Uncertainty in Building Energy Performance Characterization: Impact of Gas Consumption Decomposition on Estimated Heat Loss Coefficient

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ABSTRACT
Characterization of building energy performance indicators such as the Heat Loss Coefficient (HLC) based on in-situ measurement data calls for thorough building physical insight, a well-designed measurement set-up to collect sufficient, qualitative data and adequate data analysis methods. On-board monitoring may be an alternative for dedicated experiments to perform the data collection task. This paper analyses the sensitivity of the end-result of the characterization, the HLC estimate, to flaws in the monitoring data set. More specifically, the impact of not installing submeters to disentangle the gas consumption for space heating and the production of domestic hot water is evaluated. Hereto, multiple gas decomposition methods are applied on a case study monitoring data set, after which the HLC is assessed. The results show deviations up to 33% for the mean estimate. Nevertheless, the 95% confidence intervals largely overlap.

KEYWORDS
Characterization, Heat Loss Coefficient, On-board Monitoring,
Gas Consumption Decomposition, Sensitivity Analysis.

INTRODUCTION
Building energy performance (BEP) characterization based on in-situ measurements has recently been gaining much attention in the framework of IEA EBC Annex projects 58 and 71. Furthermore, Bauwens (2015), Deconinck (2017) and Farmer et al. (2017) demonstrate how the thermal resistance of building elements and the HLC of building envelopes can be estimated through application of statistical modelling techniques on data collected in on site steady-state an dynamical measurement experiments. The HLC hereby describes the amount of heating power needed to maintain a temperature difference of 1 degree Kelvin over the entire building envelope [W/K]. The case studies investigated to date, however, mainly focus on mock-ups or unoccupied dwellings. Not only because the measurement conditions can be better controlled, but also because the measurement set-up can be perceived as intrusive and costly.
On-board monitoring, using sensors to collect data of an occupied, in-use building, is put forward as a solution to the issues of cost and intrusiveness (Saelens and Reynders, 2016). However, much uncertainty still exists about the optimal sensor set-up, the way disturbances induced by occupants should be handled, etc.

The present paper aims to address a particular data related challenge that researchers, aspiring to estimate the HLC, might have to face; namely that the same type of fuel has been used for both space heating (SH) and the production of domestic hot water (DHW), and that no submeters can or have been installed to differentiate between both end uses.
The dynamic heat balance for a single zone (Eq.1), which forms the framework for both the

monitoring campaign and the data analysis model, stipulates that the HLC at each timestep *t* depends on the effective heat capacity C_i [J/K] of the zone, the difference between the interior and exterior temperature (T_i and T_e resp. in [K]), the heat flow rates due to mechanical ventilation with heat recovery, internal and solar gains ($\varphi_{vent,hr}$, φ_{int} and φ_{sol} resp.), and the net power supplied by the heating system φ_H [W]. This final term not only implies that the gross fuel consumption has to be conversed in net energy use on the basis of the system efficiency, but also that the energy use for SH should be separated from that for DHW production and that the latter should be eliminated from the analysis for as far that it does not induce internal gains.

$$C_i \cdot \frac{dT_i}{dt} = HLC \cdot \left(T_{i;t} - T_{e;t}\right) + \varphi_{vent,hr;t} + \varphi_{int;t} + \varphi_{sol;t} + \varphi_{H;t} \quad (1)$$

Not decomposing the gas consumption results in an overestimate of the HLC. However, disentangling it incorrectly might just as much lead to an erroneous estimate. This paper will therefore evaluate the sensitivity of the HLC estimate to the approach used to determine the not-monitored gas consumption for space heating.
The first part of the methodology section describes the case study dwelling and on-board monitoring campaign used to this end. Next, three different ways to decompose the gas consumption and thus approach φ_H are discussed. In the final part of the methodology section, the data analysis procedure used to estimate the HLC is delineated. In the results section, differences between the decomposition outcomes are shown, and, more importantly, their impact on the characterization of HLC is demonstrated. Finally, conclusions are drawn on the present study and recommendations are given for future research.

METHODOLOGY

Case study dwelling and on-board monitoring campaign

The object of this study is a semi-detached, two-story house built in 2012 in Gainsborough, UK. Based on the target thermal transmittance and surface area of the building envelope parts, and the average result of three blowerdoor tests, a theoretical HLC of 50W/K is calculated. SH and DHW are provided by a gas fired combi boiler. Together with the other dwellings in its terrace, the house has been the subject of a monitoring campaign conducted from October 2012 until November 2015. During this period, the dwelling was inhabited by three persons. The interior temperature of the living room and bed room (both from the studied and neighbouring dwelling), the exterior temperature, the gas, water and electricity consumption and the PV production were monitored with a 5 min sample frequency. Hourly averaged values of the global horizontal solar irradiance (GHR) were obtained from a RAF weather station located 30km from the site. A detailed description of the dwelling and performed monitoring campaign can be found in (Sodagar and Starkey, 2016), in which the dwelling is referred to as 'House 1'.

Gas consumption decomposition methods (DMs)

Classifying all gas consumption for the production of DHW as internal gains and thus assessing HLC based on the total gas consumption ('No decomposition') is incorrect since the hot tap water directly leaves the dwelling through the sewage system.
A first decomposition method to disentangle both end uses ('DM1') could therefore be the application of a default distribution. In this case study there will be opted for a 76/24 distribution for the end uses SH/DHW, as reported by Menkveld (2009). A major drawback of this method is that it does not take the actual consumption, SH demand or occupant behavior into account.

The second decomposition method ('DM2') is fully based on the assumptions that (1) in the case of the combi boiler, the production of DHW and SH do not occur at the same time and (2) the gas consumption for DHW production perfectly coincides with the DHW consumption. It

involves the implementation of two rules on the 5min-interval monitoring data. The first rule stipulates that the gas consumption for DHW production must be set to 0 when mains water consumption is 0, else gas consumption for the production of DHW must be set equal to the total monitored gas consumption. The second rule states that the gas consumption for SH must be set to 0 when mains water is consumed, else gas consumption for SH must be set equal to the total monitored gas consumption.
This DM is straightforward and easy to implement. However, a number of potential flaws can be identified. First, the assumptions imply that all cold water tappings occurring while gas is used for SH are classified as DHW usage. The fact that grey water is used to flush the toilets though makes this assumption more reasonable. Secondly, the hot water tappings could be significantly shorter than the 5min sampling time. Yet, from the moment water consumption is observed, however small, the full gas consumption for that 5min period is allocated to DHW production. Higher frequency logging could solve this issue. Thirdly, small time delays between starting and stopping of water and gas consumption will create some error.

The third approach, 'DM3', which was demonstrated by Bacher et al (2016), uses a robust, zero order, Gaussian kernel smoother to estimate the 'gas consumption for SH'-profile underlying the noisy 5min gas consumption data. Next, all spikes of the total gas consumption significantly above this kernel (smoother) estimate are classified as DHW heating spikes and their values are obtained by subtraction of the kernel estimate. Finally, subtraction of the estimated heat load for the production of DHW from the total heat load gives an estimate for the heat load for SH.
The parameters of the kernel smoother procedure were tuned with an eye on limiting the gas consumption classified as 'gas used for space heating' during the summer months. The final model parameter values are as follows: kernel window: 1h, bandwidth: 0.5h, threshold for bisquare robust estimation γ: 7MJ/h, separation threshold q_{tres}: 1.1.
Just like DM2, this decomposition method has not been verified on a case study were the total gas consumption and the consumption for the production of DHW and SH were measured separately. In contrast with the previously described approach, this method assumes that gas consumption for both end uses can occur simultaneously. It should furthermore be noted that all peaks are classified as DHW heating, although the start-up of the space heating might also result in a similar peak in the fuel consumption.

Determination of HLC
For the characterization exercise, four periods were selected from the entire data set: a relatively long model training period, extending from the 1st of October 2014 till the 31st of March 2015, and three different shorter model validation periods, in January, February and March 2014. With the heat balance equation (Eq.1) in mind, the following variables were selected from the monitoring data; the exterior temperature T_e, the interior temperature of the dwelling itself and the neighbouring dwelling (T_i and T_n, resp). Both T_i and T_n are approximately determined as the arithmetic mean of the sensor data collected in the living and bed room. In the absence of data on the incident radiation on the different facades, the GHR will be used to represent I_{sol}. After adaptation with the calorific values published by National Grid (2017) and decomposition through one of the above-mentioned decomposition methods, the gas consumption data will be used as φ_H. The system efficiency is thus assumed to be equal to 100%. Although this value is uncertain and in reality not even constant, this will not pose an issue for this study, which focuses on the relative differences caused by DMs used for gas consumption. The same holds for the other assumptions made. Finally, the internal gains φ_{int} are neglected in a first run ('$\varphi_{int} = 0$') and assumed to equal the total electricity consumption in a second run ('$\varphi_{int} > 0$'). The latter variable is hereby approximated as the mains electricity consumption plus half of the PV production to account for the not-submetered electricity that is directly fed to the grid.

Next, an Auto-regressive with eXogenous input (ARX) model is fitted on the selected time series data, utilizing the 'lm' function in R-Studio:

$$\varphi_i(B) \cdot \boldsymbol{T_{i;t}} = \omega_e(B) \cdot \boldsymbol{T_{e;t}} + \omega_n(B) \cdot \boldsymbol{T_{n;t}} + \omega_{sol}(B) \cdot \boldsymbol{I_{sol;t}} + \omega_H(B) \cdot \left(\boldsymbol{\varphi_{H;t}} + \boldsymbol{\varphi_{int;t}}\right) + Int + \varepsilon_t \quad (4)$$

with T_i, T_e, T_n, I_{sol}, φ_H and φ_{int} the previously determined variables, resampled to 1h values, and $\varphi_i(B)$ an input polynomial of order p_i in the backshift operator B. Likewise, the $\omega_x(B)$'s are output polynomials of order p_x. Int is a constant intercept term and ε_t the residual (error) (Madsen, 2016).

To decide on the model order, a backward elimination procedure is followed, starting from a model including 24 lags for each of the considered polynomials. After every run, the significance of the fitted model parameters is verified using a t-test (threshold of $p < 0.05$), starting with the highest available order. When parameters of a certain order prove insignificant, their variables are eliminated from the model description and the model is refitted. The iterative process ends when all parameters present are significant.

To validate the developed models, it is verified whether their residuals resemble white-noise in plots of the autocorrelation function (ACF) and cumulated periodogram (CP). By comparing the normalized RMSE (nRMSE) [%] between the measured interior temperature and its one-step-ahead prediction for both the training and a validation period, it is checked whether the model is not overfitted.

If the model is accepted, HLC is calculated as the quotient of steady-state gains $\omega_e(1)/\omega_H(1)$. Finally, the models are compared based on (1) their score for the Akaike Information Criterion (AIC) and (2) the nRMSE between the observed and simulated interior temperature for the cross validation periods. For both criteria, a lower value indicates a better model.

RESULTS ANALYSIS AND DISCUSSION

Differences between the gas consumption for SH estimated by the DMs

Table 1 compares the decomposition of gas consumption for SH and DHW production obtained through the different approaches. The default method (DM1) almost always results in a higher gas consumption for SH than DM2 and DM3. The method with the robust kernel smoother (DM3) uses a certain threshold instead of selectively classifying the gas consumption as either gas consumption for SH or production of DHW as DM2 does. This way it appears to systematically obtain a lower gas consumption for SH.

Table 1: Total gas consumption [kWh] and the gas consumption for SH as estimated by the four approaches [expressed as a percentage of the total gas consumption], per month.

	Oct 2014	Nov 2014	Dec 2014	Jan 2015	Feb 2015	Mar 2015
Total gas consumption	188 kWh	286 kWh	486 kWh	526 kWh	428 kWh	267 kWh
No decomposition	100%	100%	100%	100%	100%	100%
DM 1	76%	76%	76%	76%	76%	76%
DM 2	58%	69%	74%	77%	74%	59%
DM 3	44%	55%	62%	63%	59%	45%

Validation of developed ARX models

Given the applied model selection procedure, all finally included parameters of the 8 models (4 variants for φ_H times 2 scenarios for φ_{int}) are significant. Except for the models with φ_H based on DM2 or DM3 and φ_{int}=0, the interior temperature of the neighboring dwelling appeared to be an insignificant model input, probably because of a nearly constant profile of T_n. For the other validation tests, the results were positive for all models: the nRMSE did only increase with about 1% for the one-step ahead cross validation test, and the ACF and CP plots indicated white noise residuals. All models thus appear to be statistically valid.

Comparison of resulting HLC

Figure 1 shows the impact of the applied decomposition method on the HLC estimate, and this for the two different φ_{int} scenarios. The models appear to yield fairly different results, although the 95% confidence intervals are sufficiently large to overlap. In the case of $\varphi_{int} = 0$ the mean estimates range from 47.32 to 70.97W/K, which is a difference of 33%. The assumption that the internal gains equal the (approximated) total electricity consumption not only reduces the uncertainty on the outcomes, but also slightly lowers the impact of the choice for a certain gas decomposition method (maximal difference of 25% between the means). Nonetheless, the mean outcomes for DM2 and DM3 still differ with 14%. Notably, the observed deviances are dwelling and occupant specific. In the case of a less-insulated dwelling, with a higher setpoint temperature of the heating system and a lower DHW consumption, the impact of the choice for one of the 4 demonstrated DM approaches may be smaller.

As neither DM2 nor DM3 has yet been validated and the information available on the boiler is limited, it is impossible to claim that one of the HLC outcomes is correct. However, some

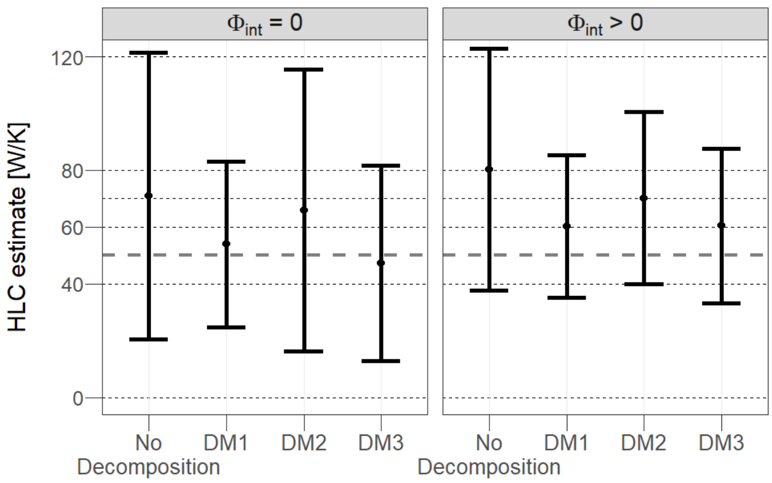

Figure 1: Overview of the HLC estimates and their related 95% confidence intervals for the different models. The dotted line indicates the theoretically calculated reference value.

Table 2: Comparison of the different models based on the AIC and nRMSE between the measured and simulated interior temperature.

	AIC	nRMSE(T_i, $\hat{T}_i$) [%] for validation periods in:		
	Training period	Jan '14	Jan-Feb '14	Feb-Mar '14
$\varphi_{int} = 0$				
No decomposition	-4319.60	22.20	17.60	31.90
DM 1	-4316.53	22.19	17.62	31.97
DM 2	-4585.14	12.73	9.58	13.97
DM 3	-4515.00	16.39	16.33	15.90
$\varphi_{int} > 0$				
No decomposition	-3415.77	32.08	26.97	41.58
DM 1	-3390.58	38.66	32.45	46.43
DM 2	-3558.96	19.21	15.22	22.90
DM 3	-3548.66	24.35	25.36	28.95

conclusions can be drawn from a statistical point of view. When comparing the model's AIC and their nRMSE's for the simulation validation periods (Table 2), we see that the models with $\varphi_{int} = 0$ in general, and the models where DM2 and DM3 are applied in specific, are better capable of predicting the interior temperature. The more accurate predictions on cross validation data may indicate more correct input data and a more accurate model structure, and are therefore argued to be a reason for favoring the outcome of those models.

CONCLUSION

The present paper explored how the HLC of a building envelope can be characterized based on on-board monitoring data. The focus was on the sensitivity of the characterization outcome to the preciseness of the knowledge on the supplied net heating power. This way the paper aimed to address the common problem that the two end-uses of gas (SH and DHW) are not submetered. By means of a case study, diverse approaches to approximate the unknown gas consumption for SH were illustrated. It was uncovered how, depending on the approach used, the HLC outcome can be 33% apart. Uncertainty regarding other variables involved, e.g. the internal gains, furthermore influence this result. Since the applied gas decomposition methods have not yet been validated, the 'correct' characterization outcome could not be identified. However, based on statistical model comparison tests, suggestions on the trustworthiness of the outcomes were given. Submetering the gas consumption would, however, clear all doubts and increase the accuracy of the outcome. In next steps the applied decomposition techniques should be validated and the sensitivity of the HLC estimate towards assumptions on other variables (e.g. the system efficiency, interior temperature, incident solar radiation) should be explored.

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REFERENCES

Bacher P., de Saint-Aubain P.A., Christiansen L.E., and Madsen H. 2016. Non-parametric method for separating domestic hot water heating spikes and space heating. *Energy and Buildings,* 130, 107-112.

Bauwens G. 2015. In situ testing of a building's overall heat loss coefficient. *Ph.D. Thesis*, KU Leuven (Belgium), 200 pages.

Deconinck A.H. 2017. Reliable thermal resistance estimation of buildings components from on-site measurements. *Ph.D. Thesis*, KU Leuven (Belgium), 224 pages.

Farmer D., Gorse C., Swan W., Fitton R., Brooke-Peat M., Miles-Shenton D., and Johnston D. 2017. Measuring thermal performance in steady-state conditions at each stage of a full fabric retrofit to a solid wall dwelling. *Energy and Buildings*, 156, 404-414

Madsen H., Bacher P., Bauwens G., Deconinck A., Reynders G., Roels S., … Lethé G. 2016. IEA EBC Annex 58: Report of Subtask 3, part 2: Thermal performance characterisation using time series data - statistical guidelines. KU Leuven (Belgium), 83 pages.

Menkveld M. 2009. Kentallen warmtevraag woningen. Final Report for RVO. ECN, 7 pages.

National Grid UK. 2017. Calorific Value (CV): CV Data: Data Item Explorer. National Grid UK: https://www.nationalgrid.com/uk/gas/market-operations-and-data/calorific-value-c, consulted October 6, 2017.

Saelens D., and Reynders G. 2016. IEA EBC Annex 58: Report of Subtask 4b: Towards a characterisation of buildings based on in situ testing and smart meter readings and potential for applications in smart grids. KU Leuven (Belgium), 25 pages.

Sodagar B., and Starkey D. 2016. The monitored performance of four social houses certified to the Code for Sustainable Homes Level 5. E*nergy and Buildings*, 110, 245-256.