Feasibility Study of Single-Well Dual-Cable DAS for Micro-seismic Monitoring of Geothermal Operations

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Performance analysis based on parameter identification

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Abstract

A next generation of models is needed to guarantee energy performances of buildings and systems in practice. Current energy performance models use assumptions on climate, user behavior, characteristics of building and systems that may deviate from reality. Improvement of the accuracy of these models and assumptions is necessary to better predict the real energy performance of buildings and systems. Joining calculation models with data, using dynamic parameter identification (DPI), is a promising way for a better prediction of energy use in practice. Three example cases for identifying deviating building and system properties are discussed.

Keywords: energy; performance; dynamic; identification; building

1. Introduction

The annual energy consumption of the building stock accounted for 40% of the total energy consumption in 2011, see Atanasiu et al. [1]. The residential building stock accounts for 68 % and the non-residential stock accounts for 32 % of this fraction. Over the last decades analyses of the actual building energy consumption has rapidly increased as the EU strives to reduce the overall energy consumption drastically (EU energy reduction goal for 2020). A crucial instrument has been the development and implementation of the Energy Performance of Building Directive (EPBD) in 2002 (recent recast: EPBD 2010). Here the emphasis is on energy performance of new or renovated buildings, on energy performance certification of existing buildings and on regular inspection of systems. This called for suitable

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and reliable calculation procedures, which were developed under a mandate from the European Commission to CEN (M/343, 2004-2007; and current new mandate M/480, 2011-2015).

In recent years, the analysis of the actual building energy consumption has emerged. This is also stimulated by the large gap between actual and calculated building energy demand. This so-called performance gap relates to the difficulty in making a realistic prediction of the complexity of the building and the various factors that affect the building energy performance. As is outlined in the IEA EBC Annex 53 project, see e.g. Polinder et al. [2], building energy consumption is influenced by climate, building envelope, building energy systems, building operation and maintenance, occupant behavior, and indoor environmental quality and comfort. Understanding user behavior as well as knowing the actual performance of buildings and systems are mandatory for reducing this gap.

Current models are not sufficiently accurate in energy use predictions, due to assumptions on climate, user behavior, or characteristics of building and systems that may deviate from reality. A next generation of models is necessary to better predict the real energy performance of buildings and systems.

Detailed modelling of the energy use of buildings is time consuming. Furthermore, characterization of the energy performance of buildings by measurements using a short assessment time is not possible. Currently there are no proper methods to assess energy use of individual buildings effectively within a limited time frame. Joining calculation models with dynamic measurements, using dynamic parameter identification (DPI), seems promising for better predicting energy use in practice. In addition, an analysis of the energy performance based on dynamic parameter identification may allow for fault detection, timely detection of the needs for additional measurements or for adjusting the (model-based) control of the indoor climate.

2. Methodology

Since the 1980's, forward simulation tools (e.g. ESP-r, TRNSYS, BLAST, DOE-2 and EnergyPlus) have been developed to simulate the transient energy consumption and thermal loads behavior of buildings, given user behavior, outdoor climate, building construction and installations. Each component in the building is modeled and thus the performance can be simulated. These simulation tools have the advantage that each part of the building can be modeled and that energy consumption and thermal loads can be analyzed dynamically. Drawbacks are the complexity and time-consuming calculations of these tools and the requirement of substantial input (e.g. detailed building geometry, properties of constructions layers, installations, etc.) and right model assumptions. To analyze the relative impact of input parameters on the output, these tools may be combined with sensitivity analysis, see e.g. Garcia Sanchez et al. [3]. Despite the in depth functionality, still a gap may remain between predicted and actual recorded energy consumption of a building.

A different method for predicting the building energy performance is based on inverse modeling. In this case the input variables (e.g. energy consumption) and output variables (e.g. indoor temperature) are monitored and used to estimate the system parameters based on (relatively) simple mathematical models and statistical analysis. In this way it is possible to evaluate building/system performance allowing for fault detection (of retrofit actions), or more accurate energy use prediction based on measured data. Basically, two approaches can be employed.

One approach is an empirical or "black-box" approach, in which the output variables are correlated with weather data or other input data. This approach can be used at various time scales and applied for different parameters, such as climate variables and building operation settings. Purely statistical techniques are employed to determine the correlation between the output and the input. Advantage of this approach is its simplicity and fast calculation times; disadvantage is a lack of physical understanding.

In the other "grey box" approach, simple models (including basic physics and dynamics) are formulated to describe the building and installations, e.g. Madsen et al.[4]. This approach is used to identify and estimate the model parameters given the recorded data, and bridges the gap between physical and statistical modelling. The methodology of such grey box models has been developed in the 1990's in the framework of several EU research projects (PASSYS, PASLINK, DAME-BC) using outdoor test facilities focusing on the building envelope.

Advantage of these dynamic models is that they can handle temporal effects such as thermal mass behavior (which requires the solution of a set of differential equations). Dynamic inverse models are more complex compared with steady state models and need more detailed measurement data to parameterize the model. To estimate the model parameters in the grey box approach, usually an error function is defined and minimized. Minimization can be performed using a variety of methods like Monte-Carlo method or downhill simplex method, or other methods such as the maximum likelihood method and the maximum a posteriori methods, see Madsen et al. [4].

General software tools/environments (e.g. Matlab, Modelica, SimulationX) can be used for modeling and dynamic parameter identification. These tools may offer diverse functionality such as equation-based modeling. In above mentioned EU projects, the tool LORD has been developed, which is used for parameter identification of thermal systems. The tool is aimed at energy performance of buildings and uses RC-network models. A combination of downhill simplex and Monte-Carlo minimization procedures are applied in this tool for model parameter identification. Our work is based on parameter identification with the LORD software tool.

3. Building model and parameter identification

A lot of experience with the modelling of heat balances in buildings already exists. Focus has often been on well controlled rooms for which all heat flows are measured and all resistances are well known. Relatively new is applying parameter identification based on fitting lumped RC-network models for less well controlled situations of actual buildings. Data recorded at buildings in practice typically consists of climate data measured at the location and measurements of the indoor temperature and heating energy consumption.

In the first stage of our study, presented in this paper, input data used for the parameter identification procedure has been generated using the dynamic building simulation tool TRNSYS (in a next stage, a study will be performed with actual measurement data). A simple RC-network model having three conductance's and three nodes has been used to model the building and identify some basic properties. Three example cases of performance analysis based on dynamic parameter identification will be presented; one case on transmission losses, a second case on solar admittance, and a third case on the efficiency of a heating system.

3.1. Reference building

The simple RC-network model considered contains three nodes and three conductance's, see Fig.1. The three nodes relate to the outdoor and indoor air temperature and to the wall temperature. The conductance's relate to ventilation losses (and losses through glazing), convective heat transfer between indoor air and walls, and transmission losses through the envelope. The two heat capacitances relate to the thermal mass of the building envelope at the inner side of the insulation layer and to the indoor air volume.

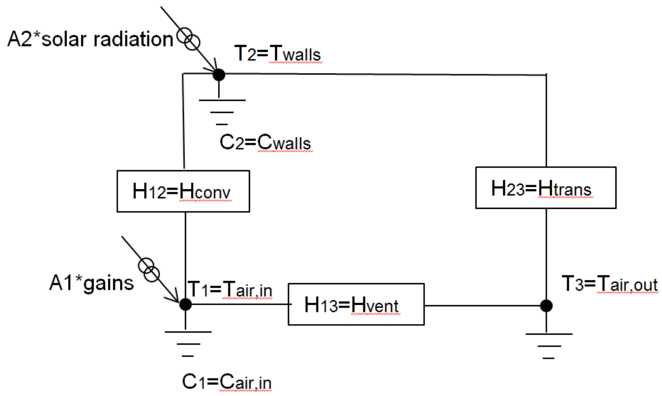

Fig. 1. Employed simple RC-network of the building.

The simple RC-network model consists of two differential equations relating the physical quantities shown in Fig. 1; they are given by Equations (1) and (2):

$$\frac{dT_1}{dt}.C_1 = -(T_1 - T_2).H_{12} - (T_1 - T_3).H_{13} + Q_1.A_1 \; ; \tag{1}$$

$$\frac{dT_2}{dt}.C_2 = -(T_2 - T_1).H_{12} - (T_2 - T_3).H_{23} + Q_2.A_2 \; . \tag{2}$$

The parameters of the RC-network model in these equations are indoor air capacitance (C_1), envelope capacitance (C_2), convective conductance (H_{12}), transmission conductance (H_{23}), ventilation conductance (H_{13}), efficiency (A_1) of heat gain (e.g. heating system with power Q_1), fraction (A_2) of incident solar radiation (with power Q_2) passing through windows and absorbed by internal surfaces.

Next, a TRNSYS model for the building has been constructed and applied to generate data to identify the parameters of the RC-network model. The building considered has a volume of 41.6m^3, the floor and roof area are 16m^2, the area of the facades is 41.6m^2. The south-oriented façade contains a window. The following building properties and assumptions are used for the reference case:

- Envelope (concrete – mineral wool – concrete) insulation values of R_c=5 m^{2}K/W;
- Window glazing U=1.4 W/(m^{2}K), g-value 0.6; window size 4m^2;
- Ventilation rate, constant value of 50m^3/hr.

Indoor air temperatures generated with TRNSYS for this building, as well as data on outdoor air temperature, solar radiation at the south façade, and energy use for heating, for a period of nine weeks are considered. Data of weeks 2-5 are used to identify parameters of the simple RC-network model. Results of the parameter identification procedures are displayed in Figs. 2-3 and listed in Table 1 for three different building heating schedules:

- Reference 1: week 1-9: 20°C set point from 07.00-22.00 hr.;
- Reference 2: week 1-3: 300W heating; week 4-6: 600W heating from 07.00-22.00 hr.; week 7-9: free floating;
- Reference 3: week 1-3: 20°C set point constantly; week 4-9 free floating.

Table 1. Parameter identification reference, for three heating schedules. Parameters with an asterisk were kept constant.

Parameters	Units	Estimate	Reference 1	Reference 2	Reference 3
H_{13}	W/K	17.3	17.75 ± 0.5%	17.27 ± 0.3%	17.55 ± 2.7%
H_{23}	W/K	18.0	20.10 ± 0.8%	20.77 ± 0.2%	19.19 ± 3.8%
H_{12}	W/K	125.0	122.63 ± 0.4%	123.56 ± 0.3%	129.78 ± 4.3%
C_1	MJ/K	0.05	0.05*	0.05*	0.05*
C_2	MJ/K	14.6	16.84 ± 0.7%	16.20 ± 0.5%	14.55 ± 2.7%
A_1	-	1.0	1.00*	1.00*	1.00*
A_2	-	1.4	1.65 ± 0.7%	1.67 ± 0.4%	1.50 ± 4.4%

The third column in Table 1 lists estimated values for the parameters based on known building properties and assumptions in the TRNSYS model. For three different heating schedules, the identified parameters of the RC-network model are listed in columns 4-6. Consistent values for the parameters are found for the three different heating schedules. The parameter errors are larger in the last column. For this case the set point temperature was constant during the first period (identification of capacity is more difficult), during the second period the indoor air temperature was free floating. Model parameters are harder to identify in case of insufficient variation of input data.

Fig. 2. shows the resemblance of the indoor air temperatures as a function of time for the nine week period in case of Reference 2. Also after the period from which data is used to identify model parameters, a similar agreement can be observed between the temperatures calculated with the RC-network model and the data. Fig. 3. zooms in at the period of day 5-15 and shows in more detail the pattern of the indoor air temperatures. The reference building model in this section is used in the next section to investigate performance identification for three example cases.

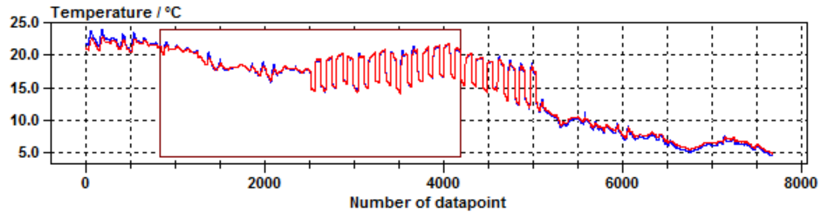

Fig. 2. Indoor air temperature, calculated (red) and data (blue), as a function of time for Reference 2. Data point 7560 corresponds with the end of the nine week period. The window indicates the time period from which data is use to identify the model parameters.

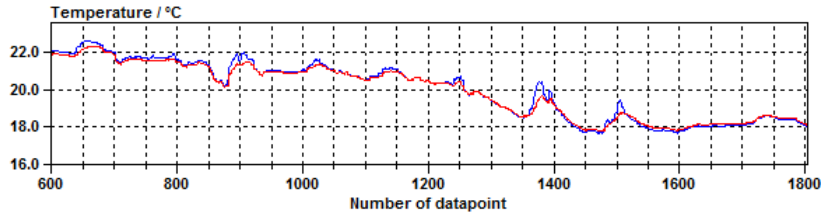

Fig. 3. Indoor air temperature, calculated (red) and data (blue), as a function of time for Reference 2. Zoomed in at the period of day 5-15.

3.2. Performance identification example cases

Three example cases for identifying the performance of the building/system are discussed in this section. The TRNSYS model of the building was used to simulate the following three example cases:

1. Transmission loss: R_c value of the building envelope is changed into 1 m^2K/W, except for the south façade;
2. Solar admittance: The solar admittance is a factor 1.5 larger with respect to the reference case;
3. Efficiency heating system: The heating system has an overall efficiency of $\eta=A_1=0.75$.

Table 2 shows values for the parameters of the RC-network model for these example cases. The third column lists the parameter values for Reference 1. For the three example cases, the identified parameters of the RC-network model are listed in columns 4-6.

For the first case on transmission loss, the value for parameter H_{23} (transmission through building envelope) has increased mostly. The increase can be explained by the decrease of the R_c value from 5 to 1 m^2K/W for a 47 m2 part of the building envelope (exposed to ambient). Values for other parameters varied up to 10 percent.

For the second case on solar admittance, the value for parameter A_2 (solar admittance) has increased mostly. The ratio of the values for A_2 in this example case and the reference case is 2.45/1.65=1.5, which agrees with the factor imposed in the TRNSYS model. Values for the other parameters varied up to 15 percent.

For the third case on heating system efficiency, parameter A_1 (efficiency of heating system) has been determined at a value of 0.69, which is close to the factor imposed in the TRNSYS model. Values for the other parameters varied less than 10 percent.

The residuals of the fit were small and the values for the fitted parameters were close to the expected values for these example cases. A good and stable identification of the building/system performance was observed in these example cases, since stable values for the parameters of the RC-network model were found (various parameter starting values were considered). Additional calculations (not presented in this paper) have also been performed for more complex RC-network models, in those cases some of the additional parameters had to be fixed at estimated values in order to be able to identify the other parameters.

Table 2. Parameter identification example cases 1-3. Parameters with an asterisks were kept constant.

Parameters	Units	Reference 1	Case 1	Case 2	Case 3
H_{13}	W/K	17.75 ± 0.5%	15.85 ± 1.4%	18.71 ± 0.2%	16.40 ± 0.2%
H_{23}	W/K	20.10 ± 0.8%	61.13 ± 0.4%	23.22 ± 0.5%	18.70 ± 0.2%
H_{12}	W/K	122.63 ± 0.4%	125.66 ± 0.4%	120.69 ± 0.2%	112.97 ± 0.1%
C_1	MJ/K	0.05*	0.05*	0.05*	0.05*
C_2	MJ/K	16.84 ± 0.7%	18.20 ± 0.7%	15.65 ± 0.5%	15.50 ± 0.3%
A_1	-	1.00*	1.00*	1.00*	0.69 ± 0.1%
A_2	-	1.65 ± 0.7%	1.61 ± 0.9%	2.45 ± 0.4%	1.56 ± 0.1%

4. Conclusions and outlook

Three example cases on performance analysis based on dynamic parameter identification have been investigated and discussed in this paper; one case on transmission losses, a second case on solar admittance, and a third case on the efficiency of a heating system. The example cases show that deviating values for building/system performance could be identified by employing DPI for a simple RC-network model. Future application of this analysis for actual buildings has to proof its potential in practice. Possible practical applications depend on the level of detail (spatial, temporal, system) of available data and level of detail of the applied RC-network model. Examples of possible application of DPI are performance analysis / fault detection for building components and installations; better forecasting of actual heating energy consumption based on measurements during a limited time period; better control of indoor climate (temperature, contaminants) and energy consumption using the identification procedure and model for an adaptive model-based control of the building systems.

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