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Evaluation of a building envelope Heat Transfer Coefficient in use: Bayesian approach to improve the inclusion of solar gains

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Abstract.

Accurately measuring the actual building performance would be a significant step toward performance contracting. Methods under occupancy have operational advantages but come with additional constraints due to the variability of weather and occupancy conditions, which cannot be overlooked. Especially in recent, well-insulated buildings, since solar gains are a larger contribution to the global heat balance. This work aims to enhance the accuracy of the Heat Transfer Coefficient estimation in an occupied building by taking better account of solar gains in multilinear regression models. The approach adopted here considers solar gains from both the incident solar heat flux through glazing and from the opaque elements of a building by calculating an equivalent outdoor temperature. This model feeds a multilinear regression model whose parameters are estimated by Bayesian inference. Our model for estimating HTC is validated against a set of virtual data from a simulated detached house under different weather conditions.

Keywords: thermal performance, building envelope, HTC, solar gains , Bayesian inference

1. Introduction

Towards the European Commission's target of achieving carbon neutrality in the building stock by 2050, the construction industry needs to build dwellings that are highly energy-efficient and low-carbon, and also carry out massive renovation work on the existing stock. Today, a clear evaluation of the energy performance of buildings is a necessity, but there are still difficulties to be overcome in bridging the gap between actual consumption and that anticipated at the design stage (Gorse et al. 2013), (de Wilde 2014).

1.1 Overview of existing methods for determining HTC

Numerous studies are therefore seeking to understand and reduce this discrepancy by characterising the HTC coefficient using in-situ measurements. There are currently two

categories of methods for measuring the HTC: in unoccupied buildings and in occupied buildings. Methods for unoccupied conditions allow to overcome large uncertainties generated by occupants, direct solar radiation and ventilation. The methods without occupancy avoid the uncertainty of solar gains by closing the shutters. These methods enable to set a specific measurement protocol with a large number of measuring sensors, and place the building under specific conditions, such as in the co-heating test (Sonderegger and Modera 1979), (Bauwens and Roels 2014), the QUB method (Ghiaus and Alzetto 2019) or the SEREINE method (Juricic et al. 2023).

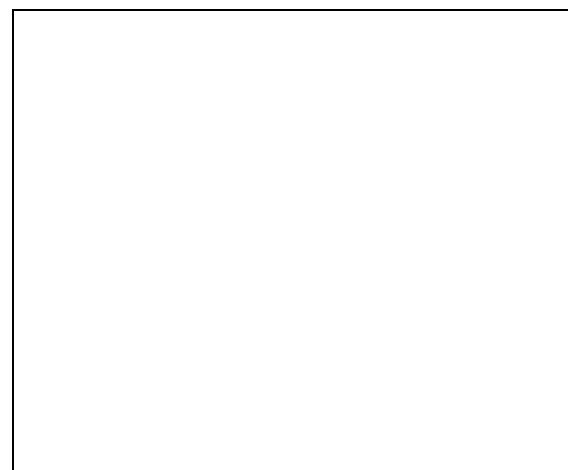
Conversely, the methods currently being developed for occupied buildings use non-intrusive instrumentation and are occupancy-friendly. They offer therefore a significant operational advantage. Senave and al. (Senave

et al. 2020) and the International Energy Agency Annex 71 (International Energy Agency IEA 2021) review the various approaches that have been considered for determining the HTC of a building under actual conditions of use. For each method, whether static (average method, linear regression, energy signature) or dynamic (RC model and ARX model), the results obtained have been compared with each other and with the building's reference value (estimated by co-heating tests or by a design calculation). (Senave et al. 2020) carry out a numerical study. To determine the reference value for their case study, they return to the definition of the heat transfer coefficient, as the sum of the infiltration and transmission transfer coefficients, and manually calculate the HTC. This study shows that, with 26 weeks of winter data, the ARX model gives a good estimation of the HTC, with a deviation from the reference value of no more than 5%. The average method gives good results too, but fails to provide an uncertainty estimation other than that related to the sensor uncertainties. The energy signature method is quickly discarded because it is not preferred when indoor temperature data is available. With a long measurement period, the linear regression model shows a deviation from the reference value below 10%. However, this study does not consider real occupancy, since the data analysed comes from numerical simulations. In the work of the IEA EBC Annex 71 (International Energy Agency IEA 2021), with real residential buildings in England and Belgium, and real occupancy, the results with linear regression and ARX models often differ from the reference value by 20%. Based on these results, Senave and al. (Senave et al. 2020) and IEA EBC Annex 71 (International Energy Agency IEA 2021), recommend further research into a practical and reliable formulation of internal and solar heat gains. In the remainder of this article, the focus will be on linear regression models which are showing consistent results to determine the HTC from measurements.

The advantage of the HTC estimation methods during occupancy is that they can be used both at the end of the construction work and during the building's operating phase, which is useful for renovations. However, performance assessment under occupancy is more uncertain, since the sources of uncertainty and bias are more numerous and random. Additional constraints due to occupancy need to be considered when measuring thermal performance. It is necessary to determine the various input parameters of the building's heat balance, based on measured data, in order to estimate the HTC in use. In particular, solar gain has a major influence (Bauwens and Roels 2014) on the measurement of thermal performance during occupancy, especially in well-insulated buildings (Li, Allinson, and Lomas 2019). In fact, unlike the unoccupied methods where direct solar gain can be largely avoided by closing the shutters, when the occupants are present, not taking solar gain into account risks underestimating the HTC coefficient, as highlighted in (International Energy Agency IEA 2021). These studies clearly show that a reliable estimation of HTC can only be obtained if the effect of influential phenomena on the heat balance is estimated as precisely as possible.

In the remainder of this work, particular attention will be paid to the solar heat gains.

1.2 Background of accounting for solar gains



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T_e	Outdoor temperature (K)
θ	Ratio of typical average transmittance to that at normal incidence
θ_f	Ratio of typical average transmittance to that at normal incidence per facade
$F_{ref,f}$	Reflected solar flux (W/m ²)
Z_f	Solar access factor
φ_{solar}	Solar heat gains (W)
Az_s	Sun azimuth (rad)
H_s	Sun height (rad)
U_f	Thermal transmittance coefficient of a wall (W/m ² .K)
$A_{w,f}$	Total glazed area of a wall (m ²)
g_f	Total solar energy transmittance factor of the glazing
Az_f	Wall azimuth (rad)
β	Wall tilt (rad)

Nomenclature

A_f	Area of a wall (m ²)
$I_{dif,hz}$	Diffuse horizontal irradiance (W/m ²)
$F_{dif,f}$	Diffuse solar flux (W/m ²)
$I_{dir,hz}$	Direct horizontal irradiance (W/m ²)
$F_{dir,f}$	Direct solar flux (W/m ²)
φ_{elec}	Electrical appliances heat gains (W)
T_{exteq}	Equivalent outdoor temperature (K)
T_{feq}	Equivalent outdoor temperature of a wall (K)
h_{ce}	External convective heat exchange coefficient (W/m ² .K)
α_e	External energy absorption coefficient of a wall
h_{re}	External radiative heat exchange coefficient (W/m ² .K)
HTC	Heat Transfer Coefficient (W/K)
$\varphi_{heating}$	Heating power (W)
F_f	Incident solar flux on a wall (W/m ²)
T_i	Indoor temperature (K)
$\varphi_{ventilation}$	Mechanical ventilation gains and losses (W)
$\varphi_{occupants}$	Occupants heat gains (W)

1.2.1 Current methods for modelling solar heat gains in any model aiming at HTC estimation can be divided into two categories, depending on whether the models used are static or dynamic. The main methods for modelling solar gains are based on the solar aperture coefficient. This coefficient describes the equivalent global transparent area of the envelope, i.e. the ratio from global outside horizontal radiation to indoor solar gain (Bauwens and Roels 2014). Noteworthy is that this coefficient is in the same order of a magnitude as a window surface area, but is not identifiable to this area, because of partial shading when the window is perfectly aligned with the outdoor envelope, or because non-perpendicular solar beam, etc... Solar gains static formulation

The static approach most commonly used to estimate solar gains is based on multiplying the measurement of horizontal global solar irradiation by a constant solar aperture coefficient (International Energy Agency IEA 2021). Horizontal solar irradiation has the advantage of being an easily accessible measurement at weather stations. However, this measurement is likely to be biased because it does not explicitly describe the solar gain through the glazing (Stamp, Altamirano-Medina, and Lowe 2017). In the case where the windows are uniformly distributed over the different facades of the building, the assumption of a constant solar aperture may be sufficient. However, in the case of unevenly distributed windows, poor modelling of solar gains can lead to errors in the HTC estimate, as

shown by (Senave et al. 2020). In this article, Senave and al. compare the HTC estimation obtained using linear regressions. The solar gains are modelled by multiplying the horizontal global irradiation by a constant solar aperture. The uncertainty induced by the integration of solar gains in statistical model is propagated to the evaluation of the HTC. The error deviation from the reference value of the second set can underestimate the HTC by up to 24.5%, with a 95% confidence interval on average 1.8 times greater, while in the first set, the maximum deviation is 11.9%.

These results clearly show that considering a constant solar aperture can lead to errors in the evaluation of the HTC, since the solar aperture is strongly influenced by the position of the sun, which varies throughout the day and the year.

1.2.2 Solar gains dynamic formulation (Hollick, Gori, and Elwell 2020), (Rasmussen et al. 2020) and (Zhang et al. 2022) have carried out work on the formulation of solar gains in dynamic models, in order to account for this time dependence. In its study of the thermal performance of buildings using RC models, (Hollick, Gori, and Elwell 2020) focuses on the methods for taking solar gain into account. They also present and compare different methods for integrating solar gains in statistical model: constant solar aperture, as a function of facade orientation, and the impact of diffuse radiation. Several RC models are thus defined, including solar radiation formulation of varying complexity. As a result, the approach that considered one solar aperture per facade with a separation of diffuse and direct radiation was considered to be the most appropriate. Nevertheless, the study shows that the choice of model, which best explains the observed data, depends on both the building and the period of the year considered.

(Rasmussen et al. 2020) describes a technique for estimating solar heat gains as a function of sun position from measured data. This method incorporates the use of splines, combined with

grey box models. (Zhang et al. 2022) and (Zhang, Saelens, and Roels 2022) use this same spline approach and develop a statistical method, based on in situ measurements, to better account for the position of the sun in the formulation of solar gain. In the first study, the authors use RC models to model the building, and in the second study, the estimation of solar gains using B-splines is integrated into an ARX model. A comparison is also made with the solar gains modelling used in building energy simulation. This comparison shows that both approaches (modelling with B-splines on the one hand, and solar gain simulation on the other) can estimate the main dynamic characteristics of the solar aperture curve. However, the suggested method based on B-splines is considered a promising approach since it solves the problem of the constant aperture assumption and uses in situ measurements (unlike a dynamic simulation). The proposed method has been tested on an experimental building. The authors therefore recommend carrying out studies on buildings with more realistic conditions to study the robustness of the proposed method.

1.2.3 The Facade Solar Gains Estimation Method

Other works (Jack 2015) are proposing a new approach for estimating solar gains, both during mid-season co-heating tests and subsequently for estimating the HTC of an occupied building using a static model. The method, called the Facade Solar Gains Estimation Method (FSGEM), is based on the direct measurement of incident solar flux on each wall of the building. By directly quantifying solar gains in a building, this approach seeks to avoid the potential risks associated with statistical analysis. However, using pyranometers to measure solar flux is a fairly expensive piece of equipment. A "translation" method is also proposed, which estimates solar gains from global horizontal irradiance, the slope and orientation of the wall, the latitude of the facade and local solar time. This determination of solar gains is then

added to the other heat sources in the building's heat balance. These two methods show good results with a + or - 15% estimated uncertainty in calculated HTC, but nevertheless have disadvantages, in particular solar gains on unglazed elements are not considered. In (Li 2022), the FSGEM method is reused to model solar gains and then estimate the HTC using static methods such as linear regression models. The HTC thus estimated using the FSGEM method is underestimated by 18%, compared with 25% using a constant solar aperture coefficient.

1.2.4 State of art summary and problem statement

As the literature review shows, a large number of works (Hollick, Gori, and Elwell 2020), (Rasmussen et al. 2020), (Zhang et al. 2022), (Zhang, Saelens, and Roels 2022) are based on the use of dynamic models for the temporal estimation of solar gains. For a sufficiently long measurement period, the use of linear regression relies less on expertise and provides HTC results that are consistent with the reference value, particularly for poorly insulated buildings. However, the formulation of solar gains is too simplified and does not always allow for an accurate estimate of the HTC, in particular for insulated buildings. The use of splines is better suited to integrating solar gains into dynamic models. The benefit of using splines in static model is actually quite small because of the daily data. The model is more complex with no gain in accuracy at the end. It is therefore interesting to develop a formulation of solar heat gains adapted to linear regression models.

1.3 Aims of this paper

The aim of this paper is to enhance the accuracy of the Heat Transfer Coefficient estimation in occupied building by taking better account of solar gains in multilinear regression models. The Bayesian approach was chosen to improve the regularisation of the problem. Four linear regression models, considering different formulations for solar heat gains, are evaluated and compared on the HTC estimation. Two of these linear regression

models come from the literature (using global solar aperture coefficient and FSGEM method), and the other two are developed in the context of this work.

First, in this article, different formulations for direct solar gains and their integration into the linear regression model are described (Section 2.2). Next, an equivalent outdoor air temperature is introduced to take into account the impact of solar radiation to the opaque walls (Section 2.3). In Section 3, the two developed linear regression models are calibrated using Bayesian inference to incorporate a prior knowledge of the input parameters. The advantage of this probabilistic approach is that measurement uncertainties are automatically considered in the model and that it acts as a regularisation feature. A numerical case study is defined and used (Section 4.1) to assess the ability of the four models to estimate a reliable HTC. Finally, the results are presented in Section 5 and the relevance of the two models developed in this paper is illustrated by a comparison with the two models from the literature.

2. Solar gain formulation in linear regression model and estimation of HTC

2.1 Linear regression to determine HTC

For an occupied building, the heat balance equation can be written as a linear regression model, assuming a steady state with a daily time step (Bauwens 2015):

$$\varphi_{heating} + \varphi_{ventilation} + \varphi_{elec} + \varphi_{occupants} + \varphi_{solar} = HTC(T_i - T_e) \quad (1)$$

With $\varphi_{heating}$ the heating power, $\varphi_{ventilation}$ the mechanical ventilation gains and losses, φ_{elec} the power dissipated by the electrical appliances, $\varphi_{occupants}$ the heat power released by the occupants, φ_{solar} the solar heat gains from direct solar radiation entering glazed surfaces, HTC the heat transfer

coefficient and $(T_i - T_e)$ the temperature difference between the indoor and outdoor.

In this linear regression model, the different heat gains or losses on the left-hand side of the equation are considered the dependent variable of the model (model output) while the temperature difference is the independent variable (model input). The regression analysis minimises the sum of squared residuals and thus allows the estimation of the model parameters, HTC , in Equation 1.

In order to determine the HTC of an occupied building, it is necessary to estimate the various variables of the model. One of the most impacting the HTC in occupancy is the solar heat gain. We are therefore looking for a formulation of the solar heat gain to include in our linear regression model in order to estimate a reliable HTC in occupied building.

We will compare different levels of detail for the integration of solar gains in linear regression models. We start with a common approach, which we then make more complex. As we analyse our data using linear regression models to determine the HTC, the integration of dynamic modelling of solar gains is not appropriate for the daily time step. Only static approaches for solar gains are integrated in models.

In a first step, we look at direct solar gains and how we can optimize their estimation. Different formulations for direct solar gains are described and then integrated into the linear regression model. Two of these linear regression models come from the literature (using global solar aperture coefficient and FSGEM method), and the other two are developed in the context of this work. The second step is to account for indirect solar gains, i.e. on each opaque wall of the building, by calculating an equivalent outdoor temperature.

2.2 Taking direct solar gains into account

2.2.1 Global solar aperture coefficient

The most commonly approach of solar gains typically found in literature in heat balance equation in linear regression models estimates solar gains by multiplying the global horizontal irradiance I_{sol} by a solar aperture coefficient A_{sol} , assumed to be constant (Bauwens and Roels 2014), (International Energy Agency IEA 2021).

$$\varphi_{solar} = A_{sol}I_{sol} \quad (2)$$

With:

φ_{solar} : the solar heat gains from direct solar radiation entering glazed surfaces (W)

A_{sol} : solar aperture coefficient (m²)

I_{sol} : global horizontal irradiance (W/m²)

Because we focus on solar heat gains, for greater clarity, the other gains or losses in the heat balance are grouped together under a common total flow φ_{total} .

$$\varphi_{total} = \varphi_{heating} + \varphi_{ventilation} + \varphi_{elec} + \varphi_{occupants} \quad (3)$$

The linear regression model of Equation 1 is then written as:

$$\varphi_{total} = HTC(T_i - T_{ext}) - A_{sol}I_{sol} \quad (4)$$

The coefficients HTC and A_{sol} are parameters of the model and are estimated by calibration.

But, as the literature review shows (International Energy Agency IEA 2021), (Stamp, Altamirano-Medina, and Lowe 2017), this global solar aperture coefficient approach is insufficient to describe accurately the solar gain received by vertical glazing.

2.2.2 FSGEM method

(Jack 2015) developed the Facade Solar Gains Estimation Method to estimate direct solar gains. This method estimates the solar gain of a building's walls using the following expression:

$$\varphi_{solar,f} = \theta A_{w,f}F_f g_f Z_f \quad (4)$$

With:

$A_{w,f}$: total glazed area of a wall (m²)

F_f : incident solar flux on a wall (W/m²)

g_f : total solar energy transmittance factor of the glazing

Z_f : solar access factor, defined by (BRE 2014). It depends on the degree of shading of the sky. In other words, which percentage of the sky is blocked by surrounding obstacles. $Z_f = 1$ according to (BRE 2014) in case of very little overshadowing.

$\theta = 0.9$: the factor representing the ratio between the typical mean transmittance and the transmittance at normal incidence, defined according to (BRE 2011).

The total solar gains is so given by:

$$\varphi_{solar} = \theta \sum_f g_f A_{w,f} F_f Z_f \quad (5)$$

In this work, (Jack 2015), the solar heat gains are directly added to the other heat sources in the building heat balance. In that case, Equation 1 becomes:

$$\varphi_{total} + \theta \sum_f g_f A_{w,f} F_f Z_f = HTC(T_i - T_{ext}) \quad (6)$$

The aim here is to improve the formulation of the solar gains φ_{solar} so that they can be integrated as input to the linear regression model.

2.2.3 Global facade solar gain coefficient

The estimation of solar heat gains that we choose to integrate in our linear regression model relies strongly on the FSGEM method (Equation 5).

The incident solar flux on the wall is determined either by direct measurement, in a similar way to (Jack 2015), if the measurement sensors in place allow, or by a simplified calculation, we proposed, of the direct, diffuse and reflected fluxes. This second option,

Equation 7, will be applied hereafter, for the reasons of cost and practicality mentioned above.

$$F_f = F_{dir,f} + F_{dif,f} + F_{ref,f} \quad (7)$$

These different fluxes are calculated using trigonometry rules, depending on the position of the sun in relation to the wall being studied. The quantities required for the calculation are:

- Measurable meteorological data: direct $I_{dir,hz}$ and diffuse $I_{dif,hz}$ horizontal irradiation and the position of the sun (height H_s and azimuth Az_s).
- The orientation of the wall: the angle to the ground β and the azimuth Az_f .
- The albedo of the ground alb .

$$F_{dir,f} = \frac{I_{dir,hz}}{\sin(H_s)} (\cos(H_s) \sin(\beta) \cos(Az_s - Az_f) + \sin(H_s) \cos(\beta)) \quad (8)$$

$$F_{dif,f} = I_{dif,hz} \frac{1 + \cos(\beta)}{2} \quad (9)$$

$$F_{ref,f} = (I_{dir,hz} + I_{dif,hz}) \frac{1 - \cos(\beta)}{2} alb \quad (10)$$

In practical case, the global horizontal irradiance is one of the most common solar measurement. The position of the sun is known at every hour of the year from the latitude and longitude of the location of the building. It may happen that direct and diffuse horizontal irradiation are not available measurements. In that case, there are models for breaking down global radiation into direct and diffuse radiation.

This approach for solar gain estimation is therefore virtually identical to FSGEM method, but it is the integration into the linear regression model that is different. Unlike the FSGEM method, in our linear regression model, the solar heat gains are not added to the other heat sources in the building heat balance, but we consider the θ factor as a parameter to be estimated by regression, rather than fixed. This approach avoids the need to consider constant fixed values, whatever the building, for the transmittance ratio factor or the solar access

factor, both of which are assessed using the standard British procedure in FSGEM method (Jack 2015). Thus, in our linear regression model, the inputs are the difference of temperatures and the sum of the solar gains. The coefficients HTC and θ , corresponding to the ratio of transmittances, are therefore the two parameters of the model to be estimated.

The heat balance therefore becomes:

$$\varphi_{total} = HTC(T_i - T_{ext}) - \theta \sum_f g_f A_{w,f} F_f Z_f \quad (11)$$

2.2.4 Separated façade solar coefficients

In order to take greater account of the position of the sun during the day, the previous approach of solar gains estimation, Equation 5, is extended by considering a coefficient θ_f per façade orientation.

$$\varphi_{solar} = \sum_f \theta_f g_f A_{w,f} F_f Z_f \quad (12)$$

And finally, in our linear regression model using separated façade solar coefficients, each ratio of transmittances θ_f , for each wall direction, are estimated by calibrating the model.

$$\varphi_{total} = HTC(T_i - T_{ext}) - \sum_f \theta_f g_f A_{w,f} F_f Z_f \quad (13)$$

2.3 Taking external boundary conditions on opaque elements into account: outdoor equivalent temperature

As mentioned in the beginning of this section, solar radiation also impacts the outdoor wall surface temperature and so impacts the heat conduction through walls. To take this into account, the method used here and developed in (Bouchié et al. 2014), consists of grouping all

the flows from the outside environment into an equivalent outdoor temperature. This equivalent outdoor temperature allows the radiative effects on the opaque walls of the building to be considered. The experimental protocol is based on measuring the external surface temperature of each wall of the building, using SENS sensors. The sensor operates by measuring the surface temperature of a wall with known absorption and emissivity characteristics. According to (Bouchié et al. 2014), and assuming that radiation from the celestial dome is negligible, the equivalent outdoor temperature of a surface can be determined by the Equation 15.

$$T_{feq} = T_e + \frac{\alpha_e \cdot F_f}{h_{ce} + h_{re}} \quad (15)$$

With:

T_e : outdoor temperature (K)

α_e : external energy absorption coefficient of a wall

F_f : incident solar flux on a wall (W/m²)

h_{ce} : external convective heat exchange coefficient (W/m².K)

h_{re} : external radiative heat exchange coefficient (W/m².K)

The overall equivalent temperature is determined by a weighted average of the heat

transmission coefficients U_f and the areas A_f of the different walls.

$$T_{exteq} = \frac{\sum_f U_f A_f T_{feq}}{\sum_f U_f A_f} \quad (16)$$

To consider external boundary conditions on opaque elements in the regression model equation, the outdoor temperature is replaced by this equivalent outdoor temperature, averaged over all the walls, to characterise all the external boundary conditions. This equivalent outdoor temperature frees us from the questions asked by Matthew Li in his thesis (Li 2022) on surface thermal resistances. Thanks to a simulated building, Li compared the determination of reference HTC and studied discrepancies between simulated HTC value and U-values calculated with standard methods. These discrepancies are caused by the dependence of HTC on environmental temperatures. Using the equivalent outdoor temperature enable therefore to reduce the variability due to radiative transfers and solar radiation on opaque elements.

Table 1 : Summary of different studied linear regression models Table 1 summaries the different linear regression models with the different formulations for solar gains.

Table 1 : Summary of different studied linear regression models and the formulations for solar gains

	Model names	Equations	Fomulations for φ_{solar}	Estimated parameters
1	Global solar aperture coefficient	$\varphi_{total} = HTC (T_i - T_{exteq}) - A_{sol} I_{sol}$	$A_{sol} I_{sol}$	HTC A_{sol}
2	FSGEM method	$\varphi_{total} + \theta \sum_f g_f A_{w,f} F_f Z_f = HTC (T_i - T_{exteq})$	$\theta \sum_f g_f A_{w,f} F_f Z_f$	HTC
3	Global façade solar gain coefficient	$\varphi_{total} = HTC (T_i - T_{exteq}) - \theta \sum_f g_f A_{w,f} F_f Z_f$	$\theta \sum_f g_f A_{w,f} F_f Z_f$	HTC θ
4	Separated façade solar coefficients	$\varphi_{total} = HTC (T_i - T_{exteq}) - \sum_f \theta_f g_f A_{w,f} F_f Z_f$	$\sum_f \theta_f g_f A_{w,f} F_f Z_f$	HTC $\theta_1, \dots, \theta_n$

3. Construction of a Bayesian linear regression model

3.1 Global overview of methodology

The methodology developed in this article consists of determining a reliable HTC in occupied building thanks to an optimize solar gains formulation. We therefore turn to the framework of Bayesian data analysis to compare different approaches for solar gain integration into the estimation of HTC. This step consists in introducing Bayesian inference to use prior knowledge for model calibration.

3.2 Bayesian inference description

The ordinary linear regression formulates the distribution of heat sources as a normal with a mean that is a linear function of temperature difference. This frequentist approach to parameter optimisation does not allow any prior knowledge about the model parameters to be incorporated, independently of the observed data. Furthermore, uncertainties cannot be fully integrated in this approach.

In contrast, the Bayesian approach has a lot of advantages, as described by (Carstens, Xia, and Yadavalli 2018), including the automatic quantification of uncertainties and the inclusion of prior information. This probabilistic approach involves exploiting Bayes' relation, Equation 17, and expressing the probability distribution of parameters as a function of a prior knowledge and knowledge acquired from measured data. Bayesian inference thus makes it possible to estimate the distribution of parameters a posteriori from the measured data. If the data is informative, then the posterior will be much more refined, otherwise it will remain close to the prior distribution.

A Bayesian model therefore consists of an observation $p(y|\theta)$, and a function of $p(\theta)$. The observation $p(y|\theta)$, also known as the likelihood function, describes the relationship between the data y and the model parameters

θ . The prior function $p(\theta)$ considers any assumptions about the model parameters. Bayes' equation is used to link these two elements and defines the posterior probability distribution of the parameters as a function of the observed data $p(\theta|y)$.

$$p(\theta|y) = \frac{p(y|\theta)p(\theta)}{p(y)} \propto p(y|\theta)p(\theta) \quad (17)$$

The Bayesian approach can thus be applied to calibrate thermal building models. (Chong and Menberg 2018) gives the main guidelines for calibrating thermal building models using Bayesian inference. (Artiges et al. 2021) obtains results which show the advantages of Bayesian inference in the process of measurement and verification. All variables, including predictions of energy use and savings, can be defined as probabilistic distribution and training complex models is facilitated thanks prior knowledge.

3.3 Bayesian multilinear regression model

Bayesian inference is applied to linear regression models, using respectively the "global facade solar gain coefficient" approach and the "separated facade solar coefficients" approach. The model using the "global façade solar gain coefficient" approach can be defined as follows:

$$\varphi_{total} \sim N \left(HTC (T_i - T_{exteq}) - \theta \sum_f g_f A_{w,f} F_f Z_f, \sigma \right) \quad (18)$$

$$HTC \sim N(\mu_1, \sigma_1) \quad (19)$$

$$\theta \sim N(\mu_2, \sigma_2) \quad (20)$$

The sum of heat flows φ_{total} follows a normal distribution with the mean is a linear function of the explanatory input variables $(T_i - T_{exteq})$ and $\sum_f g_f A_{w,f} F_f Z_f$ and the two parameters HTC and θ , with a standard deviation σ . Equation 19 and Equation 20 correspond to the prior distributions of the parameters, which follow here a normal

distribution centred on a mean μ_i and with a standard deviation σ_i . The advantage of Bayesian inference, here, is to introduce the priors which compensates for the addition of variables and the addition of complexity in linear regression model. Bayesian inference is more reliable while keeping some margin for the estimation.

Bayesian inference makes it possible to define a prior knowledge for the factor θ representing the ratio between the typical mean transmittance and the transmittance at normal incidence in the form of a probability distribution, rather than as a constant. This prior distribution is defined using information from (Jack 2015). The prior value is supposed to reflect what we assume on the building before data are considered. This value indeed influences the result, which is a compromise between the prior and the information brought by the data. However, it is expected that with sufficient data, the influence of the exact value of the prior is marginal, especially if the distribution is wide enough.

In the same way, Bayesian inference is applied to our second linear regression model

considering a coefficient θ_f per façade orientation. This model can be expressed as follows:

$$\varphi_{total} \sim N \left(HTC(T_i - T_{ext_{eq}}) - \sum_f \theta_f g_f A_{w,f} F_f Z_f, \sigma \right) \quad (21)$$

$$HTC \sim N(\mu_1, \sigma_1) \quad (22)$$

$$\theta_f \sim N(\mu_f, \sigma_f) \quad (23)$$

Considering a coefficient θ_f per facade orientation increases the number of parameters in the model, which can lead to overfitting and be problematic if the data are not sufficiently informative. Consequently, the two models described by Equation 18 and Equation 21, using respectively the “global facade solar gain coefficient” approach and the “separated facade solar coefficients” approach are tested in order to assess a posteriori which model is more suitable. Table 1 summaries the different linear regression models, which will be compared.

Table 1 : Overview of the analysis linear regression models

Model names	Equations	Calibration	Estimated parameters
1 Global solar aperture coefficient	$\varphi_{total} = HTC(T_i - T_{ext_{eq}}) - A_{sol} I_{sol}$	Frequentist	HTC A_{sol}
2 FSGEM method	$+ \theta \sum_f g_f A_{w,f} F_f Z_f = HTC(T_i - T_{ext_{eq}})$	Frequentist	HTC
3 Global façade solar gain coefficient	$\sim N \left(HTC(T_i - T_{ext_{eq}}) - \theta \sum_f g_f A_{w,f} F_f Z_f, \sigma \right)$ $HTC \sim N(\mu_1, \sigma_1)$ $\theta \sim N(\mu_2, \sigma_2)$	Bayesian	HTC θ

	φ_{total}			
4 Separated façade solar coefficients	$\sim N \left(HTC (T_i - T_{ext_{eq}}) - \sum_f \theta_f g_f A_{w,f} F_f Z_f, \sigma \right)$	Bayesian	HTC	$\theta_1, \dots, \theta_n$
	$HTC \sim N(\mu_1, \sigma_1)$			
	$\theta_f \sim N(\mu_f, \sigma_f)$			

4. Assessment methodology

4.1 In order to validate the relevance of our two developed models, the ability of our models to estimate the HTC will be assessed using virtual data from numerical simulation, and compared with HTC estimation from the two existing models (using global solar aperture coefficient and FSGEM method). The HTC estimation will be compared for different weather files. Case study

Virtual data come from a numerical case study of a detached house., These virtual data are generated by the EnergyPlus dynamic thermal simulation software. This house has already been the subject of a case study in (Pacquaut et al. 2023). In the case of this work, the house was reduced to just two thermal zones.

4.1.1 Envelope description

Geometric modelling was carried out in Sketchup 8. Figure 1 shows the 3D modelling of the house.



Figure 1 : 3D modelling of the house: south view

The house has two levels: a ground floor with a surface area of 85 m² and a first floor with a surface area of 78 m². Table 2 summarises the composition of the different walls of the building's thermal envelope, and the values of the transmission coefficient U.

The ground floor is supposed adiabatic. This assumption of an adiabatic ground avoids dealing with the problem of losses toward the ground and allows to focus on the solar gains.

Table 2 : Compositions and thermal characteristics of the elements of the envelope

	Walls compositions	U (W/m ² /K)
Exterior walls	Outdoor	
	MI 335: 25cm	
	PSE: 12cm	0.183
	Gypsum: 1cm	
	Indoor	
Floor over ground	Adiabatic	
Roof	Outdoor	
	Stone wool: 40cm	0.112
	Indoor	
Windows	Solar factor: 0.45	
	Visible transmittance: 0.56	1.1

The glazed surfaces are distributed throughout the walls of the house as detailed in Table 3.

Table 3 : Glazing surfaces and orientations

Orientation	Total area (m ²)
North-West	1.52
North-East	5.13
South-East	5.39
South-West	15.6

4.1.2 Simulation hypothesis

The shutters are considered to be closed at night between 7pm and 7am. This scenario is applied to all windows at 100% with an additional thermal resistance of 0.15 m².K/W. For the rest of the time, the shutters are fully open.

Four occupants are simulated in the house. The presence rates and power ratings of electrical appliances are stochastically generated and integrated into the EnergyPlus software. The metabolic release is set at 80 W and 80% of the electrical power consumed is dissipated in the two thermal zones. Mechanical ventilation is activated during occupancy.

The heating system is modelled in the ideal way to achieve the required heating setpoints: between 18.5°C and 20°C during the day and a constant reduced temperature of 15°C at night.

No shading is considered in the simulation. Consequently, the solar access factor is assumed to be equal to 1 according to (BRE 2014).

4.1.3 Weather files

The EnergyPlus simulations are carried out for eight French IWEK weather files, which correspond to different towns scattered across France, and will enable climates comparison. Table 4, also presented in (Pacquaut et al. 2023) compares the meteorological climates in terms of outdoor temperature and solar energy over the period studied from 15/11 to 01/03.

Table 4 : Daily outdoor temperature and average sunshine

Weather	Outdoor temperature (°C)			Global horizontal solar energy (kWh/m ²)
	Maximum	Minimum	Mean	
Bordeaux	19.2	-8.1	7.3	291.3
Brest	16.4	-4.0	7.7	193.7
Clermont-Ferrand	19.5	-12.0	4.7	293.1
Lyon	17.9	-8.3	4.4	198.5
Marseille	19.6	-4.0	8.0	389.0
Nice	19.0	2.0	9.6	411.6
Paris	14.5	-5.5	4.7	181.4
Strasbourg	17.8	-9.7	3.7	221.2

4.2 Reference value calculation

As the co-heating test is considered as the main method for estimating a building's HTC reference value, a numerical co-heating test is realised to determine the reference value of the building. The conditions for carrying out the co-heating test protocol are applied during the EnergyPlus simulation: indoor temperature equal to 25°C, closed shutters, no ventilation or infiltrations and no occupation.

Figure 2 shows the evaluation of the HTC reference value by numerical co-heating test for the eight weather files studied. The HTC estimation shows a small variability depending on the different weather files studied. These small discrepancies are caused by weather-dependent heat loss phenomena that the HTC includes by definition: heat loss towards the ground, infiltration heat loss, solar heat gain on the facades (Li 2022). Losses towards the ground are eliminated with the assumption of

an adiabatic ground in order to focus on the problem of solar gain. The variability of HTC caused by the latter term should however be mitigated by the use of the equivalent outdoor temperature rather than the ambient temperature (Juricic et al. 2023).

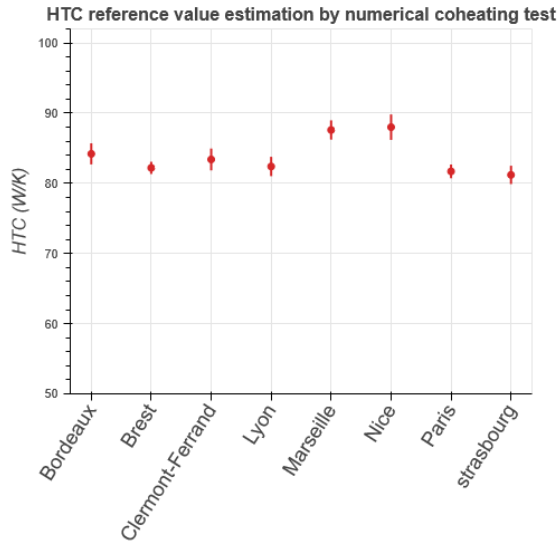


Figure 2 : HTC reference value estimation by numerical co-heating test with the equivalent outdoor temperature

Given the low dispersion of the reference value, and to be able to compare the different methods, an average reference value is calculated for all climates.

So, the HTC reference value is equal to 84 ± 1.3 W/K.

4.3 Equivalent outdoor temperature and incident solar fluxes calculation

In our study, the EnergyPlus software corresponds to a data generator. The incident solar fluxes and the equivalent outdoor temperature are therefore calculated using the output variables and simulation parameters.

Meteorological data comes from the weather files. The angle to the ground β , the azimuth Az_f , the albedo and the external energy absorption coefficient α_e are simulation parameters. Indoor and outdoor temperature and the external convective heat exchange coefficient h_{ce} and the external radiative heat exchange coefficient h_{re} are output variables.

4.4 Data analysis

In order to take advantage of the greatest possible indoor/outdoor temperature difference and therefore obtain more accurate results for estimating the HTC, the data are simulated and analysed during the winter period from 15/11 to 01/03.

The data is also averaging over daily time steps.

In order to focus on solar heat gains, other heat gains or losses due to occupancy are considered to be known in the model.

In the model using the “global façade solar gain coefficient” approach, the prior distribution of θ is centred on 0.9, the value defined according to BRE table (BRE 2011).

For the model using the “separated façade solar coefficient” approach, each θ_f also follows a normal distribution centred on 0.9 and with a standard deviation of 0.05.

The prior distribution of HTC is centred on 50 W/K, chosen arbitrarily, with the only knowledge we have of the house is that it is fairly well insulated. Indeed, we want the model to calculate HTC even if we make a mistake in the prior definition. The standard deviation is equal to 15, so more or less 30 W/K of uncertainty, because we are taking a very wide range and we do not want it to be too informative. If we take a lower standard deviation, we run the risk of giving too much importance to the prior.

5. Results

5.1 Comparison of direct solar gains estimation

Direct solar gains are estimated over the entire analysis period, for each meteorological file and after calibration of each linear regression model summarised in Table 1. They are compared to the solar gains computed by EnergyPlus, corresponding to the solar gain entering the house. Here, for the determination of the solar gains with the FSGEM method, the incident solar fluxes of

EnergyPlus are directly included in the calculation of the solar gains.

The solar gain estimation for the model with global façade solar gain coefficient (model 3) and the model using separated façade solar coefficient (model 4) is made after Bayesian calibration: solar gains are determined from the median value of the solar factor distribution and the quantiles 0.03 and 0.97. These quantiles make up a band of uncertainty for the estimation.

Figure 3 and Figure 4 compare the four solar gains estimation for two climates: Nice for a Mediterranean climate and Paris for a degraded oceanic climate.

For the climate of Paris, the difference between the solar gains estimated using a global solar aperture and the reference is on average 60%. For a warm and sunny climate, such as Nice, where the global horizontal solar energy is twice as high as Paris, the difference is even larger. The solar gains estimated using a global solar aperture are significantly underestimated compared with the reference value. The difference is more than 80%.

For solar gains estimated using the developed model using global façade solar gain coefficient, the difference between the estimation and the reference value is smaller than of 20% for Paris, and about 40% for Nice.

For solar gains estimated using the developed model with separated facades solar coefficient, the difference between the estimation and the reference value is smaller than of 10% for Paris, and about 20% for Nice.

The difference between the estimated gains and the reference is four times smaller for Nice

with the developed model using separated facades solar coefficient than with common linear regression model using a global solar aperture coefficient.

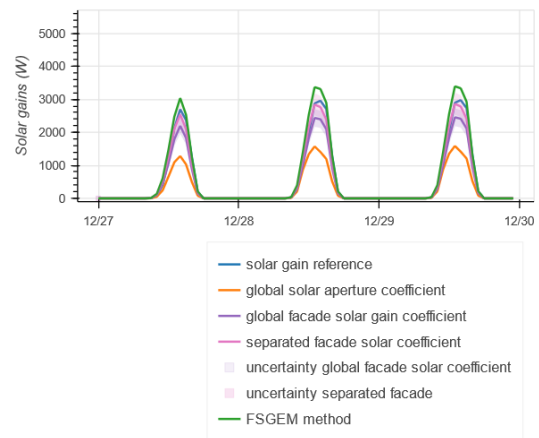


Figure 3 : Comparison of estimated solar gains in Paris

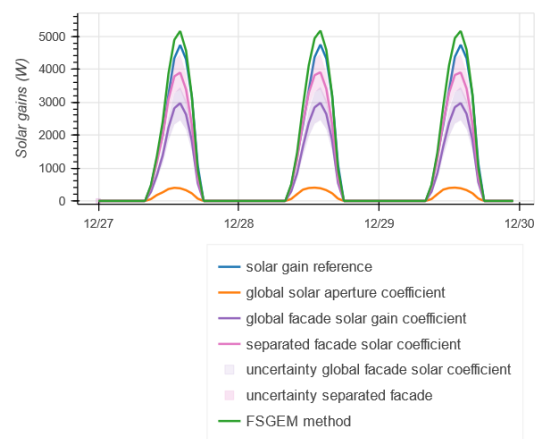


Figure 4 : Comparison of estimated solar gains in Nice

In order to compare the solar gain estimations for each model and each weather file, the relative error percentage is calculated between each estimation and the solar gain reference. These results are illustrated using a violin plot, Figure 5, that compares the relative error percentage distributions between each model and for each weather file.

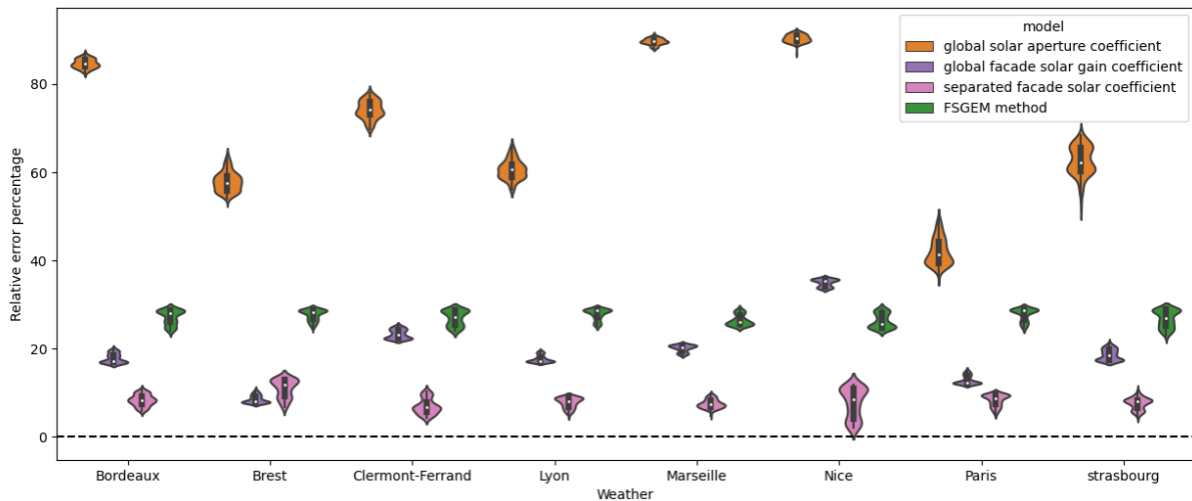


Figure 5 : Relative error percentage between the solar gain reference and the solar gain estimations of the different formulations: global solar aperture coefficient, FSGEM method, global façade solar gain coefficient and separated façade solar coefficient

The violin plot shows that the relative error percentage of the estimated solar gains with the “global solar aperture coefficient” approach is always higher than 30%. For the sunniest climates, Bordeaux, Nice and Marseille, the gap exceeds 80%. With the “global façade solar gain coefficient” approach, the error is lower than the common approach using a global solar aperture coefficient, but the percentage for Marseille and Nice is higher than 20%. Finally, with the “separated facades solar coefficient” approach, the relative error is reduced for all the climates and smaller than 20% in average. With more accurate solar gain estimations, both developed models can be expected to yield more accurate HTC results.

5.2 Assessment of HTC and comparison of different methods

As previously mentioned, solar gains have a strong impact on the heat balance of a building (Pacquaut et al. 2023) and therefore on the estimation of the HTC, so an underestimation of solar gains can lead to an underestimation of the HTC. In the following paragraph, the HTC is assessed using the different methods discussed above, and the error percentages with the reference value are compared.

Figure 6 compares the HTC assessment by the common linear regression model using a global solar aperture coefficient and the model developed with a global façade solar gain coefficient, with the HTC reference value obtained by co-heating test, for each of the eight weather files.

The confidence intervals of the errors are displayed as well as an error band of 10% and 20%. The error percentage for the common linear model using a global solar aperture coefficient is not less than 10%. The difference between the HTC estimate and the reference value is on average 20% only for the least sunny climates. For the sunniest climates of Bordeaux, Marseille and Nice, the difference from the reference value exceeds 40%. Despite taking indirect radiative stresses into account, the values estimated with this common approach are still a long way from the reference value.

Given Marseille and Nice have poor results, we can assume that direct solar gains play a role on the HTC estimate, and which therefore require more accurate estimation.

The estimation of HTC for the developed model using a global façade solar coefficient is calculated from the HTC mean values of the

resulting distributions. For this model, the error rates are below 20%, except for Nice.

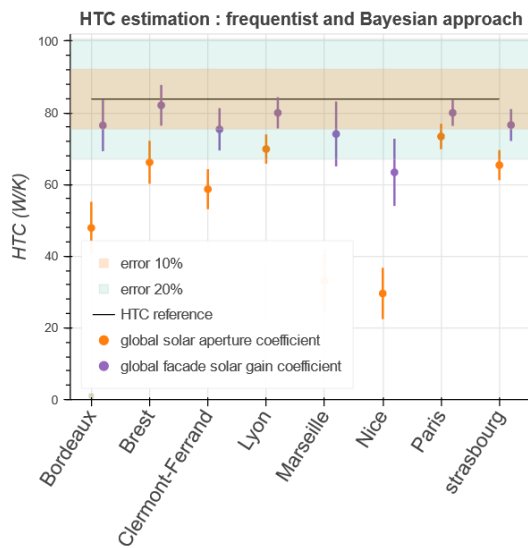


Figure 6 : Comparison between the HTC estimation and the reference value by co-heating - comparison between model using a global solar aperture coefficient model (orange) and model using global façade solar gain coefficient (violet)

The developed model using a better estimation of solar gains and the use of Bayesian inference make it possible to reduce the gap between the HTC estimate and the reference value, particularly for warm, sunny climates.

Figure 7 compares the two Bayesian approaches considered: the first developed model with a unique ratio θ between the typical mean transmittance and the transmittance at normal incidence for all the facades of the building, and the second developed model with separated facades, in other words with a coefficient θ_f per façade orientation.

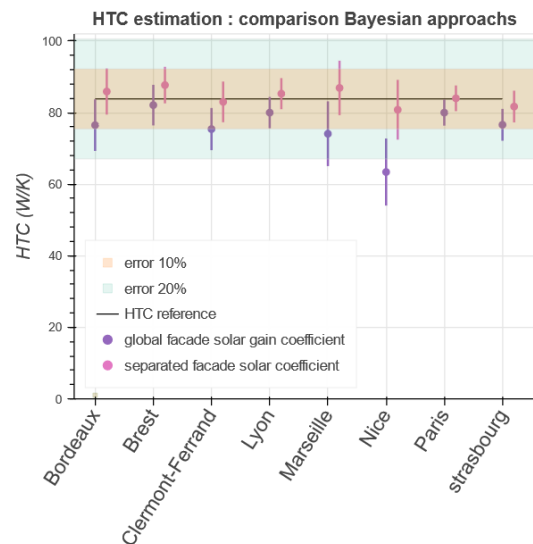


Figure 7 : Comparison between the HTC estimation and the reference value by co-heating - comparison between two developed models: with global façade solar gain coefficient (violet) and with separated facades solar coefficient (pink)

By modelling solar gains by facade orientation in the second developed model, using separated façade solar coefficient, the relative percentage differences between the HTC estimation and the reference value by co-heating are less than 10% for all weather. The results show less variability in the estimation of HTC with the developed model with separated facades. The estimation uncertainty for Nice and Marseille is larger than for the other climates.

Finally, the results obtained with the developed model with separated facades are compared with those obtained using the FSGEM method (Jack 2015), which according to the literature can be considered a detailed method suitable for linear regression.

In order to be able to compare our model and the FSGEM method on the same reference frame, we applied the FSGEM method with the equivalent outdoor temperature.

Figure 8 shows that the difference between the HTC estimation and the reference value is slightly smaller for the new model with separated facades than the FSGEM method. For the sunniest climates of Marseille and Nice, the difference between the HTC estimation by

FSGEM method and the reference value is slightly larger than 20%.

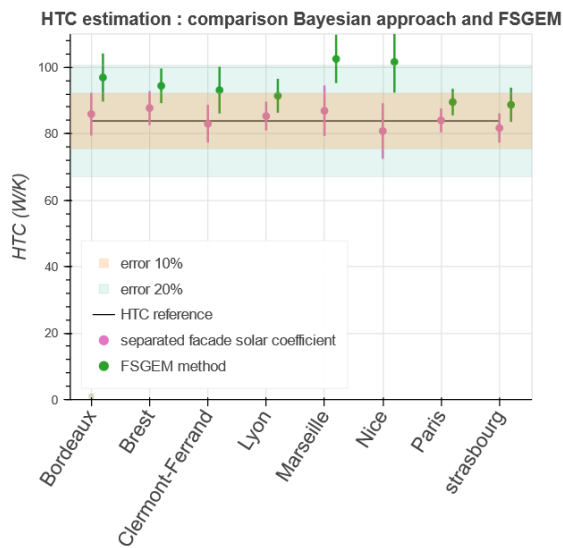


Figure 8 : Comparison between the HTC estimation and the reference value by co-heating – comparison between developed model with separated facades solar coefficient (pink) and FSGEM method (green)

6. Discussion

6.1 Advantages of Bayesian approach in linear regression model

This paper proposes a new approach to improve the estimation of solar heat gain on opaque walls and through glazed surfaces in multilinear regression models in order to improve the assessment of the HTC of a building envelope under occupancy. The Bayesian approach is used for the model calibration to reliable HTC estimation.

A comparison is made between four models: the common formulation of solar gains in the linear regression model with a global solar aperture coefficient, the FSGEM method (Jack 2015), a new model developed with a global solar factor θ and a new model developed with a solar factor per facade orientation θ_f . . The difference between the resulting HTC estimates and the reference value determined by co-heating are compared.

The model developed with separated facade solar coefficients presents results with less

variability depending on the meteorological climate than all other studied models. Particularly for sunny climates, the deviation from the reference value is less than 10% while it is larger than 40% in the common linear regression using a global solar aperture coefficient.

The recent studies mentioned in the literature review (Senave et al. 2020), (International Energy Agency IEA 2021) and (Jack 2015) worked on Belgian and English climates and the difference between the HTC estimates and the reference value was less than 20% or 10% with linear regression using a global solar aperture coefficient. But as we have seen, in very sunny climates, this common regression model cannot reliably estimate the HTC. The improvement of the solar gains estimation in the new model, considering a solar coefficient per façade orientation, and the integration of the Bayesian inference reduce the variability of HTC depending on the climate, and make the results more reliable.

Another advantage of using Bayesian inference is the addition of a prior knowledge for the different parameters of the model. In this work, the prior knowledge is especially useful for the coefficient θ , the ratio of mean transmittance to normal incidence. This prior definition means that we are not dependent on "empirical" values that might depend on the type of building and the characteristics of the glazing, like $\theta = 0.9$ defined in (BRE 2011). Furthermore, the integration of a prior knowledge also makes it possible to integrate the measurement uncertainty associated with the parameter. One of the major advantages of the new linear regression model using Bayesian inference is that it can fully embed measurement uncertainties and therefore the uncertainties of the different parameters and variables will be propagated to the resulting HTC distribution.

In a future work, the various phenomena linked to occupancy will be considered and their uncertainties quantified. Then the

measurement uncertainties of these different heat balance variables, such as indoor temperature or internal gains, will be propagated to the resulting HTC distribution. In this case, linear regression models have a good advantage: unlike modelling solar gains with dynamic models, the calibration of linear regression models allows long measurement periods. Analysis of data taken over long periods to estimated HTC during occupancy is also beneficial because it means that all uncertainties can be considered.

Another point of discussion concerns the calculation of the reference value. The HTC reference value determined does not correspond exactly to the definition given in the ISO 13789:2017 standard (ISO 13789:2017). However, because of the HTC dependence on environmental temperatures, (Li 2022) showed that it is necessary to consider outdoor boundary conditions for the reference calculation. (Juricic et al. 2023) proposes therefore to use the equivalent temperature for the reference value calculation instead of the outdoor temperature and shows that measuring this equivalent temperature reduces HTC variability.

6.2 Study limits

6.2.1 No considering of masks and shadowing

To simplify this initial study, no masks or distant shadows were considered in the 3D modelling of the house. The new model developed in this way does not consider potential distant shading from other buildings or the external environment. But, in reality, the effect of shading affects the measurement and calculation of the incident solar flux reaching each window.

In the same way, in the FSGEM method, direct measurement of incident solar fluxes on windows, or calculation of these fluxes, do not provide accurate information on the solar radiation reaching each window, taking shading into account. To overcome this problem, (Jack 2015) suggests installing several

sensors, one on each window, which are less accurate and expensive than pyranometers, to determine whether the window is shaded or not. These measurements could be combined with global solar irradiation measurement taken at a weather station to obtain precise information on the level of solar radiation reaching each window. In the FSGEM equation, a fixed solar coefficient is also included for shading. In the same way as for the coefficient θ , our new model could estimate a shading parameter that would vary according to the level of shading.

6.2.2 Typology of building

Finally, the relevance of our two models was confirmed using a numerical case study. In order to fully validate the methodology developed, the study needs to be extended to include more houses. (Senave et al. 2020) compared the different analysis methods on four different building typologies. No clear dependency was found between the type of building and the accuracy of the HTC assessment. However, broadening the scope of our case study by examining a larger number of buildings, such as the effects of the thermal inertia. According to (Jay et al. 2023), solar gain will not be exploited in the same way in a high-inertia building with a concrete core as in a low-inertia building with a wooden frame. In a building with low inertia, the solar energy passing through the glazing will be released more quickly through ventilation. Conversely, if the sunspot strikes the concrete slab of a high-inertia building directly, the energy will be captured by the slab during the day and released later. It would also be interesting to analyse the sensitivity of the HTC estimation to other phenomena.

6.2.3 Shutters management

Similarly, the inclusion of fixed solar caps or shading devices has not yet been considered. Note that in some countries, such as Belgium or England, shutters are not very common.

Our numerical case study enabled us to develop and test our new model. However, the

simulated occupancy, in particular the management of shutters, remains very theoretical. The random and unpredictable behaviour of occupants may therefore have a greater impact on the shutters and obviously on the solar gains in the building in reality. It is therefore necessary to explore how solar gains can be modelled in real use. In future work, the model will be used on real data from instrumented and occupied houses.

6.3 Method operationality

In this paper, as a first step to assess the ability of the two developed models to estimate a reliable HTC, a numerical study is used and a focus on solar gains is made. Although the data comes from a numerical study, only data that is available in reality is used (the global horizontal irradiance and the position of the sun). Thanks to the ease with which measurements can be obtained, the method is straightforward to use and could be operational.

In order to have a reliable method for determining the HTC of an occupied building, it is necessary to estimate the different gains and losses linked to occupancy. It will be necessary to focus on the other variables in the building's heat balance (internal loads, mechanical ventilation...).

7. The work in this article is a first step before testing the models on real data.

Conclusion

Methods under occupancy have operational advantages for Heat Transfer Coefficient measurement and characterisation. But they come with additional constraints due to the variability of weather and occupancy conditions. In particular, solar gains are highly influential on performance assessment under occupancy.

Actual multilinear regression models would tend to underestimate the HTC of an occupied building, depending on the climate and the

building typology, because of a poor modelling of solar gains. This present work considers a better estimation of solar gains in linear regression model and uses Bayesian approach to contribute to more accurate the estimate of HTC, and therefore make this estimate more reliable.

The method proposed here therefore allows an analysis of the data, without the need for additional measurements on the building. The addition of an equivalent external temperature accounts for solar gains on opaque elements. Direct solar gains are estimated and incorporated into the linear regression model.

With this novel Bayesian inference integration in linear regression models, the new model produces better results than the common formulation, reducing the deviation from the reference value and the variability between different climates. The advantage of this probabilistic approach is that measurement uncertainties are automatically considered in the model and that it acts as a regularisation feature.

The use of Bayesian inference will enable to consider unpredictable phenomena linked to occupancy in linear regression model, and to quantify their uncertainty and thus estimate the HTC. Because more uncertainty will be incorporated in future work, using linear regression models and long measurement periods represent a great advantage. Thanks to their improved reliability, linear regression models would enable to assess an occupied building's performance.

Disclosure statement

No potential conflict of interest was reported by the authors.

Informed consent statement

Written informed consent for publication of their details was obtained from all the co-authors.

Data availability statement

The data that support the findings of this study are available from the corresponding author, upon reasonable request.

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