

NEW METHOD FOR QUICK EVALUATION OF THE HEATING ENERGY DEMAND OF RESIDENTIAL BUILDINGS

Tiberiu Catalina¹, Florin Iordache¹, Vlad Iordache¹

¹Technical University of Civil Engineering, Faculty of Building Services, CAMBI Advanced Research Center for Ambiantal Quality and Building Physics, Bucharest, ROMANIA

ABSTRACT

In this article, the main research goal is to present a model for rapid assessment of specific heating energy consumption of residential buildings. In the first part of this research paper the main inputs that could influence the building heating demand are identified. The next step in the development of the prediction model was to conduct dynamic simulations with different combinations of the inputs and to obtain a database of results. With this database, a multiple regression was applied and a simple (3 inputs) and accurate ($R^2=0.987$) model was obtained.

INTRODUCTION

Among the most important constituents of the energy consumers inside a building, space heating accounts for more than 50% of the primary energy demand of residential and service buildings in the EU (Caldera et al., 2008). Therefore, many researches aim to better understand this phenomenon and to predict the heat consumption for both the design stage and further building operation. Numerous methods and models for the energy demand forecasting were proposed during the last decade, including Fourier series models (Dhar et al., 1998), regression models (RM) (O'Neill et al., 1991) and neural network (NN) models (Olofsson et al., 2002). (Tsanas and Xifara, 2012) developed a statistical learning framework to study the effect of eight input variables for such a prediction model (relative compactness, occupation surface area, wall area, roof area, overall height of the building, orientation, glazing area, glazing area distribution). (Ekici and Aksoy, 2009) considered as inputs for an artificial neural network (ANN) model the following parameters: the physical environment parameters and artificial design parameters, like the transparency ratio, the building form factor, orientation and thermo-physical properties of the materials of the building envelope. (Kwok et al., 2011) discussed the use of the multi-layer perceptron (MLP) model to estimate the cooling load of a building. (Kalogirou, 2000) has constructed and developed an ANN model to estimate the heating loads of buildings and for forecasting the energy consumption of passive solar buildings. We conclude that in order to learn a statistical model to predict the yearly heat consumption we need to take into account as input data all these parameters that highly influence the yearly heat consumption or those

other parameters that regroup the effect of these main parameters, similar to the principal component analysis. The European and national standards present two such coefficients: (1) the building global heat loss coefficient G ($W/m^3/K$) (Romanian Norm C107, 2005) and (2) the building global heat transfer coefficient H (W/K) (EN13790, 2008), this second parameter being equal to the first one multiplied by the indoor air volume of the building.

The simplicity of the model is an important characteristic for such prediction models because it will enable the integration with other more general models like: the Indoor Environment Quality prediction (Catalina and Iordache, 2012), or the building permeability measurement model (Iordache and Catalina, 2012). In this paper, with the development of a new forecast model, we want to advance the knowledge in this direction by highlighting the importance of the climatic conditions, the model accuracy, the error analysis and probably the most important for the designers, the practicality of the model. In this paper, we are presenting the simulation carried out for the model learning, the prediction model, and the model test upon a study case.

SIMULATIONS

The article study is based on the dynamic simulations, performed with an hourly time-step, by TRNSYS (TRNSYS, 2005) building simulation software. In order to develop the model it was necessary to find which were the parameters that had to be taken into consideration. The second step, after finding the most relevant inputs for the heating demand assessment, was to conduct a parametric study using TRNSYS. The third step was to analyze the obtained database and to try to find a simple model that could best fit the simulations results. We will first present how we obtained the model inputs. It is well-known that the heating consumption is influenced mainly by the external vertical walls surfaces, the windows surfaces, the thermal resistances, the indoor and outdoor temperatures, the indoor heat sources and the air change rate. There are other parameters (eg. solar absorption coefficients) but their influence on the results is less important. It is clear that we do have two directions that must be considered: the particular characteristics of the building and the climate surrounding this building. The thermal balance of a building can be expressed as:

$$\sum(V \cdot \rho \cdot c) \cdot \frac{d\theta}{d\tau} = \Phi_h + \Phi_i + \Phi_s - \Phi_L \quad (1)$$

$$\Phi_h = \Phi_L - \eta_u(\Phi_i + \Phi_s)$$

where Φ_h (W) is the supplied heat by means of indoor heating system, Φ_i (W) is the indoor thermal gains, Φ_s (W) the thermal gains from the solar radiation, Φ_L (W) is the heat losses of the building, θ ($^{\circ}\text{C}$) is the temperature, η_u is the utilization factor of heat gains to the heating demand, τ (s) is the time, c (J/kg/K) is the specific heat, ρ (kg/m³) is the density, V (m³) is the volume and term $\sum(V \cdot \rho \cdot c) \cdot d\theta/d\tau$ (W) represents the heat accumulated in the building in its different elements (walls, air and other materials indoors). The heat losses Φ_L represent the product between the global building heat loss coefficient G (W/m²K), the air heated volume V (m³) and the indoor-outdoor temperature difference $\Delta\theta$ (K)

$$\Phi_L = G \cdot V \cdot \Delta\theta \quad (2)$$

Where G is the global building heat loss coefficient calculated as follows:

$$G = \frac{\sum A}{V} \cdot U_{ma} + 0.34 \cdot n \quad (3)$$

where A (m²) is the area of a building element, R (m²K/W) is the thermal resistance of a building element, β (-) temperature correction coefficient, n (ach) the number of air change rate, $\Sigma A/V$ (m²/m³) is the compactness factor characterizing the building, U_{ma} (W/m²/K) is the average transmittance of the building envelope. Eq. (1) can be written in steady state as:

$$\Phi_h = \Phi_L - \Phi_s - \Phi_i \quad (4)$$

$$\Phi_h = \Phi_{LS} - \Phi_i$$

From Eq. (4) we are interested only in the term Φ_{LS} which can be expressed as:

$$\Phi_{LS} = \Phi_L - \Phi_s \quad (5)$$

$$\Phi_{LS} = G \cdot V \cdot \Delta\theta - \Phi_s$$

Φ_{LS} which represents the influence of the building characteristics and climate on the heat load. Using this, we take into account the two most important parts of the heat loss of a building: the thermal characteristics (G) and the weather conditions impact (Φ_s and $\Delta\theta$). Using the building global heat loss coefficient (G) as input for the prediction model seems a good solution for two reasons: it incorporates in one single variable (G) several parameters that influence the heat loss of a building and, secondly, this variable is a mandatory data when constructing a building. In Romania, before starting a construction, it is mandatory to demonstrate that G is lower than a G reference, which is found the Romanian National Standard (Romanian Norm C107, 2005). In other European countries, this variable is also a well-known way to compare the thermal insulation of a building.

As what concerns the weather input, we have found from previous studies [9] that the most important climate variables for a building heat loss are the outdoor air temperature and the solar irradiance. Besides the accuracy, another purpose for the model is to be simple and easy to use. For that, it is obvious that a small number of inputs should be necessary. The two climate variables presented above can be linked using the sol-air temperature $\theta_{sol-air}$ which is a simple solution to characterize the climatic zone [8].

$$\theta_{sol-air} = \theta_o + \frac{\alpha I_h}{h_o} \quad (5)$$

where θ_o ($^{\circ}\text{C}$) is the average outdoor temperature in the heating season, I_h (W/m²) the average global solar irradiance on horizontal during the heating season, α (-) the solar absorptance with a default value of 0.6 (-) and h_o (W/m²K) the external surface heat transfer coefficient with a default value of 17. The α and h_o values of 0.6 and 17 were chosen because they are the most common. The heating season is considered from October to April and, therefore, the θ_o and I_h are the average values for that period. In our case they are constant for all climates and this way only the outdoor temperature and the solar irradiance modify the sol-air temperature. As the indoor set point temperature (θ_{in}) can greatly change the heating consumption of a building, it seems prudent to also take into account this variable. The second input of the model will be the temperature difference $\Delta\theta = \theta_{in} - \theta_{sol-air}$. Among other important parameters, the glazing area, represents a decisive variable for natural lighting of the building, along with its potential to reduce the heating demand, especially in the mid-season. (Persson et al., 2006) showed that, by means of energy-efficient windows, we could achieve lower energy consumption than having a highly insulated wall without windows. This is due to the fact that the windows can collect and use the solar energy to heat the indoor spaces during shiny days. (Bojic and Yic, 2007) compared different types of glazing and found that the cooling consumption may be reduced with 6.6% if using double-pane glazing (low-e). From all these studies, it is clear that the heating demand can be reduced or increased, depending on the glazing area and the orientation. To solve this problem we have found a good solution to use the south equivalent surface (SES) (Catalina and Iordache, 2012), which translates the glazing area and its distribution on the building facades.

$$SES = \sum_{i=1}^n (A_i \cdot C_i) \quad (6)$$

Where A (m²) is the glazing area, C (-) is the orientation coefficients (see Table 1) and i (-) is the façade index. The SES will be the third and last input of the model.

Table1
South equivalent coefficients C_i

Slope	SSE-	SSE- ESE	ESE- ENE	ENE- NNE	NNE-
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(degree)	SSO	and SSO- OSO	and OSO- ONO	and ONO- NNO	NNO
85° to 90°	1.00	0.85	0.55	0.30	0.20
70° to 84°	1.15	0.95	0.60	0.35	0.20
55° to 69°	1.20	1.05	0.65	0.35	0.25
40° to 54°	1.20	1.05	0.75	0.40	0.30
25° to 39°	1.15	1.00	0.75	0.50	0.40
10° to 24°	1.00	0.95	0.80	0.65	0.55
0° to 9°	0.80	0.80	0.80	0.80	0.80

Finally, the three inputs of the model are:

- G – building global heat loss coefficient;
- $\Delta\theta$ – temperature difference between indoor set point temperature and sol-air temperature;
- SES – south equivalent surface.

The next step was to obtain a database of values from dynamic simulations. This will be made through a parametric study. The prediction model presented in this article aims to be general and to be usable on any weather conditions. Therefore, we have decided that a very cold climate like Moscow, Russia could represent the minimum of the valid range while the maximum may be considered a warm-Mediterranean climate like Nice, France. Bucharest, Romania is chosen as an intermediate point. For the three analysed climates the value of the heating season $\theta_{sol-air}$ is -0.18°C (Moscow), 7.61°C (Bucharest) and 15.53°C (Nice). Another part of the parametric study was to obtain multiple combinations out of the following parameters:

- Building envelope thermal resistances,
- Glazing surface and distribution on the façade,
- Heat loss area and heated volume,
- Air change rate,
- Indoor heating set point temperature.

These variables are part of the three input models. We have considered three levels (min., mean and max.) of thermal resistances for the walls, roof, windows and floor. The total number of combinations is 27.

To express this overall value, the average thermal resistance of the building can be written as:

$$R_m = \sum_{i=1}^n A_i / \sum_{i=1}^n \frac{A_i}{R_i} \quad (7)$$

Where R_i are the thermal resistances ($\text{m}^2\text{K/W}$), A_i are the surfaces of the construction element, i – is the construction element (eg. floor). The minimum value in our case was $0.408 \text{ m}^2\text{K/W}$ ($U_m=2.45 \text{ W/ m}^2\text{K}$) and a maximum of $2.67 \text{ m}^2\text{K/W}$ ($U_m=0.37 \text{ W/ m}^2\text{K}$). The parametric study was also made with two types of glazing areas, which are expressed as percentages of the wall area, in our case 20% and 30%. These values are the most common for residential buildings. For each of these two window areas percentages several distributions on the facade were simulated and the south equivalent surface (SES) was calculated for each of them. Three building forms are

used in the parametric study with S/V (sum of all heat loss surfaces/heated volume) ratios of 0.31 (tall building), 0.75 (medium) and 1.33 (small building). The following air change rates were analysed: 0.5 ach, 1.2 ach, 2 ach and finally, three values of indoor set point temperatures were considered in the parametric study (18°C , 20°C and 22°C). By doing all the combinations between the variables previously presented, we have obtained a total number of 8748 simulations. This represents a solid database for the model development, which also covers a wide range of building characteristics. Usually, the specific heating consumption is expressed in $\text{kWh/m}^2\text{year}$, but, to better consider a building variable height level, we have decided to use as measuring unit the $\text{kWh/m}^3\text{year}$.

From the simulations results we have found that:

- Increasing the overall thermal resistance of the envelope from $0.5 \text{ m}^2\text{K/W}$ to $2.5 \text{ m}^2\text{K/W}$ will reduce the energy demand by 56% to 61%;
- Increasing the SES by 60% can reduce the heating consumption by 10% to 13% (warm climate). This is valid for energy efficient windows;
- Reducing the indoor set point temperature from 22°C to 18°C can be translated by an energy reduction of 12% to 19% (warm climate);
- An increase of the infiltration rate from 0.5 ach to 2 ach will increase the heating demand by double;
- The influence of the variable G on the specific energy consumption gather the impact of all parameters that are part of the variable G calculation. The high value of the correlation between the heat consumption q and the global heat loss coefficient G proves the influence of the coefficient G upon the building heat consumption (see Fig.1).

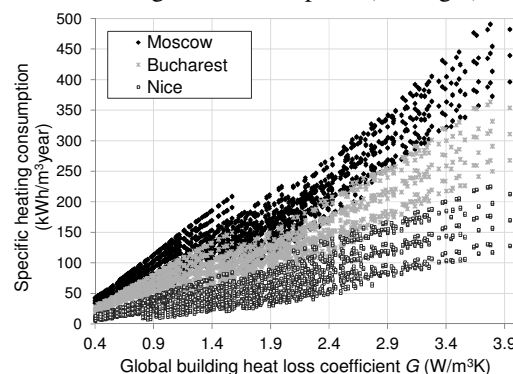


Figure 1 Influence of the variable G and of climate on the specific heating consumption

The conclusion of this section is that the variables were correctly chosen as they have a great impact on the heating demand.

MODEL DEVELOPMENT

The third step in the model development was to find a model that could correlate the results of the model with those of the simulation database. In our case, the objective of multiple regression analysis is to predict the single dependent variable (specific heating consumption) using a set of independent variables (G , $\Delta\theta$ and SES). After testing multiple models, it was found that the best fit was obtained in the following model:

$$q_{LS} = 18.454 - 21.498(G) - 1.844(\Delta\theta) + 0.024(SES) + 4.668(G \cdot \Delta\theta) + 0.067(G \cdot SES) + 0.006(SES \cdot \Delta\theta) + 12.352(G)^2 - 0.012(\Delta\theta)^2 - 0.0002(SES)^2 \quad (8)$$

Where q_{LS} is the specific heating consumption ($\text{kWh/m}^3\text{year}$). The model is a polynomial function, which was the best choice for our case, although it has the inconvenience of not being valid outside the range of the observed data. However, we do consider that the applicability and the proposed range cover almost all cases of residential buildings. Should one use this data model, using data from outside the valid range, there can be expected greater errors. The statistical analysis was mandatory and several conclusions followed. Firstly, an analysis of residuals showed that the differences between the model results and the simulations are higher for the variable G , values higher than $1.5 \text{ W/m}^3\text{K}$ (see Fig.2). This seems logical, as the heating consumption values are also higher for higher variable G values.

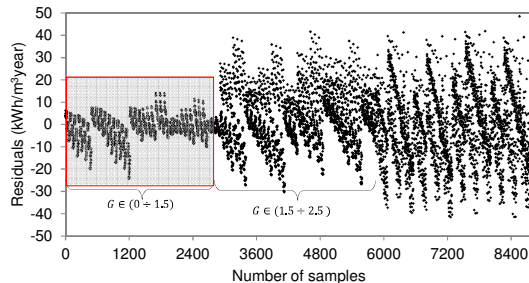


Figure 2 Residual plot of the prediction model

In what concerns the errors, these were evaluated using the mean absolute error ($MAE=9.303$), the mean square error ($MSE=156.13$), the root mean square error ($RMSE=12.495$), the mean absolute percentage error ($MAPE=-0.0036$) and finally the multiple determination coefficients ($R^2=0.9744$). The model is well correlated and the expected mean error is less than 10%. For parametric studies or fast assessment of the heating energy demand, this error is more than acceptable, as the model requires no knowledge of software use, instantaneous calculation or any other expensive program.

The proposed model calculates only the heating demand of the building. In order to take into consideration the internal heat gains and the heating distribution/emission efficiency, the following equation can be further used:

$$q_{building} = \left(\frac{q_{LS} \cdot V - (\phi_i \cdot A \cdot t) / 1000}{\eta_s} \right) / V \quad (7)$$

Where $q_{building}$ is the building specific energy consumption ($\text{kWh/m}^3\text{year}$), ϕ_i are the internal heat gains (W/m^2), V is the heated volume (m^3), A is the occupied floor area (m^2), t is the number of hours and η_s (-) is the heating system distribution/emission efficiency. The dynamic effect of internal heat gains was not considered as this parameter is extremely variable from one building to other. However, the dynamic impact of external heat gains, which are the most important heat gains for residential buildings, was considered.

STUDY CASE

We will use as study case a non-renovated block of flats situated in Bucharest, Romania.



Figure 3 Non-renovated residential building

This building is not renovated and the thermal resistances of the envelope are:

- $R_{walls}=0.717 \text{ m}^2\text{K/W}$
- $R_{roof}=1.123 \text{ m}^2\text{K/W}$
- $R_{floor_basement}=0.694 \text{ m}^2\text{K/W}$
- $R_{windows}=0.43 \text{ m}^2\text{K/W}$

The heated volume is of 11345 m^3 and the corresponding global coefficient of insulation $G=0.885 \text{ W/m}^3\text{K}$. This is the first input of the prediction model. The infiltration rate was evaluated to a value of 0.7 ach . The indoor set point is 20°C and the sol-air temperature corresponding to Bucharest climate is of 7.61°C . Therefore, the second input of model is $\Delta\theta=12.39^\circ\text{C}$. The last input is the south equivalent surface which for this building is $SES=612.4 \text{ m}^2$. We will demonstrate how the model can be applied in the case of a thermal renovation of the façade. We will consider four cases of thermal rehabilitation:

- C1 = increasing the R_{walls} to $1.8 \text{ m}^2\text{K/W}$
- C2 = C1+increasing the R_{roof} to $5 \text{ m}^2\text{K/W}$
- C3 = C2+increasing the $R_{windows}$ to $1 \text{ m}^2\text{K/W}$
- C4 = C+increasing the $R_{floor_basement}$ to $2 \text{ m}^2\text{K/W}$

A more detailed parametric study or other cases can be easily conducted with the model. The results are presented in Tab.2. The highest benefits are mainly

related to the windows change and the thermal insulation of the walls.

Table2

Application of the model for thermal renovation

Reference building	C 1	C 2	C3	C4
Heating consumption (kWh)				
630171	463593	398135	268331	231865
Heating consumption (%)				
100	73.6	63.2	42.6	36.8

CONCLUSION

The prediction model learned in this research work predicts the heating consumption of a building. The mathematical prediction model proposed in this work has several advantages compared to other already developed models. First of all, it is a simple model (three variable regression model) overcoming the inconvenient of a complex model (e.g. neural network) and this simplicity makes it ideal to be implemented in a software tool or in an Excel file. Secondly, it has a large applicability on climates, building thermal characteristics, glazing area and distribution on the facades, indoor heating set point temperatures. The model is developed for a wide climate values because the validity of $\theta_{sol-air}$ is between -0.18°C (Moscow) to 15.53°C (warm climate). The model is valid for any climate (eg. Berlin, Zurich, Helsinki, etc) in this area of values. The use of South Equivalent Surface was the only solution to have a single surface (input for the model) that can take into account the orientation of the glazing. The solar transmission of the windows is not considered as input. The model was developed using 8748 results obtained from a database of simulations. The accuracy of the model is acceptable for its purpose. The prediction model is developed only from simulations and it is clear that there are errors compared to real consumptions. However, this model is only a tool of design and does not attempt to replace dynamic simulations, but to give the designer the possibility to make a fast prediction or a quick parametric study. Another important aspect that must be pointed out is the possibility of using this model for a fast verification of the energy certificates correctness. If the authorities found errors larger than 30-40%, then a more thorough analysis of that certificate should be made. The study case presented at the end of the paper shows how simple it actually is to determine the building heat consumption for both design and real conditions. The applicability of this model would be further enhanced if integrated in other more general models like the indoor environment quality or multi-criteria decision approach for hybrid systems.

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