaving behind our triangle and percussions in the back. Moreover under different criteria and cut-off limits, different instruments will be prominent. And so the question becomes, do we want to explain the error by using the most influential elements? Is it any wonder then, that in most sensitivity analysis, outside weather conditions, and room units are always on top? Would we want an oversized radiator to explain the temperature error in our zone, which will overshadow the subtle effect of insulation density, and shading factor of our glazing? The fact of the matter is, in a physically meaningful equation every parameter is important for calibration. *And therefore a better selection criteria, than sensitivity, is parameter uncertainty*. We would simply like to calibrate the physical parameters that we are most uncertain about. More so we would like to quantify the uncertainty range for each physical parameter.

1.4 Lumped vs local

When we are done selecting the parameters with the highest uncertainty, we are faced with yet another question. Should one consider calibrating lumped parameters instead of local ones? Lumped parameters are those describing a set of local parameters, such as average U-value of all walls, total thermal bridge losses, etc. Whilst it is clear that considering lumped parameters, which is similar to tuning the instrument section of the orchestra by tuning a representative single violin, will simply not suffice. The underlying question is how do we consider all local parameters in our calibration without rendering

the problem infeasible?

To be able to accomplish this we have to state our first assumption. *Most zones can be thermally decoupled*. Decoupling is a useful technique in analysing complex systems, and one we will rely on in calibrating iBEPS models. If we ensure our zones have all openings closed in the commissioning phase, then it is not an unfair assumption to consider these zones to be thermally decoupled. This turns an NP-complete problem into an NP one([5]), by enabling us to compute in parallel all zone level calibrations.

1.5 Capturing events

Performing calibration of all parts of an iBEPS model in sequence, with decoupled zones, and whilst considering local parameters which entail high uncertainty is a solid approach. However an important factor in the calibration process is the optimization methodology put in use. Most simulation solvers implement fixed time steps to solve the set of Ordinary Differential Equations describing the building, and support discontinuous models with fixed tolerances. This will produce an objective function surface that is a challenge to navigate across to reach an optimal point([6]). The best option in this case is make use of genetic algorithms, and suffer through the high number of optimization runs. However some simulation solvers actually implement variable stepping, and support continuous models with the ability to tighten tolerances, thus generating a smoothed objective function surface curve([4]). This allows us to utilize the much more efficient gradient based optimization methods, which consider surface properties to manoeuvre to an optimal point, thus requiring fewer runs. This is a practical issue to consider, since each single annual simulation run entails a cost in magnitude of hours in most cases. However, for gradient based approaches, it is vital to navigate around events caused by schedules and controls, as they will lead to discontinuities in the objective function surface.

Regardless of which optimization method is used, the sequential calibration approach requires us to calibrate the different iBEPS parts at different time slots. That is to say, to calibrate the building envelope at times when the systems are off, and with absence of occupants. This in turn can limit the number of observational points used in the optimization scheme, thus leaving us with an ill-posed, and under-determined system. To solve this issue, we have to make sure we maintain a level of captured critical events in our observed data. That is to say if our sensor data set, contains very few events, then our evaluation points for the optimization scheme will contain a lot of redundancy. In the commissioning phase of a building we can control the level of excitation to ensure our data set is rich with information for the use of the optimization process. *However if one is restricted with a historical data set for calibration, then avoiding under-determined system necessitates some sort of dimensionality reduction.* Principle Component Analysis, PCA, can remove dependent parameters based on their degree of correlation. Moreover, many regularization techniques can be implemented to address the ill-posed problem. Another interesting method, used in “Narrowing the Gap - A Framework for Connecting

and Auto-Tuning a Design BPS Model to a Physical Building", is to rely on frequency based information to decouple the local parameters. Different physical parameters in a building will affect the behaviour of the building at different intervals in time. For instance windows tend to affect the zone temperature during solar peak hours, whilst the building envelope has a more prolonged effect on the zone's temperature depending on the thermal mass of the building.

1.6 Evaluating the calibrated model

The most common approach for evaluating the calibration process is the Coefficient of Variation of the Root Mean Square Error CV(RMSE). It is a popular measure in time series, and is averaged with respect to the mean measured value. It is also the recommended by ASHRAE's guideline 14-2002 ([1]). The main issue with relying only on the CV(RMSE) is that it will only test how well the simulated value of the current period compares with the observed value. The CV(RMSE) offers no indication what-so-ever as to how well the calibrated model performs with future observed data. The CV(RMSE) by itself is has no indication of how the predictability power of the calibrated model. In turn this means that it does not consider the effect of over-fitting, nor how well the iBEPS model will perform when it is asked to make new predictions for data it has not yet seen. *Hence it is vital that we do not use the same data set for optimization and for evaluation.* To properly evaluate our calibrated model we have to perform a cross-validation test. By either "holding out" part of the data set for evaluation and using the rest for the optimization process, or by performing a K-fold cross validation when the data set is too small to partition.

It is also necessary to analyse the physicality of the parameters in the end result of a calibration process. That is to say, if the calibration output of the physical parameters is on the border of the box constraints, this is a clear indication that the optimization process did not converge well. Nor is the case when the parameter end value exhibits little change, indicating the optimization process could not find an appropriate step due to a poor initial starting point selection.

1.7 How much error do we want to explain?

Every iBEPS model can have four types of errors and disturbances. Calibration tries to account for only one of those. Calibration tries to rectify the parameter error, however our system will also contain modelling errors, measurement errors, and stochastic errors. Modelling errors are errors which were not accounted for in the modelling process, such as not accounting for condensation on the cooling panels, or not accounting for the radiation heat transfer on the back of the radiator towards the wall, or even forgetting to model the shades on a specific window, or underestimating the buoyancy flows in a glazed atrium, or using a rough estimate to calculate the film coefficients, and excluding the moisture transfer within walls, ect. Would we want our selected parameters to compensate for these errors? Measurement errors, are those inherent in the sensor network.

They can lead to bias in measurements due to inappropriate positioning of the sensors, or lack of sensor calibration and maintenance. Moreover measurements can entail lags, and can be sensitive to disturbances. Finally, stochastic errors can originate from occupant's behaviour and stochastic presence. All these different types of errors are reflected in the total error deviation represented in the CV(RMSE) value, making it unreasonable to rely solely on the CV(RMSE) optimization to calibrate our physical parameters.

To address this issue it is vital to filter the states whilst running the optimization algorithm. If we were to state our second assumption, it would be that *our model contains additive error*. Hence we can make use of a Kalman filter to adjust the states of our model whilst running the optimization algorithm. This method is known as Simultaneous Optimization and Data Assimilation, SODA, in different fields([7, 8]). Without applying any sort of filter, the only useful result we could conclude from the calibration process is identifying which physical parameters need attention, and in which direction they should be adjusted. However the precise end value of which will remain out of reach.

2. Implementation

The highlights of the methodology established above can be summarized as follows:

- Select local parameters based on their level of uncertainty
- Define the range or constraints of each parameter
- Select different time periods which contain a reasonable amount of information. The time periods should reveal different aspects of the iBEPS model, such as when the systems are off, at time of no occupancy, when each specific system activates, etc.
- If no such period exist, consider reducing the number of parameters selected, or decoupling them using frequency information.
- Apply a Kalman filter to the state of each physical model while running the optimization algorithm.
- Cross-validate the calibrated model and analyse the final value of the physical parameters.

The implementation of our proposed method was detailed in "Narrowing the Gap - A Framework for Connecting and Auto-Tuning a Design BPS Model to a Physical Building". A variation of the Simultaneous Optimization and Data Assimilation method was implemented, incorporating continuous real-time data assimilation, alongside an on-line Key Parameter optimization conducted at intervals, as shown in *Figure 1*.

The framework in *Figure 1* establishes several communication channels between the sensor network, the Building Management System (BMS), and an IDA-ICE simulation model. Communications between the real-time and on-line modes are done through model snapshots, and injected back by hot-starts. Hot-starting an iBEPS model involves copying the last state of the simulation model, modifying the model parameters, and

re-starting the modified simulation model with the previous last state solution. The real-time state controllers will handle the sensor signals, and tune the states. When on-line optimization is required to tune the Key Parameters, a copy of the sensor data is extracted and stored along with their equivalent mapped signals from the simulation model. Finally the optimized IDA-ICE simulation model is injected back by a hot-start without interrupting the continuous data assimilation mode. *Figure 2* depicts the inputs and outputs of each component involved at the real-time mode.

The environmental signals collected from weather stations, along with the set-points and predefined schedules are fed to both the controls of the real building, as well as the initial IDA-ICE simulation model. Occupancy is shown as a separate component in the real building module to differentiate its role in the tuning algorithm. The output of the IDA-ICE simulation model is then compared to the output of the sensor network and BMS system. The appropriate control adjustment signal is fed back to the IDA-ICE model to tune the states of the simulation model according to the states of the real building. Note that a load estimator component handles separately logged electricity meters and plug loads to update the occupancy model. In a typical thermal zone, state variables might include:

- Heating $[W]$
- Cooling $[W]$
- Outdoor air exchange $[ACH]$
- Lighting $[W]$
- Humidity $[\%]$

For a typical Air Handling Unit, AHU, state variables can include:

- Fan pressure rise $[Pa]$
- Heating $[W]$
- Cooling $[W]$
- Outdoor air fraction $[\%]$
- De/Humidification $[W]$

The Key Parameters are normalized and represented as multipliers. On zone level:

- Envelope conduction
- Thermal mass
- Envelope leakage
- Solar aperture
- Moisture storage
- Heating capacity
- Cooling capacity
- Mechanical ventilation capacity
- Artificial lighting capacity

For the Building Envelope:

- Envelope conduction $\rightarrow$ *mapped to the Thermal Bridge losses* $[W/Km^2]$
- Thermal mass $\rightarrow$ *mapped to the Air Mass Density* $[kg/m^3]$
- Envelope leakage $\rightarrow$ *mapped to the Outdoor Leak Area* $[m^2]$

- Solar aperture → *mapped to the Window Geometric Height* $[m]$
- Moisture storage → *mapped to the Air Absolute Humidity* $[kg_{water}/kg_{air}]$

3. Case Study

For a controlled experimentation of the proposed approach we utilize an IDA-ICE model of the International Energy Agency Annex 58 project([9]). IEA Annex 58, which started in 2011 and is ongoing, performs instrumented experiments on two identical, uninhabited, single family houses in Holzkirchen, Germany. The Twin houses are described in detail, and empirical data is provided in full. The experiment referenced in this paper was conducted throughout August and September of 2013. The data collected from the latter include weather data from a local station, 10 min interval temperature readings, as well as control input signals for the heaters and shutters. The experiment included an initialization phase, followed by a constant set temperature period, after which a Randomly Organized Logarithmic Binary Sequence excitation of the heater was carried out, followed by a reinitialization phase, and concluded with a free-floating phase as shown in *Figure 3 and 4*.

A self tuning PID controller was implemented to mimic the behaviour of the Kalman filter. Since only temperature signals are available for the state controller, a PID is enough to be able to achieve stable performance. The PID controller is self tuned via a fuzzy control scheme ([10]), and was implemented in MATLAB and co-simulated with IDA ICE. The state controller controls a virtual heat source with 20% (200 Watts) the heating capacity of that of the existing electric heater inside the IEA Annex model. It is important to have a proper estimate of the percentage attributed to the different types of errors discussed previously. The estimate reflects the user's confidence in the sensor data. *Figure 5* shows that the self tuning PID controller was able to reduce the normalized root-mean square state error down to 0.1249. The remaining error was used for the optimization algorithm to calibrate the parameters relating only to the building envelope.

The calibration result revealed that the parameters were cycling according to the shutter schedule in the Annex 58, presented in *Figure 6*. This indicated that the schedule for the shutters inside the IDA ICE model were not accounted for. After adjusting this discrepancy and re-running the calibration, the building envelope key parameters were steady around their normalized value, as shown in *Figure 7*.

4. Future Work

Ongoing work involves the implementation of the Kalman state controller, along with its integration with the optimization algorithm. Moreover, effort is being placed on formulating an appropriate physical model for occupancy detection and behaviour, to be later included in the proposed framework. The complete framework needs to be tested on more complex case studies.

5. Conclusion

We addressed the problem of calibrating initial Building Energy Performance Simulation models, iBEPS. Highlighted a comprehensive framework for approaching iBEPS calibration, and implemented it based on the detailed method presented in our previous work "Narrowing the Gap - A Framework for Connecting and Auto-Tuning a Design BPS Model to a Physical Building". Furthermore we demonstrated the effectiveness and potential of the novel approach in a case study.

6. Figures

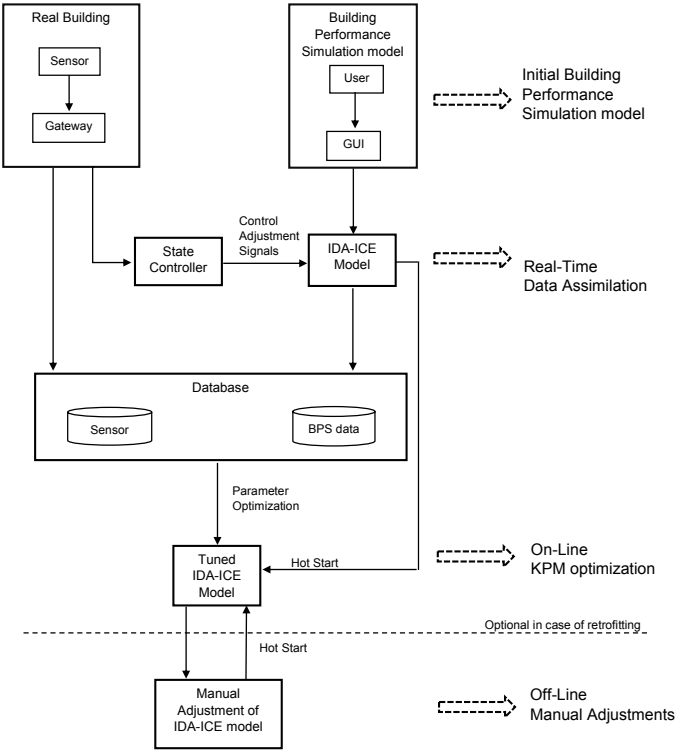


Figure 1: Layout of the proposed self-tuning procedure for iBEPS models

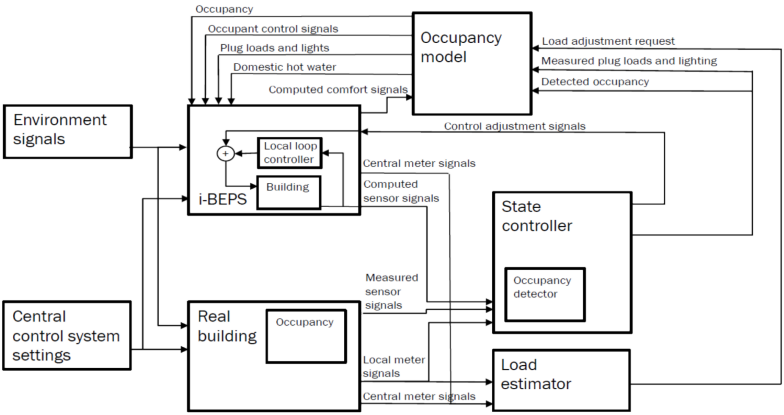


Figure 2: Real-time mode of the proposed self-tuning procedure

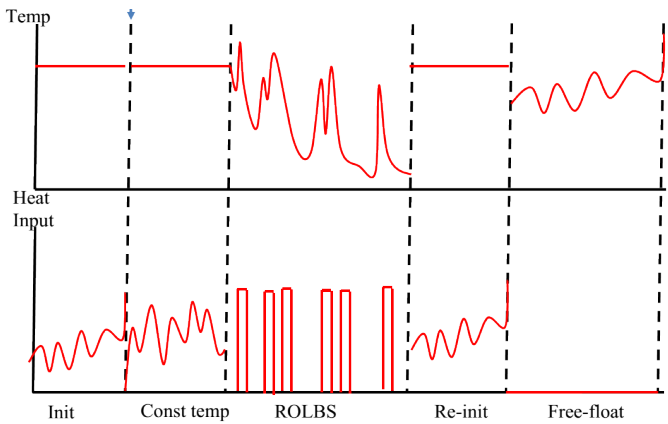


Figure 3: IEA Annex 58 test schedule schematic

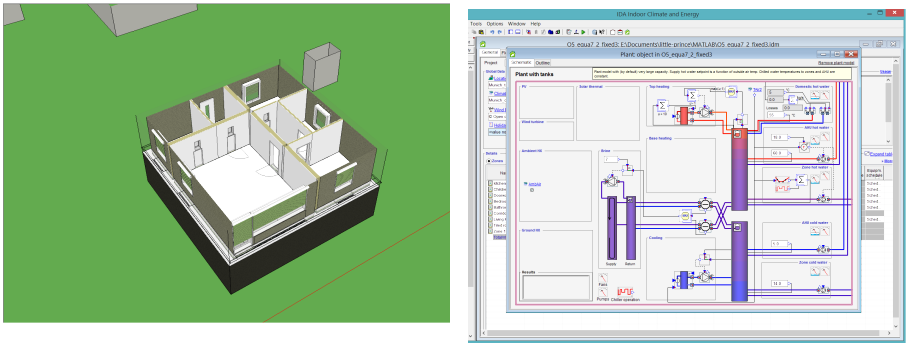


Figure 4: IDA-ICE model of the test case in IEA Annex 58

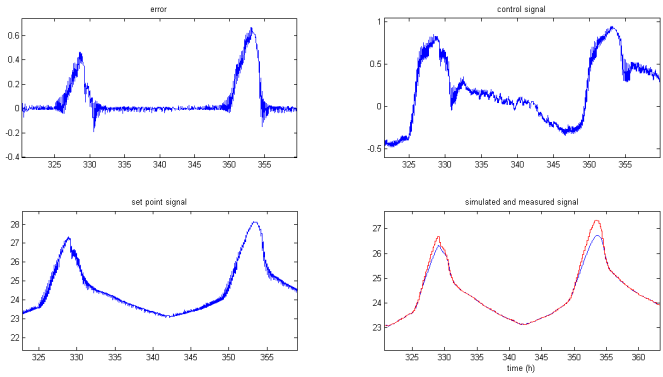
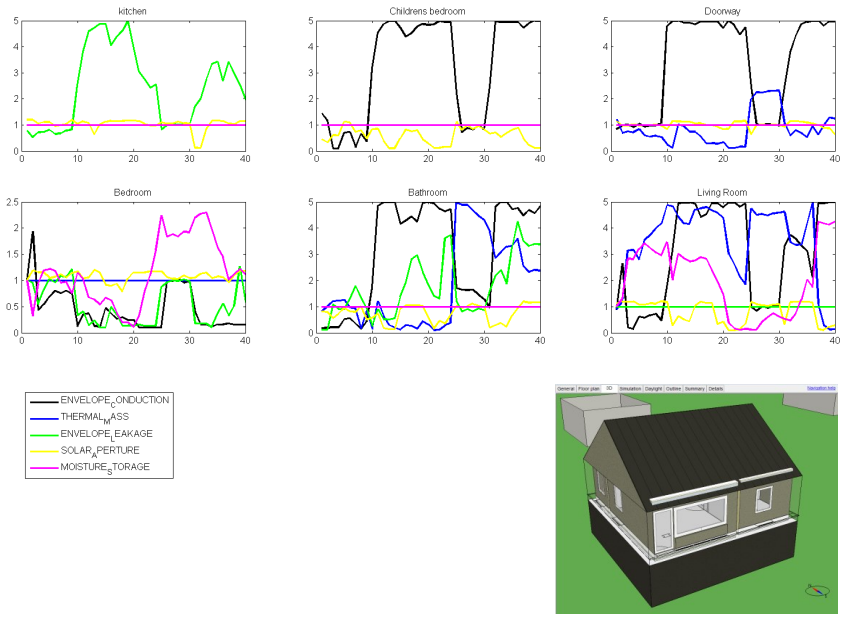


Figure 5: Output result of the state controller-from top to bottom, left to right: Residual error in °C, Control Signal issued to the heater between 0 and 1, Set-Point of the heater being adjusted by the control signal, Simulated vs Measured signal

		Twinhouse O5	Twinhouse N2
Days 1-7	Initialisation – constant temperature 30°C in all spaces	Blinds down	Blinds down
Days 8-14	Constant temperature – 30°C in all spaces	Blinds up	Blinds down
Days 15-28	ROLBS sequence in living room. No heat inputs elsewhere.	Blinds up	Blinds down
Days 29-35	Re-initialisation – constant temperature 25°C in all spaces.	Blinds down	Blinds down
Days 36-42	Free-float	Blinds up	Blinds down

Figure 6: Shutter Schedule in Annex 58



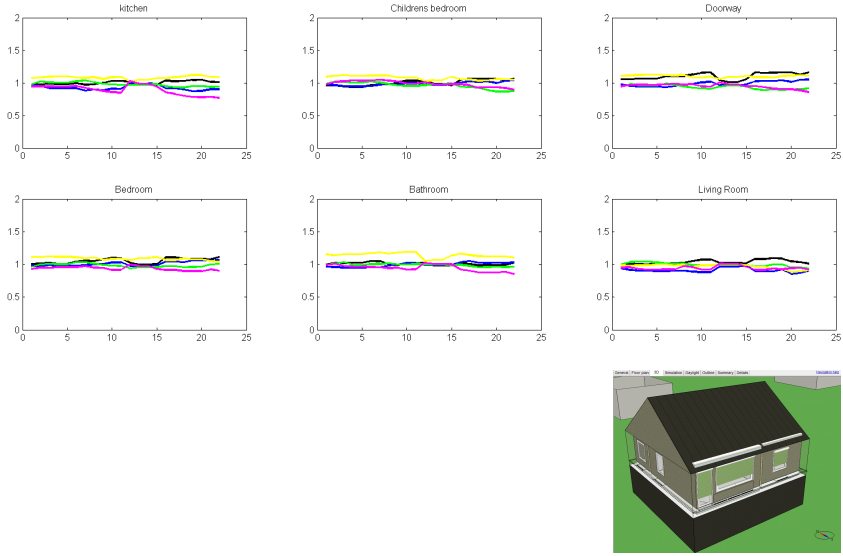


Figure 7: Initial model on the upper row without shades. The parameters are cycling according with the shutter schedule seen in Figure 6. Calibrated model on the lower row with shades drawn.

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