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A procedure for modeling buildings and their thermal zones using co-simulation and system identification[☆]

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Abstract

This paper presents a first attempt at obtaining a reusable and scalable model of buildings. To this end, a university building is first modeled using EnergyPlus, an energy simulation software. The EnergyPlus model is then validated using measured temperatures in the university building. In a second part, the EnergyPlus model is used to generate informative input/output data to perform system identification techniques: a black-box model of the building is obtained. Using simulation experiments, it is showed that the structure of the black-box model can be used to model the building at different scales: a thermal zone, a floor or the whole building.

Keywords: Thermal modeling, system identification, black-box model, EnergyPlus, co-simulation.

1. Introduction

The building sector is a greenhouse gases emitter and the largest consumer of energy among all economic sectors. In 2010, it was responsible for 40% of global CO₂ emissions and accounted for about 41% of primary energy consumption in the United States (US) [1]. In France, the building sector is representing 44% of the total energy consumption (in 2011); it has increased by almost 25% over the last 20 years [2]. Hence, reducing the energy consumption in the building sector can significantly contribute to the diminution of the power consumption and the greenhouse gases emission.

Currently, a popular approach to save energy in buildings is the application of model predictive control (MPC)

strategies to the building automation systems or to some of their parts (see [3, 4, 5] for example). To obtain on-line predictions, the MPC strategy relies on an internal model of the process to be controlled. The dynamic model used to perform the predictions is thus of great importance. The numerous modeling approaches that have been considered can be classified into three categories.

- White box modeling: in this approach models are built using *a priori* knowledge about the system and thermal balance equations. These models are often obtained through energy simulation softwares like EnergyPlus [6], TRNSYS [7], etc.
- Black box modeling: usually constituted of differential or difference equations, these models are obtained using measured input/output data and statistical estimation methods (see e.g. [8, 9]). No *a priori* knowledge is needed in this approach, but input/output data of high quality is usually needed to get accurate models.

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- Grey box modeling: a mix of the first two categories. Models are obtained using input/output data as well as some *a priori* knowledge on the system. A popular grey-box model is the equivalent RC networks (see [10, 5, 11] for example).

This work is a part of the RIDER project [12], whose objective is to improve energy efficiency of buildings and groups of buildings while preserving the thermal comfort of the occupants and/or other (economic) criteria. The use of MPC is in this case natural; a model of the thermal zones is thus needed. The nature of the RIDER project imposes two constraints on the modeling procedure.

First, the developed modeling procedure should ideally be applicable to different buildings. White box and grey box models are thus not appropriate: since they use *a priori* knowledge on the building, the procedure would not be applicable to different buildings without many changes. In order to obtain a *reusable* modeling procedure, black-box models have thus to be used.

In addition, the developed methodology should be applicable at different scales: from a single thermal zone to a whole building made up of several thermal zones. As a consequence, the structure of the black-box model should be complex enough to adapt to the various scales.

The work presented in this paper begins to explore the feasibility of this problem by studying the modeling of an university building. First, one has to get a deep knowledge on the building thermal behavior with respect to various excitation signals. This is achieved by modeling the building using the energy simulation software EnergyPlus; the second section details how this model was obtained and validated (see also [13]). Note that the EnergyPlus model is not a part of the modeling procedure: it is only instrumental in *developing* the modeling procedure. In the third section is explained how this EnergyPlus model is used to generate rich data and obtain a generic and scalable model using system identification. Finally, in the last section the results are presented and discussed.



Figure 1: Photograph of the two floors building under study and the corresponding Google Sketchup mock-up.

2. Modeling using EnergyPlus

2.1. Building geometry and materials

The university building under study (see Figure 1) was built in 2008 and is home for the Renewable Energy department of the engineering school *Polytech Montpellier*. It is located in the city of Perpignan (southern France) and consists of two floors with almost the same geometric configuration (see Figure 2). Each floor has an area of 257.45 m²; the total floor area of the building is thus 514.9 m².

The ground floor is divided in five thermal zones: two classrooms, a space for students, an office, a corridor and toilets. The first floor is identical, except that the student space and the office have been gathered into a media classroom. The glazing installed is a double glazing constituted by two clear glasses of 4 mm and a 12 mm air space between. Each window has an outside blind covering all of its glazed part. The blinds consist of flat, equally-spaced slats in PolyVinyl Chloride (PVC).

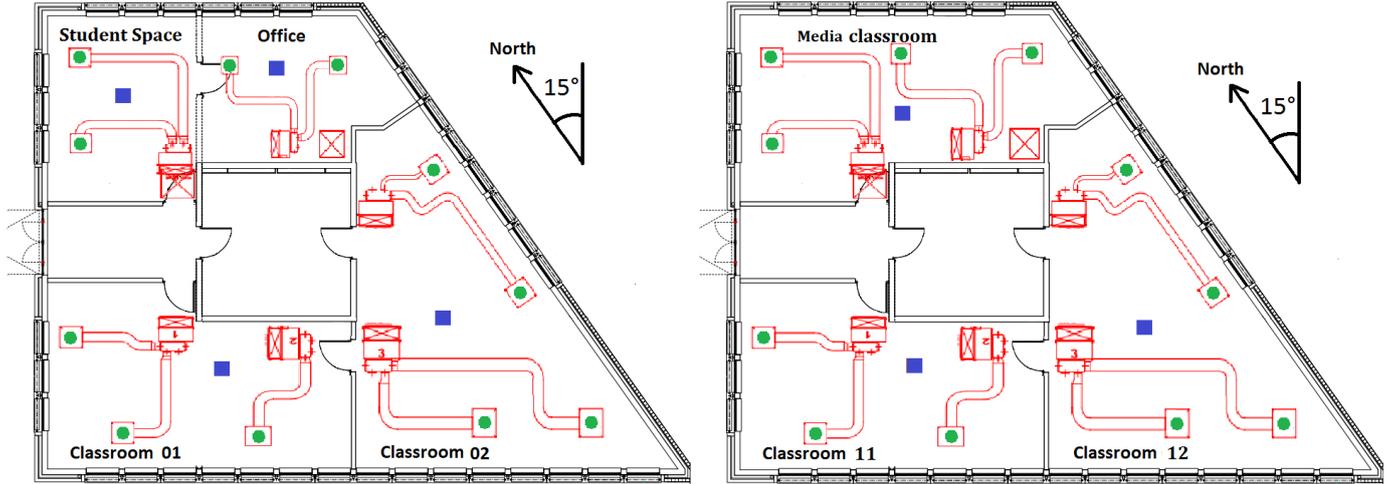


Figure 2: Ground floor (left) and first floor (right) with HVAC and temperature sensors' location. Blue squares are indoor temperature sensors and green spots are sensors measuring temperature at air duct outlets.

2.2. HVAC system

The HVAC system is a Hitachi Variable Refrigerant Flow (VRF). An external condensing unit is connected to several air handling units. As a result, the refrigerant flow can be varied either by using an inverter controlled variable speed compressor or by using more than one compressor. The heat or cold production is performed by two outside condensing units (simultaneous cooling and heating is not allowed). These air to air heat pump units are part of a ventilation group, consisting of one or two double inlet centrifugal aluminium impellers. The indoor units are manually controlled by thermostats in each room. There are three air flow speeds: 16, 15 and 13 m³/min. Finally, there is a mechanical ventilation that operates during activity in classrooms and permanently in restrooms.

2.3. EnergyPlus model

The modeling of the building and its HVAC system is made with EnergyPlus, a building energy simulation software created by the US Department of Energy [6]. The virtual architecture of the building is created with the Google Sketchup 3D design software (see Figure 1), and is linked to EnergyPlus using the Legacy OpenStudio Sketchup plug-in [14]. Building architecture informations come from the architect book, and some thermal parameters (conductivity,

specific heat, ...) come from ASHRAE's book [15]. As for the HVAC VRF system, its characteristics are derived from similar equipment found in [16].

2.4. Instrumentation

In order to validate the EnergyPlus model, comparisons between simulated and measured data have to be made. The building has been instrumented with temperature sensors wire-connected to a data archiver, that transmits measures to a central server in the building by radio protocol for storage and real time treatment. The sensors have been placed at ceiling level and acquire data with a five minutes time step. Figure 2 presents the two stories building plans along with the HVAC system and the temperature sensors location. Figure 3 presents the instrumentation and transmission architecture.

2.5. Meteorological data

The weather data has been provided by 'MeteoFrance' (MF) [17]. The meteorological station is located in Perpignan's airport, 10 km from the studied building. The main parameters needed to create a weather file for EnergyPlus are atmospheric station pressure (Pa), dew point temperature (°C), dry bulb temperature (°C), global horizontal

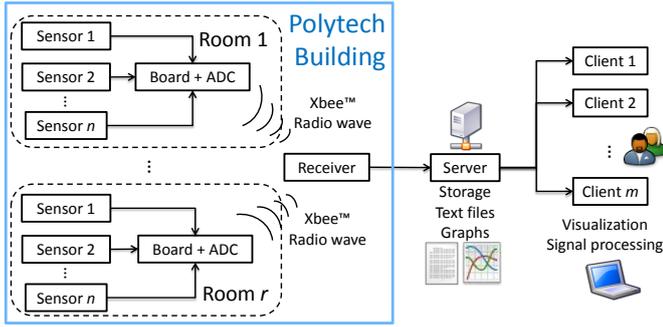


Figure 3: Instrumentation and data transmission architecture.

radiation (W/m^2), precipitable water (mm), relative humidity (%), visibility (km), wind direction ($^\circ$), wind speed (m/s), direct normal radiation (W/m^2), diffuse horizontal radiation (W/m^2).

All these data are measured with a hourly time step except for the direct normal and diffuse horizontal radiations, which are not measured but reconstructed using global horizontal radiation and the Erbs model [18], following the conclusion in [19].

2.6. EnergyPlus model validation

The validation is made in two steps: the model of building envelope is first validated (the HVAC system being switched off), then the complete model of the building with the HVAC in heating mode. The validation is realized during holidays (respectively summer and winter), so that no activity or internal gain are perturbing the results.

In the Figure 4 and Figure 5, the black curve represents the measured indoor temperature while the magenta curve represents the simulated indoor temperature using EnergyPlus; the bottom subplot represents the outdoor temperature from MF. Perceptible discontinuities on measured indoor temperature come from missing data due to sensors or server failures.

During 2012 summer test (Figure 4), curves have globally the same variations, except for two periods: around June 24th in media room, and between June 30th and July 2nd in classroom 11; these rooms were actually occupied by students and a council meeting during these periods:

the air conditioning was on. Although the amplitude of the variations seems to be higher for the simulated temperature than for the measured one, the model is rather satisfying. The standard deviation of the difference between simulated and measured temperatures is less than 1°C .

Using 2012 winter's data and turning on the heating system, it becomes possible to validate the model of the building and its HVAC system (Figure 5). One can see that there is a good agreement between simulation and measures, with similar variations, coming from air turbulence at ceiling level (exhaust and return air). With a standard deviation of roughly 0.65°C between simulated and measured data, the EnergyPlus model with HVAC system gives satisfying results.

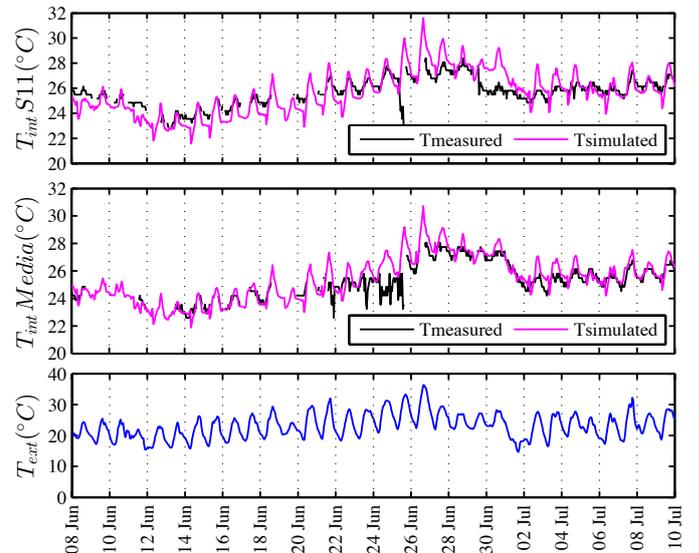


Figure 4: Classroom 11, media room and outside air temperatures during summer period with the HVAC system switched off.

3. Modeling procedure using system identification

System identification is the field of modeling dynamic systems from experimental data (see [20, 21] for details). The modeling procedure is as follows (see Figure 6); for each thermal zone that is to be modeled:

1. collect input/output data;
2. estimate the parameters of the black-box model;

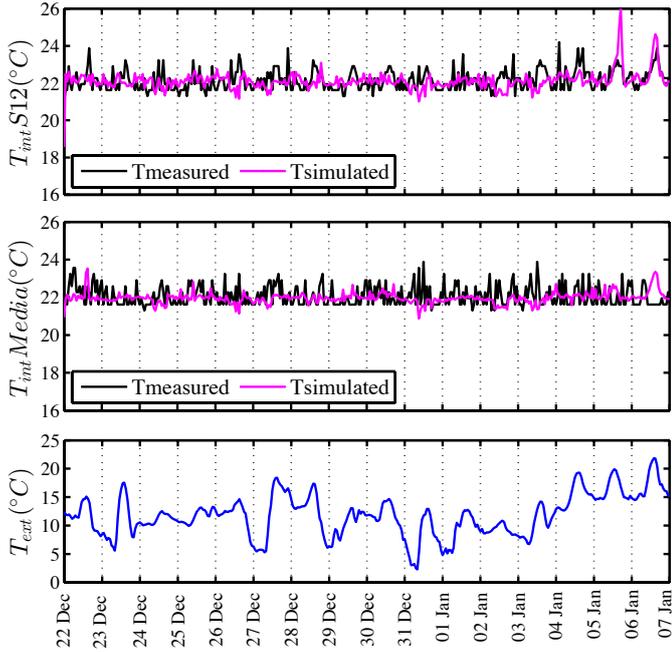


Figure 5: Classroom 12, media room and outside air temperatures during winter period with the HVAC system switched on.

3. validate the obtained model.

The identification of black-box models relies exclusively on input/output data. However, data collected from real operation of a building are usually insufficiently informative to reliably estimate the model [22]: the persistence of excitation condition (see [20] for example) is hardly met in these conditions. The idea is then to use EnergyPlus in order to generate rich data, that will in turn be used to identify the black-box model. This also allows to generate data that would be hard or impossible to get from real operation of a building.

However, the design of input signals in EnergyPlus is made through the use of schedules, which is quite impractical if, say, a pseudo-random binary sequence (PRBS) is to be generated. A solution to overcome this problem is co-simulation, that is the integration of different software components by run-time coupling [23].

3.1. Matlab and EnergyPlus interoperability

The Building Controls Virtual Test Bed (BCVTB) [24] is a software environment that allows users to link together

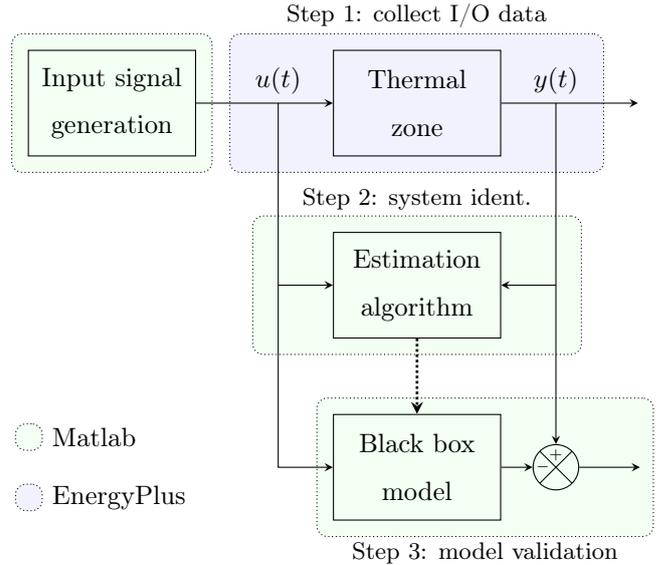


Figure 6: Modeling procedure using Matlab–EnergyPlus co-simulation. $u(t)$ is the input signal and $y(t)$ the output signal.

different simulation programs for co-simulation. Here, BCVTB is used as a middleware to couple EnergyPlus with Matlab, along with MLE+ [25], which is a toolbox providing a set of Matlab functions and classes for performing co-simulation with EnergyPlus.

The procedure is as follows: the input signals are designed with Matlab and then fed to EnergyPlus; EnergyPlus then simulates the output signals that are used to estimate the model’s parameters using Matlab system identification toolbox [26]; see also Figure 6.

3.2. Model structure

A state-space representation, more suitable for modeling MIMO systems, has been chosen. In innovation form, it is given by (see *e.g.* [20]):

$$x(t+1) = Ax(t) + Bu(t) + Ke(t) \quad (1)$$

$$y(t) = Cx(t) + Du(t) + e(t) \quad (2)$$

where $u(t)$ is the input vector, $y(t)$ the output vector, $e(t)$ the disturbance and $x(t)$ the state vector. The order of the state-space model and the coefficients of the state-space matrices A , B , C , D and K are estimated using input/output data and system identification techniques.

The input vector $u(t)$ contains three signals: outdoor temperature, direct normal solar radiation and HVAC power in the considered thermal zone. These are the main signals influencing indoor temperature. Although several additional inputs can be considered, only these three signals have been considered to keep the model simple. The output $y(t)$ is the indoor temperature in the considered thermal zone.

3.3. Design of experiments

A caveat in black-box model identification is that the input/output data have to be informative enough for the model to be reliable. In particular, the input signal almost always violates the persistence of excitation condition (see *e.g.* [20]) during the normal operation of a building [22]. However, thanks to the Matlab/EnergyPlus co-simulation, suitable inputs can be designed in Matlab and fed to EnergyPlus to get the output signal.

A common input signal for system identification is the Pseudo-Random Binary Signal (PRBS): it is a periodic, deterministic signal with white-noise-like properties [20]. In the input vector $u(t)$, only the heating/cooling power of the HVAC system is controllable. However, in EnergyPlus, there is currently no way of controlling heating or cooling power directly; the solution is then to control the indoor temperature heating and cooling setpoints, which act directly on the HVAC power. In order to ensure that the HVAC power follows the setpoint PRBS as closely as possible, the binary levels of the PRBS are set to 5 °C and 30 °C: the HVAC should thus either be on at full power, or completely off.

The EnergyPlus model is excited during 36 days (from the 6th of December 2012 to the 11th of January 2013), with a time-step of 10 minutes. Some of the generated data for one thermal zone can be found in Figure 7, where the input signals (direct normal solar radiation, HVAC power and outdoor temperature), the output signal (indoor ambient temperature) and the indoor temperature heating setpoint

are plotted. One can see that, as expected, the indoor temperature never reaches the setpoints and the HVAC power follows the PRBS rather closely. One can also notice that during the considered period, the weather is varied (sunny and cloudy days, low and high outdoor temperature, etc.), which means more information to construct the model than if there were only warm and sunny days.

3.4. Order and parameters estimation

The model order can be estimated using input/output data; tests have consistently showed that a second order model is sufficient to model the dynamics of the indoor temperature (see also the discussion in [22]). The model order has thus been set to two for all the models considered in the sequel.

In order to assess the scalability of the model structure (a state-space model of second order), several models have been identified:

- first, each room of the building is considered as a thermal zone separately;
- then the case of each floor as a unique thermal zone;
- finally, the complete building as a unique thermal zone.

Each time, the considered thermal zone is excited using the same PRBS to control the heating setpoints, while the other thermal zones are left drifting. The system matrices A , B , C and D are determined using the prediction-error method in the system identification toolbox of Matlab. The general idea of prediction error methods is as follows (see also Fig. 8):

1. use the model, whose parameters are collected in a vector θ , to compute a prediction $\hat{y}(t, \theta)$ of the output;
2. compute the prediction error $\varepsilon(t, \theta) = y(t) - \hat{y}(t, \theta)$;

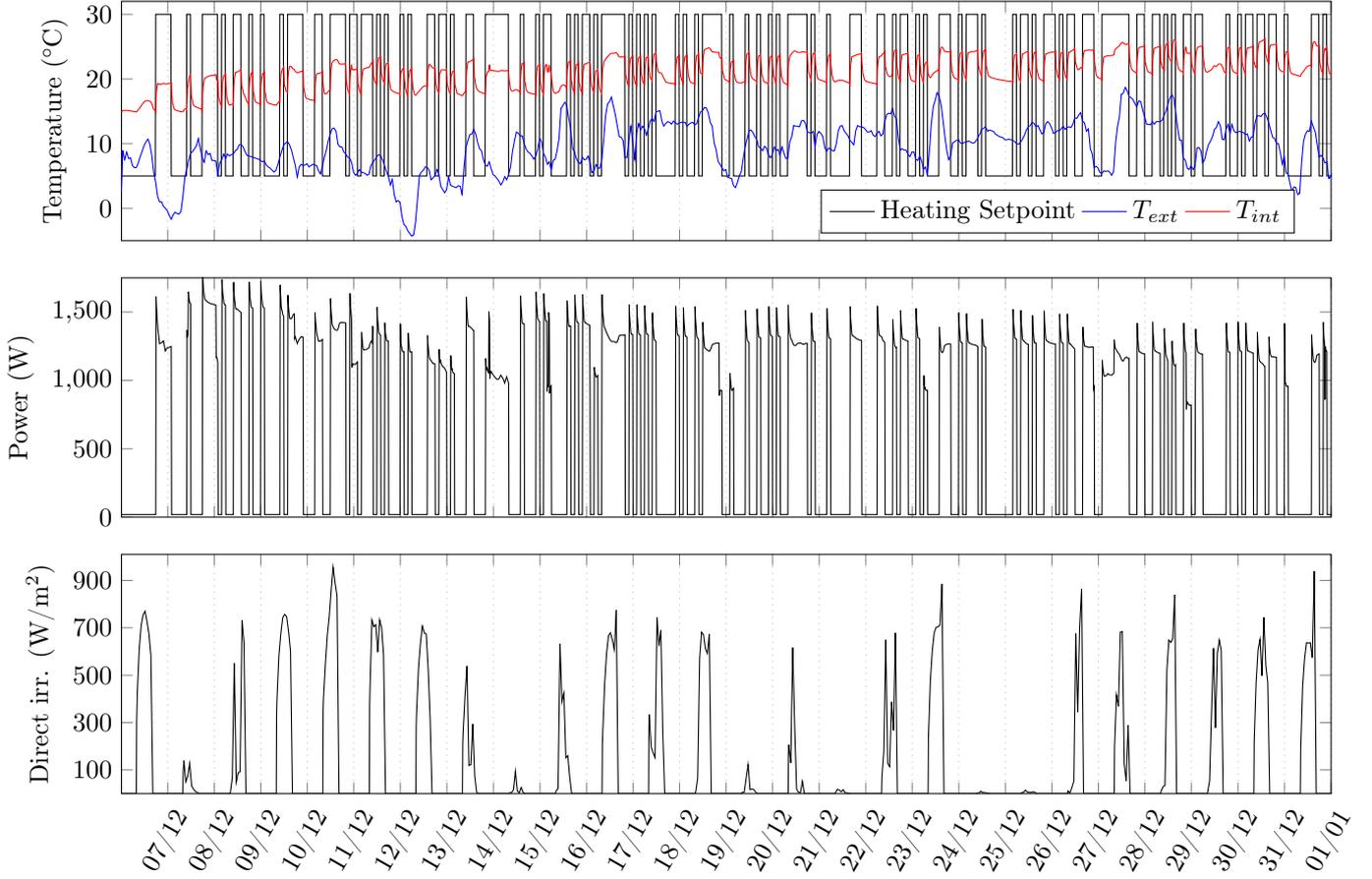


Figure 7: Part of generated data for classroom 01. Top plot: indoor temperature, outdoor temperature and temperature setpoint. Middle plot: heating power. Bottom plot: direct normal radiation.

- determine the parameter vector θ that minimize some norm (usually quadratic) of the prediction error:

$$\hat{\theta} = \arg \min_{\theta} \left[\sum_t \ell(\varepsilon(t, \theta)) \right] \quad (3)$$

In the end, one model for each thermal zone is obtained. The models have the same structure, but the value of their parameter vector θ is different (to account for their different thermal characteristics).

4. Results and discussion

The generated data is divided in two sets: the first two-thirds are used to estimate the model's parameters, while the last third of the data is used to validate the identified models. The parameters of nine distinct models are estimated:

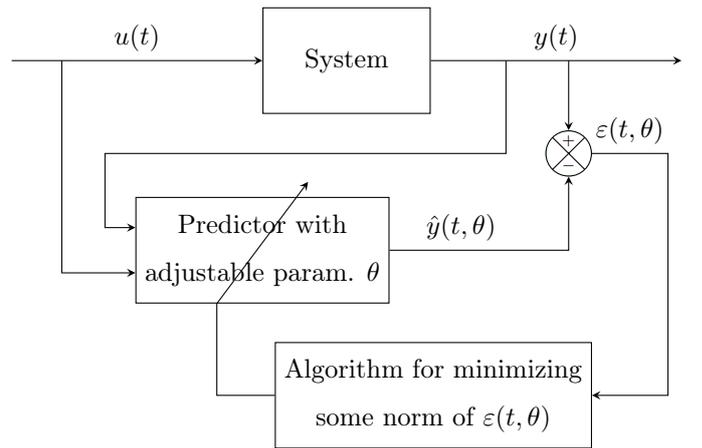


Figure 8: Schematic of the prediction error method.

- four thermal zones on the ground floor;
- three thermal zones on the first floor;
- the first floor as one thermal zone;

- the whole building as one thermal zone.

Models' quality is evaluated using the normalized root mean square error fit value, defined as:

$$\text{fit} = 100 \left(1 - \frac{\|y - \hat{y}\|_2}{\|y - \text{mean}(y)\|_2} \right) \quad (4)$$

where y is the validation data and \hat{y} is the output of the model. In addition to pure simulation (infinite prediction horizon), the ability of the identified model to predict indoor temperatures is tested on three prediction horizons: 24 h, 12 h and 3 h.

Figure 9 presents the comparison between the validation data and the temperature simulated using the models. For the sake of space, only four plots are printed (results are similar for the other zones) and only for pure simulation. The fit values for all the nine models using different prediction horizons can be found in Table 1.

It can be seen on Figure 9 that the model structure is complex enough to account for the different scales: whether it is a single thermal zone, a floor or the building as a whole, the ability of the models to simulate and predict the indoor temperature is satisfying (see Table 1).

Prediction horizon	Fit in %			
	∞	24 h	12 h	3 h
Classroom 01	88	90	89	90
Classroom 02	79	84	86	89
Student space	78	85	88	91
Office	80	88	90	91
Media room	89	91	92	93
Classroom 11	90	91	91	92
Classroom 12	84	87	89	91
First floor	88	90	92	93
Whole building	89	90	91	92

Table 1: Fit between validation data and the output signal of the nine models for pure simulation and different prediction horizons (values are rounded to the nearest integer).

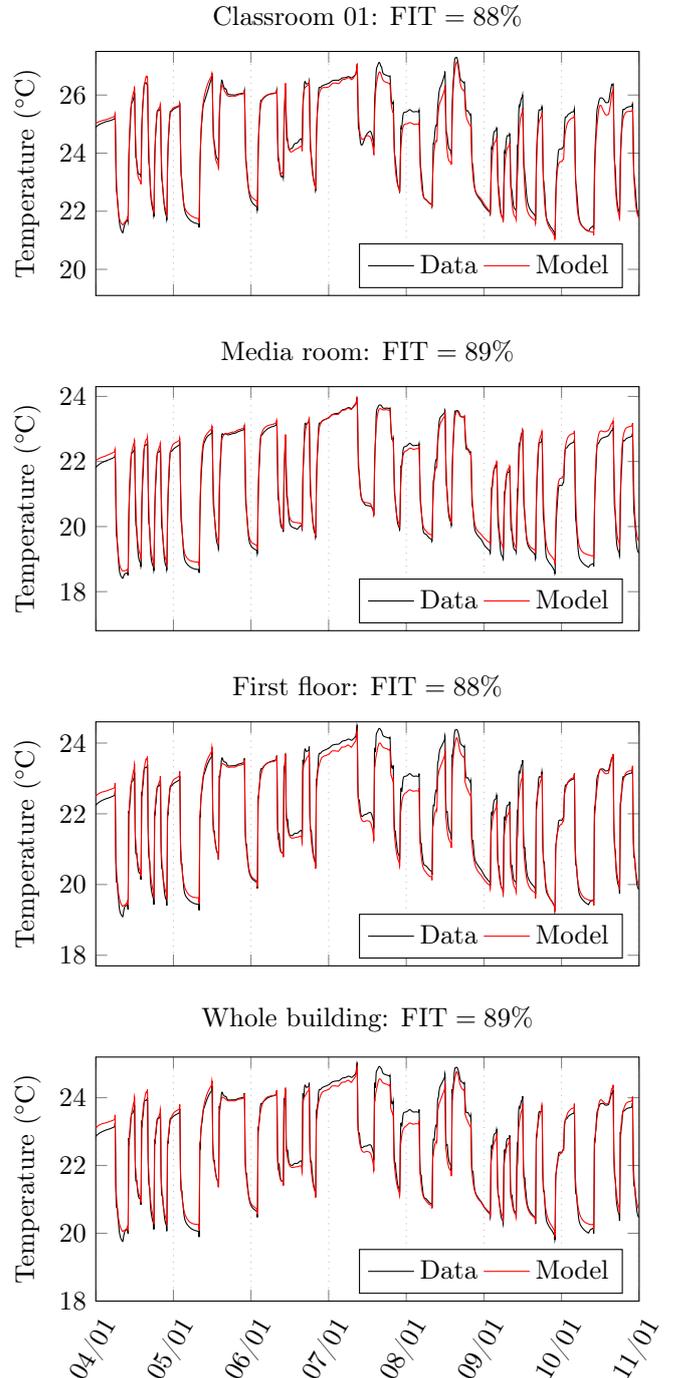


Figure 9: Comparison between validation output data and the output of four of the nine models for pure simulation (infinite prediction horizon).

5. Conclusion and perspectives

In this paper, procedure for modeling a building and its thermal zones has been developed, using a black-box model. System identification techniques have been applied to rich input/output data generated using co-simulation between EnergyPlus and Matlab. The black-box model structure, a state-space dynamical model of second order, has been shown to be scalable: the identified models of rooms, floors and the building as a whole exhibited rather satisfying prediction of indoor temperature of the considered thermal zones.

Future work will assess the reusability of the modeling procedure by applying it on several types of buildings with different heating and cooling systems, and in different locations. Also, a study will be conducted in order to determine an excitation signal that is sufficiently exciting, while also being easily applicable on a real building; the modeling procedure will then be applied to a real building without recourse to an energy simulation software.

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