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Impacts of on-board monitored data on estimated thermal characteristics of a dwelling

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Abstract. After the thermal renovation of a dwelling, there exists a gap between the actual and predicted energy performance. One of the reasons contributing to this gap is the poor assumptions of building thermal characteristics during the prediction stage. Nowadays, smart meters for gas and electricity, and home automation systems are becoming increasingly prominent in dwellings. Hence, there is potential to use the on-board monitored data from these sources to estimate the thermal characteristics of the actual dwellings. If it was possible to measure everything in a dwelling, then the estimation of these characteristics would become easy. However, the amount of data from the dwellings is limited. Hence with the available data, assumptions have to be made to estimate characteristics reflective of the actual dwelling. Therefore, this study investigates the impact these assumptions have on the estimated characteristics. First, a simple equation requiring minimum data is formulated to represent the heat dynamics in a building. Then, the characteristics are determined for one Dutch dwelling for the following conditions: 1. Different measurement periods, 2. Different time granularities, 3. With total (space heating + domestic hot water) and decomposed (only space heating) gas consumption data, 4. With different representations of indoor air temperature, and 5. Using electricity data to account for internal heat gains. In general, the estimated characteristics deviated for all the conditions. And thus, this study establishes the importance of well-chosen on-board monitored data.

1. Introduction

Renovation of residential buildings to become energy efficient and carbon neutral is the topic of the day in Europe. This paper addresses the specific case of Dutch dwellings. And, since most Dutch houses use gas for space heating, there is a more pressing need for this transition. The initial phase of a renovation project includes the energy performance prediction of a proposed retrofit option. Often, during this prediction, the values defining the thermal characteristics of the actual house are poorly assumed. This poor assumption leads to energy performance prediction that is far from reality. Thus, even after renovation, dwellings do not meet their intended targets [1–3]. This is often reflected in dissatisfied occupants (e.g., higher pay-back times), and at macro level, unattainable policy targets.

The question then is, how to determine the actual characteristics of houses? The direct way to determine them is through measurements: heat flow meter method [4], blower door test [5], PRISM (Princeton Score Keeping Method) [6], QUB (Quick U- value of Building) [7] and co-

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heating test [8]. But these measurement methods suffer limitations such as the need for special measurement equipment, cost, longer measurement durations and the limited number of characteristics each method can estimate. These measurements are also intrusive, thereby burdening the occupants. Thus, a method which uses easy-to-collect data from smart meters and home automation systems of functioning houses, and then finds its way back to determine the actual characteristics of these dwellings is the next best solution. Rasooli & Itard (2020) and EBC Annex 71 contributed to developing such methods [9,10]. The method by Rasooli & Itard (2020) will be used in this paper and further expanded for studying the on-board monitored data.

Previously, studies used different models to determine these thermal characteristics [10–12]. However, most of these studies used simulated data or involved unoccupied experimental buildings where the measurement conditions were controllable. Unlike data from experimental buildings, data from actual houses or on-board monitored data (e.g., indoor air temperature) comes with uncertainties because of the occupant interaction. Also, since it is impossible to measure everything in an occupied house, assumptions have to be made. And these assumptions have an impact on the estimated characteristics. These uncertainties in estimated parameters due to assumptions related to the on-board monitored data were pointed out by Rasooli & Itard (2020) but were not sufficiently studied. Studying these uncertainties is necessary to apply this method systematically in dwellings.

Therefore, this paper aims to study the impacts on the estimated thermal characteristics while using on-board monitored data from one occupied house. The deviations in the results are studied for the following conditions: 1. using data from different periods, 2. using data of different time granularities, 3. with and without separating total gas data into gas consumed for Space Heating (SH) and Domestic Hot Water (DHW), 4. using different indoor air temperature assumptions and, 5. using electricity data to account for internal heat gains.

2. Data Description

2.1. Dwelling description

The dwelling is an apartment located in the Netherlands. The apartment is occupied by a middle-aged man who is in the apartment all throughout the day, every day. The apartment itself is 72m^2 and has four rooms in total. There are neighbours on the west and east sides. The apartment has a north and a south façade. The building has a construction year of 2014 and belongs to the energy label A. The apartment uses a combination condensing boiler with a nominal efficiency of 0.9 for heating. During the measurement period, the thermostat was maintained at 21 ºC and the occupant never changed the thermostat settings. It is also important to note, the occupant showered only few times a week, lasting 10 minutes. The ventilation system of the house is mechanical ventilation system maintained at medium stand. In addition, the occupant used windows and doors to ventilate all rooms except the bathroom.

2.2. Description of the data used for the study

Table 1. Data used for estimating the thermal characteristics

Data	Source	Logging Interval
Indoor air temperature- all rooms	In-situ sensor	5 minutes
Relative Humidity- bathroom	In- situ sensor	5 minutes
Cumulative gas consumption	Smart meter	1 hour
Cumulative electricity consumption	Smart meter	10 seconds
Outdoor air temperature	KNMI	1 hour
Global solar radiation	KNMI	1 hour

Table 1 describes the data used for this study. Data measured from June 2017 to June 2018 is used. For additional information on the on-board monitored data refer [9]. For information on how the measurements were made refer [13].

The cumulative gas consumption (m^3) was converted into hourly heating energy consumption (Wh) by subtracting consecutive absolute values and multiplying by a calorific value of 35.17 MJ/m^3, along with the unit conversion. Similarly, consecutive values of cumulative electricity consumption were subtracted and further averaged for hourly consumption. The longer gaps of missing data (>5 hours) were ignored and not used in the analysis. The shorter gaps were filled using interpolation. The indoor air temperature and relative humidity were also averaged at hourly intervals. The indoor air temperature was calibrated according to [9]. There were no missing sensor data. Finally, the outdoor measurements were obtained by averaging data from the two closest KNMI stations (Koninklijk Nederlands Meteorologisch Instituut: Royal Dutch Meteorological Institute). All the data cleaning and processing were done using python programming.

3. Methodology

3.1. Deriving the thermal characteristics of the building

The first step is to derive the thermal characteristics of the building. If the entire house is assumed to be a single zone, then the heat interactions in the house are represented in the form of the following equation based on the law of energy conservation,

$$\left[\dot{q}_{storage}\right] = [\dot{q}_H] + [\dot{q}_{sol}] + [\dot{q}_{int}] + [\dot{q}_{vent}] + [\dot{q}_{inf}] + [\dot{q}_{trans}] \tag{1}$$

In essence, the heat stored $\left[\dot{q}_{storage}\right]$ in the house, is equal to the heat input $[\dot{q}_H]$ from the heating system into the house, the heat gains due to solar radiation $[\dot{q}_{sol}]$, the internal heat gains $[\dot{q}_{int}]$ due to the presence of occupants and usage of appliances, light, etc., heat exchange due to infiltration $[\dot{q}_{inf}]$ through cracks and crevices in the house, ventilation $[\dot{q}_{vent}]$ and through the building envelope$[\dot{q}_{trans}]$.

Equation 1 can be further expanded into equation 2,

$$C_{eq}\left[\frac{\partial T_{in}}{\partial t}\right] = \eta.\left[\dot{Q}_H\right] + S_0.A_{windows}.\left[\dot{Q}_{sol}\right] + \left[\dot{Q}_{int}\right] + \rho c\dot{V}_{vent}(T_{out} - T_{in}) + \rho c\dot{V}_{inf}(T_{out} - T_{in}) + \sum_{i=1}^{4} UA\ (T_{out} - T_{in}) \tag{2}$$

T_{in} and T_{out} are the indoor and outdoor temperatures in Kelvin respectively, ρ is the density, c is the specific heat capacity and $\dot{V}$ is the volume. $\dot{Q}_H$ is the energy flux used for heating the building in Watts. $\dot{Q}_{sol}$ is global solar radiation in W/m^2. T_{in}, T_{out}, $\dot{Q}_H$ and $\dot{Q}_{sol}$ are the measured data. For the purpose of calculation, equation 2 can be rewritten as,

$$C_{eq}\left[\frac{\partial T_{in}}{\partial t}\right] = \eta.\left[\dot{Q}_H\right] + S_0.A_{windows}.\left[\dot{Q}_{sol}\right] + S_1 + HLC.(T_{out} - T_{in}) \tag{3}$$

C_{eq} is the thermal capacitance, which is a characteristic of a building to store heat. It is a summation of the heat storing capacitance of all building components like walls, indoor air, furniture, etc. η is the nominal efficiency of the boiler. S_0 is a characteristic that represents the average fraction of radiation that enters the building. U is the thermal transmittance of each building envelope component (exterior walls, roof, glazing, floor) and, A is the corresponding area of these components. The inverse of U is resistance R, the ability of the building envelope to resist heat exchange to the surrounding. The UA value is a characteristic of the building which determines the rate of heat exchange through the building envelope when a temperature difference exists between the indoor and outdoor air. It can be seen in equation (2) that the heat exchange due to infiltration, ventilation and transmission is driven by the temperature difference. Hence, a global equivalent parameter called the heat loss coefficient (HLC) is introduced [10]. Also, a term S_1 is introduced which accounts for other effects in the building including internal heat gains $[\dot{q}_{int}]$.

Thus C_{eq}, HLC, S_0 and S_1 are the thermal characteristics to be estimated using the measured data. And equation 3 is the simplest representation of the heat dynamics in a building requiring minimum data.

3.2. The general framework

The general approach to this study follows the method by Rasooli and Itard (2020). The first step is to obtain the data required for the model. The next step is setting up the inverse model, where the inputs and outputs to the system are known, and then the parameters are estimated. The parameters are estimated by minimizing the root mean square error (RMSE) between the predicted and actual outputs. Bringing back equation 3, the inverse model is thus represented as in figure1:

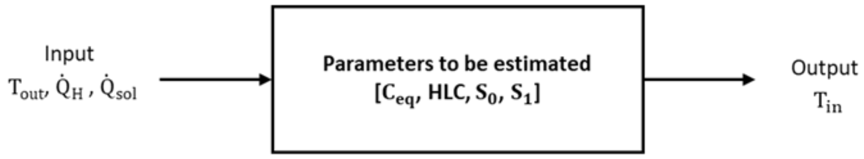

Figure 1. The figure illustrates the inverse model of estimating parameters where the inputs and the outputs to the model are known

The prediction function is therefore formulated as:

$$T^t_{in,pred} = \left(\eta.\dot{Q}^t_H + S_0.A_{windows}.\dot{Q}^t_{sol} + S_1 + HLC.T^t_{out} + \frac{C_{eq}}{3600}.T^{t-1}_{in}\right)/(HLC + C_{eq}) \quad (4)$$

Since the objective is to reduce the RMSE between the actual and predicted indoor air temperature, the objective function is represented as,

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\left(\eta.\dot{Q}^t_H + S_0.A_{windows}.\dot{Q}^t_{sol} + S_1 + HLC.T^t_{out} + \frac{C_{eq}}{3600}.T^{t-1}_{in}\right).\left(HLC + C_{eq}\right)^{-1} - T^t_{in,actual}\right)^2} \quad (5)$$

This optimisation problem is then solved using differential evolutionary algorithm from the SciPy library. The SciPy library is a free and open source library provided by python. The final boundary constraints were set to: HLC ∈ [10,300], C_eq ∈ [1e5,1e9], S_0 ∈ [0,1], S_1 ∈ [0,5000]. The boundaries were decided after running the simulations several times from broader to tighter constraints. They were also based on the possible ranges of physical properties obtained from [9].

3.3. Testing for deviations

The next step is to test for deviations based on different conditions. The deviations in the estimated parameters are studied for the following conditions:

1. **Using data from different periods:** Entire year, summer, winter, winter months, winter weeks, winter days. The winter month of December is not considered in this study because of a large gap of missing data. January and March were the most windy months among the periods considered in this study. Summer months did not have space heating gas consumption and temperature difference between the indoor and outdoor air was relatively small.

2. **Using data of different time granularities:** Hourly, daily, weekly. For example, for daily data, the hourly data is averaged to daily data. And this data is used in the simulation as if only daily data is available for the simulations.
3. **Using gas consumed data with and without separating gas consumed for space heating and domestic hot water.** Decomposition of gas data was done using the method explained by Rasooli & Itard (2020). First, the gas data corresponding to the frequent heating up of the boiler to maintain constant temperature and frequent domestic hot water (DHW) usage are removed. Then, the gas data corresponding to the relative humidity spikes in the bathroom are removed. These spikes correspond to the DHW used for showering. Finally, the remaining gas data is the gas consumed for space heating (SH).
4. **Assuming different indoor temperature:** Average of temperature in all rooms ($T_{in,avg}$), floor area based average temperature ($T_{in,\ fa}$) of the rooms, volume based average temperature ($T_{in,\ vol}$) of the rooms, temperature of the room ($T_{in,\ r}$) where the thermostat was placed.
5. **Accounting for internal heat gains using electricity data:** 0% of the electricity data, 25% of the electricity data (0.25El), 50% of the electricity data (0.5El), 75% percent of the electricity data, 100% of the electricity data (1El). To suit this condition, equation 3 was reformulated to accommodate electricity data,

$$C_{eq}\left[\frac{\partial T_{in}}{\partial t}\right] = \eta.\left[\dot{Q}_H\right] + S_0.A_{windows}.\left[\dot{Q}_{sol}\right] + S_{1,elec} + S_1 + HLC.(T_{out} - T_{in}) \quad (6)$$

4. Results and Discussions

The estimated parameters are presented in Tables 2, 3, 4 and 5. They are represented by the different conditions explained in the previous section. For easy interpretation, HLC estimates for all periods and granularities are presented. For the other characteristics only year and winter periods are shown. It is important to note, for week and day periods, table 1 shows the respective averages over the whole duration of January to March. On average, the RMSE remained around 0.4 with winter periods showing the lowest RMSE. This remained the same for all conditions except when a single room temperature was used to represent the indoor air temperature. The RMSE average then increased to 0.5.

Table 2. Estimated HLC for the different conditions explained in section 3.3

HLC in WK^{-1}										
Period	**Granularities**	**SH+DHW, $T_{in,avg}$**	**SH, $T_{in,avg}$**	**SH, $T_{in,\ fa}$**	**SH, $T_{in,\ vol}$**	**SH $T_{in,\ r}$**	**SH, $T_{in,avg}$, 0.25El**	**SH, $T_{in,avg}$, 0.50El**	**SH, $T_{in,avg}$, 0.75El**	**SH, $T_{in,avg}$, 1El**
One year										
2017-2018	Hourly	79	72	71	71	75	76	80	83	87
	Daily	79	72	71	71	74	76	80	83	87
	Weekly	80	73	71	71	75	77	80	84	88
Winter										
Jan- feb 2018	Hourly	151	160	153	152	139	158	159	160	161
	Daily	164	167	158	159	133	165	167	167	170
	Weekly	162	173	164	163	127	174	175	175	176
Jan, 2018	Hourly	140	145	138	139	126	145	149	146	148
	Daily	293	299	298	298	126	297	299	299	297
Feb, 2018	Hourly	171	171	166	167	143	173	173	171	172
	Daily	171	172	152	148	143	172	173	174	173
Mar, 2018	Hourly	59	50	49	49	131	53	59	63	66
	Daily	288	286	296	275	131	289	299	291	296
Week Jan-Mar	Hourly	149	153	146	147	139	154	155	158	159
	Daily	191	187	205	205	210	188	188	189	190
Day Jan-Mar	Hourly	176	168	171	170	169	170	172	173	176
Summer										
Aug- Sep 2017	Hourly	94	61	71	78	68	89	96	101	108
	Daily	298	263	251	261	264	294	295	291	294

The estimated HLC's were found to be consistently good during the Jan-Feb winter, the month of February and the year period. This was because the estimates were consistent across the different time granularities. The results for the other periods were inconsistent for different time granularities. And, these periods included summer and the windy months.

On comparing the HLC estimated using total and space heating gas consumption data, it is evident that the former yielded HLC values lower than the latter. The unaccounted energy use due to DHW are therefore reflected by higher S_1 values. Overall, the deviation between these two conditions is not much. This is because of the single occupancy and the infrequent showering by the occupant. However, it cannot be assumed that this would be negligible in other households.

Next comes the deviations caused due to indoor air temperature assumptions. Since it is a single floor house with the same height, the estimated parameters are almost the same when floor area based average and volume-based average indoor air temperature representations are considered. On the other hand, when the indoor air temperature is represented by the temperature of a single room ($T_{in,r}$), the estimated parameters are different. Especially the HLC ($T_{in,r}$) values during the longer winter periods remain closer. This verifies that the thermostat was placed in this particular room. The heating system is activated based on this room temperature. This can be further verified by comparing the results of using average temperature ($T_{in,avg}$) of all rooms with results obtained using $T_{in,r}$. In general, $T_{in,avg}$ yielded higher HLC's meaning that there were rooms with higher temperatures than the room with the thermostat. The heat contribution to these rooms are reflected by higher S_1values for $T_{in,avg}$.

Finally, the results obtained by including electricity data to account for internal heat gains are compared. It is more logical to compare the condition (SH, $T_{in,avg}$) with (SH, $T_{in,avg}$, 0.25El), (SH, $T_{in,avg}$, 0.50El), (SH, $T_{in,avg}$, 0.75El) and (SH, $T_{in,avg}$, 1El). It can be observed that all parameters except S_1 remain more or less the same for all the conditions. As the amount of electricity data included in the equation increased, the values of S_1 decreased accordingly.

Table 3. Estimated C_{eq} for the different conditions

Period	Granularities	C_{eq} in JK^{-1} SH+DHW, $T_{in,avg}$	SH, $T_{in,avg}$	SH, $T_{in,fa}$	SH, $T_{in,vol}$	SH $T_{in,r}$	SH, $T_{in,avg}$, 0.25El	SH, $T_{in,avg}$, 0.50El	SH, $T_{in,avg}$, 0.75El	SH, $T_{in,avg}$, 1El
One year										
2017-2018	Hourly	3.3e8	3.4e8	3.5e8	3.5e8	3.2e8	3.3e8	3.2e8	3.1e8	2.9e8
	Daily	1.4e7	1.4e7	1.5e7	1.5e7	1.3e7	1.4e7	1.3e7	1.3e7	1.2e7
	Weekly	2.0e6	2.2e6	2.3e6	2.2e6	2.1e6	2.1e6	2.0e6	2.0e6	1.9e6
Winter										
Jan- feb 2018	Hourly	1.7e8	2.0e8	1.8e8	1.8e8	1.5e8	2.0e8	2.0e8	2.0e8	2.0e8
	Daily	2.1e7	2.6e7	2.8e7	2.6e7	3.0e7	2.8e7	2.6e7	2.7e7	2.7e7
	Weekly	4.1e6	4.8e6	5.0e6	5.2e6	7.6e6	4.7e6	4.7e6	4.7e6	4.7e6
Feb, 2018	Hourly	2.0e8	1.9e8	1.7e8	1.7e8	1.2e8	1.9e8	1.9e8	1.9e8	2.0e8
	Daily	2.3e7	2.4e7	1.9e7	1.9e7	1.3e7	2.5e7	2.6e7	2.6e7	2.6e7

Table 3 shows the details of the thermal capacitance values (C_{eq}). They are the highest for the hourly granularities, and for lower granularities, daily and weekly, the values decrease substantially.This is in line with [9]. Thus, the building response time is in the order of days and at lower granularities this dynamic effect cannot be captured.

The values of S_o (see table 4) remain the same across all conditions. In some periods and granularities S_o leans towards the constraints. The constraints are logical, in the sense, the fraction of irradiation entering the house should lie between 0 and 1. Then one possible uncertainty could be because of using global solar irradiation instead of the actual irradiation based on orientation.

Some meaning was given to the values of S_1 (see table 5) in the above discussions. However to provide an accurate meaning to this parameter, further models must be developed that accounts for occupant behaviour.

Table 4. Estimated S_o for the different conditions

		S_o								
Period	**Granularities**	**SH+DHW, $T_{in,avg}$**	**SH, $T_{in,avg}$**	**SH, $T_{in,fa}$**	**SH, $T_{in,vol}$**	**SH $T_{in,r}$**	**SH, $T_{in,avg}$, 0.25El**	**SH, $T_{in,avg}$, 0.50El**	**SH, $T_{in,avg}$, 0.75El**	**SH, $T_{in,avg}$, 1El**
One year										
2017-2018	Hourly	0.20	0.22	0.22	0.22	0.21	0.21	0.20	0.20	0.19
	Daily	0.21	0.22	0.22	0.22	0.21	0.22	0.21	0.20	0.20
	Weekly	0.22	0.23	0.23	0.23	0.22	0.22	0.21	0.21	0.20
Winter										
Jan- feb 2018	Hourly	0.83	0.84	0.82	0.81	0.79	0.83	0.83	0.82	0.83
	Daily	1	1	1	1	1	1	1	1	1
	Weekly	1	1	1	1	1	1	1	1	1
Feb, 2018	Hourly	0.71	0.67	0.68	0.68	0.68	0.67	0.67	0.65	0.65
	Daily	0.15	0.07	0.13	0.13	0.28	0.05	0.03	0.03	0

Table 5. Estimated S_1 for the different conditions

		S_1 in W								
Period	**Granularities**	**SH+DHW, $T_{in,avg}$**	**SH, $T_{in,avg}$**	**SH, $T_{in,fa}$**	**SH, $T_{in,vol}$**	**SH $T_{in,r}$**	**SH, $T_{in,avg}$, 0.25El**	**SH, $T_{in,avg}$, 0.50El**	**SH, $T_{in,avg}$, 0.75El**	**SH, $T_{in,avg}$, 1El**
One year										
2017-2018	Hourly	1.4	0.16	0.51	0.22	0	0.81	0.15	0	0
	Daily	0.03	0.44	0.09	0.24	0	0.46	0.87	0.13	0.54
	Weekly	0.3	0.002	0	0.24	0.34	0	0.15	0	0.11
Winter										
Jan- feb 2018	Hourly	796	1058	1013	1005	682	978	939	884	843
	Daily	928	1094	1013	1038	554	1002	985	918	908
	Weekly	924	1250	1173	1152	582	1197	1148	1094	1049
Feb, 2018	Hourly	1312	1454	1396	1415	844	1412	1366	1271	1223
	Daily	1959	2182	1773	1699	792	2134	2111	2061	2016

5. Conclusion

This paper addressed the impacts of on-board monitored data assumptions on the estimated characteristics . The characteristics were determined for the following conditions: 1. Different measurement periods, 2. Different time granularities, 3. With total and space heating gas consumption data, 4. With different representations of indoor air temperature and, 5. Using electricity data to account for internal heat gains. Finally, the results were presented, and the deviations analysed. The main conclusions and recommendations are as follows:

1. The inconsistencies of HLC estimates can be improved by separating the variable (infiltration and ventilation) and the stationary (UA value) components. Wind velocity models to account for infiltration can be a possible first step.
2. The C_{eq} values have very large magnitudes. This is a drawback of using a simple equation to represent the heat dynamics of a building. Breaking up this component into smaller bits like C_{walls}, C_{air}, etc. can increase the accuracy of estimation.
3. The parameters S_o and S_1 should be further researched. The inclusion of additional models could improve these estimated parameters. For example, occupant behaviour models and models that calculate the amount of irradiation entering the house based on orientation.
4. Moving stepwise from simple to complex models can improve the accuracy of the estimates. Further, validation of the estimated characteristics is important to advance such parameter estimation methods.
5. Finally, it can be expected that the deviations presented in this study can vary when different dwellings and households are used. Hence, this study should be further extended to more dwellings.

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