Building design and thermal renovation measures proposal by means of regression models issued from dynamic simulations

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SUMMARY

This paper presents the heating demand evaluation by means of regression models obtained from a parametrical study of dynamic simulations data. The aim of these models is to be used by architects or design engineers as support tools in the very first stage of the building design and also in thermal rehabilitation of new or existing constructions. These models are based on five input parameters, among them the building shape factor, climate coefficient or south equivalent surface. Compared to the dynamic simulations results, a maximum error of 7% is observed for all the validation cases. Probably the most important advantage of the models is that parametric studies could be done in a fast way compared to a simulation analysis. They could be used to make comparison between different energy reduction strategies, like improving the insulation levels or increasing the thermal inertia. An example of their use and a data comparison with a dynamic simulation is shown in last part of this research paper.

INTRODUCTION

In a report realized by the „European Commission for Energy„ the major issues of EU citizens is the energy security which was translated by "shortages of fossil fuel supplies compared to increasing world demand", "high fossil fuel prices", "supplier or transit countries using their positions to exert political pressure" , "inadequate energy efficiency measures in Europe" or "impact of EU climate strategy" [1]. Buildings account for 40–45% of energy consumption in Europe and China (and about 30–40% world-wide) [2]. Most of this energy is for supplying the energy for lighting, heating, cooling, and ventilation. Increased awareness of the environmental impact of CO_2 and NOx emissions triggered a renewed attention in environmentally friendly cooling and heating innovative technologies [3].

The building sector has the advantage that with thermal reglementation and with a good design support, a considerable reduction of the energy may be possible. Thermal renovation of existing buildings that are not compiling with the current directives is a key point of this energy sector. Several measures in terms of envelope insulation or replacement of the glazing elements are required in order to reduce the heating demand of this type of old buildings. In most of the cases, in the early stages of a project, parametric studies have to be realized to find an optimum solution among a large number of alternatives. Payback time calculations are needed for this type of studies, because in most of the cases the decision is a compromise between the financial budget and the economies that could be realized with different solutions.

Nowadays, the most reliable solutions to calculate the energy demand are the simulation energy tools to estimate the impact of design alternatives. Simulation tools like Simbad [4], Energy+ [5] or Trnsys 16 [6] are a good way to simulate and to analyze the building and the systems but this software tools demand however a considerable amount of detailed input data and time from even an experienced user or in some cases powerful informatics equipments. The energy prediction models could be the wanted answer in the early stages of design, with their accuracy and most important their simplicity and calculation speed. The energy equations could be obtained from the data issue from simulations or experimental campaigns.

During the last years, several prediction models have been proposed by various researchers including Fourier series models [7], regression models [8] and neural network (NN) models [9]. The multiple regression analysis could be a good approach when dealing with a certain pattern and it is possible to obtain accurate models from a database of values [9]. The energy prediction models that were developed simplify the parametrical studies and replace in the early building design phase, the numerical simulation tools. They allow fast optimizing of the building energy consumption versus environmental or financial criteria.

REGRESSION MODELS

To develop the estimation models the regression technique analysis was used. The regression technique [10] is applied to help us predict the value of one variable (also called response variable or measurement) from one or more other variables (also known as explanatory variables or predictors) whose values can be predetermined. Thus, the final objective is to predict the single dependent variable (heating demand) by a set of independent variables (shape coefficient, building time constant, etc). Developing a correlation method, it is essential to generate a database by doing many parametric studies and then create a simple equation by using regression analysis. In order to obtain the database necessary to identify the correlation function, dynamic simulations were conducted using Trnsys 16 (Transient Systems Simulation Program)[6] and more than 18.000 data values were analyzed.

Models input/output parameters

One of the challenges of the study was to identify the models input parameters in order to describe as best as possible the building energy flow. The principle of a "black-box" was used on this part where the inputs and outputs where first identified and then the process continued with the research of the "black-box" structure model. A "black-box" model of a system is the one whose internal structure is unknown and when the inputs/outputs are known and therefore is a question of "curve-fitting" by finding the most appropriate function. Accurate knowledge of the consequence of parameters and the relationship between them is essential for optimal and feasible finding of the researched function. After an extended research on the possible variables it was found that the necessary inputs needed to define the building and the outdoor environment should be:

a) Building morphology

Ourghi et al.[11] have developed a simplified analysis method to predict the impact of morphology for an office building on its annual cooling demand. This method was based on detailed simulation investigations using several scenarios of building geometry, glazing type, window area and climate. A direct correlation has been established between relative compactness and total building energy use as well as the cooling energy requirement.

Based on a literature review it was found a pertinent solution to define the building geometry and implicitly the heat loss surfaces, by using the building shape factor (S_f) (also called building characteristic length) which is defined as the ratio between the heated volume of the building (V_b) and the sum of all heat loss surfaces that are in contact with the exterior, ground or adjacent non-heated spaces (ΣS_i) (see Eq.1). Another indicator of the form is the building relative compactness (R_c). The R_c of a shape is derived in that its volume to surface ratio is compared to that of the most compact shape with the same volume [12].

$$S_f = V_b / \sum_{i=1}^{n} S_i \text{ and } S_f = R_c \cdot V_b^{0.66} \cdot 6^{-1}, \qquad (1)$$

A building is more compact as the building shape factor takes higher values and it's deficient in form when it has lower values. Werner et al. [12] found that the association between the values of such indicators and simulated heating loads of buildings with various shapes, orientation, glazing percentage and glazing distribution is significant. Accordingly, the use of such indicators in energy standards (for heating load prediction and evaluation purposes) may be justified. For the development of regression models a number of buildings with the corresponding shape factor have been studied. The models were created to evaluate the heating energy demand for single family residential sector where the S_f takes values from 0.7 m to 1.25m.

b) Building envelope heat loss coefficient

One of the most important components of a building is the building envelope insulation because it is essential in the energy consumption and the regulation of the indoor environment. The building's elements (roof, windows, walls and floors) control the flow of energy between the indoor and the outdoor of the building and are the pathway to an efficient and less consuming energy building. In new and old buildings, different strategies have been adopted in order to reduce their energy requirements by improving the air tightness of the envelope and increasing the thickness of insulation [13].

The second input of the regression models is the U_{bui} coefficient defined by the French Standard 2005 [14] as the building average coefficient of heat losses through building envelope including thermal bridges. The heat losses through building elements that separate the heated volume to the external conditions, ground or unheated spaces of the facility are considered in this coefficient. The U_{bui} is calculated using Eq.2 and is expressed in W/m²K:

$$U_{bui} = H_t / \sum S_i, \qquad (2)$$

$$H_t = H_d + H_s + H_u, \qquad (3)$$

where ΣS_i is the total internal surface of walls separating the heated volume from outdoor, ground on unheated spaces (m²) and H_t is the transmission heat loss coefficient (W/K) and it is calculated based on Eq. 3. The H_d is the transmission heat loss coefficient of the elements in contact with the outdoor conditions, for the H_s the walls are in contact with the ground or the basement and for H_u they are in contact with non-heated spaces. Because the building heat loss coefficient depends on the building heat loss surfaces and due to a variation of the building morphology input parameters, the calculations needed for the regression were realized for all the cases.

c) Building time constant

Thermal mass can give a positive contribution to the indoor environment and to the energy performance of buildings, both summer and winter. In the winter time, energy from the sun and internal heat gains can be absorbed in the thermal mass of the construction during the day, and gradually released to the indoor air at night, thus completely or partially reduce the need for heating. The most representative design parameters for efficient exterior walls and roofs are heat transfer coefficients and index of thermal inertia [15].

To express the thermal inertia of the building, the building time constant was considered as the third input for the models. The time constant of a building, τ, is defined as the ratio of the heat surface energy accumulation of the building E_b (J/K) and the total heat loss coefficient of the building Q_b (W/K), which includes the transmission heat loss coefficient of the building envelope and the ventilation heat loss coefficient [16].

The envelope structure can absorb larger fraction of solar and internal gains if the time constant of the building is high and the building responds slower to sudden changes. To obtain higher time constants the thermal mass of the volume or the thermal insulation should be increased. Noren et al. [17] simulated with three different simulation programs the thermal inertia of a reference building. Their results showed that a reduction of 16–18% of the energy heating demand could be obtained when using heavyweight inertia (τ = 325h) compared to a lightweight one (τ = 31h). The building time constants have been calculated for all the cases that were studied in the simulation parametrical analysis.

d) South equivalent glazing surface

Another input of the regression models is the South equivalent glazing surface. The importance of this parameter is especially high due to its potential on reducing the heating demand in mid-season and for the natural lighting. In certain cases, the use of energy-efficient windows can be a better solution than an insulated wall and this is due from the fact that the windows can collect and use the solar energy to heat the indoor spaces during shinny days.

The French thermal directive [14] propose a 16.5% of window/floor area ratio as a reference but this value can be increased to higher values, but with the advice of using solar blinds and energy efficient glazing. To calculate the south equivalent glazing surface (S_{es}), an older version of French thermal directive was used and in which this parameter is defined as follows:

$$S_{es}=\sum_{i=1}^{n} S_i \cdot S_{fs_i} \cdot S_{t_i} \cdot C_i \,, \qquad (4)$$

$$S_{fs}=S_{fs_1} \cdot S_{fs_2} \,, \qquad (5)$$

where S_i is the surface of the glazing i, S_{fsi} is the solar transmission factor, S_{ti} is the sunshine factor and C_i are the declination/orientation coefficients (see Table 1). The sunshine factor translates the reduction of solar energy due to shading masks or different obstacles. It is calculated as in Eq.5. The S_{fs1} is the reduction coefficient due to loggias, balconies or building morphology (ex. L-shape geometry) and S_{fs2} is related to the environment reduction (ex. shading from other buildings).

Table1. South equivalent coefficients C_i

Slope (degree)	SSE-SSO	SSE-ESE and SSO-OSO	ESE-ENE and OSO-ONO	ENE-NNE and ONO-NNO	NNE-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

For the parametric study a high number of south equivalent glazing surfaces (S_{es}) were analyzed by a variation of the windows surfaces and for different percentage of the glazing on the orientations.

e) Climate coefficient

The last parameter used as an input in the energy prediction model is the climate coefficient (C_{cl}), which is going to be defined as the temperature difference between the heating set-point temperature (T_{in}) and the sol-air temperature ($T_{sol\text{-}air}$) [17]. The combined impact of incident solar radiation and outdoor air temperature on the building envelope is indicated by an imaginary temperature called sol-air temperature. The sol-air is used as an outdoor design temperature and was calculated by using a monthly average sol-air temperature of the considered climate ($T_{sol\text{-}air}$ see Eq.6). It is computed using the monthly outdoor dry-bulb temperature (T_a), the monthly average daily global radiation on horizontal (H_g), a default external convection coefficient (h_e) with a default value of 23 W/m²K [14] and a solar absorptance (α) of 0.6 (default mean value of the building elements that were simulated).

$$T_{sol\text{-}air} = T_a + \frac{\alpha \cdot H_g}{h_e}, \qquad (6)$$

$$C_{cl} = T_{in} - T_{sol\text{-}air}, \qquad (7)$$

The heating set-point temperature (T_{in}) was considered to be 19°C for all the simulations, value that represents the best the French houses heating regime. The latest French thermal directive divided the France map in 8climatic zones compared to the previous directive where only 3 climatic zones were identified. Nice and Strasbourg were found to be the minimum respectively the maximum limits on the outdoor climatic conditions of France. Because the energy consumption of a building is particularly sensitive to outside conditions, a number of 16 cities all across the France map were simulated. The models were tested for a temperate climate, like the one of France, but an extension to colder /warmer climates is possible, knowing that the principle will be the same.

f) Output results

The outputs of the models were considered to be the building annual/monthly energy demands (kWh/m^3) obtained from the dynamic simulations. The heating months that have been studied are from October to April.

Regression analysis and coefficients

In order to predict the building heating demand as a function of the 5 selected parameters, different models have been studied. Based on the relationship between the input parameters a clear inter-connection is observed. These interdependences may be modeled by adding interaction terms to a pure quadratic function obtaining thus an interaction model. Once the form of the models was chosen, the next step consisted in the identification of the coefficients, β_i, which minimize the errors between the models outputs and the dynamic simulation results. Using the least square method the regression coefficients for the polynomial models were obtained (see Table 2).

Table 2. Regression coefficients and models accuracy

$$Y = \beta_0 + \sum_{i=1}^{5}\beta_i X_i + \sum_{i=1}^{5}\sum_{j=i+1}^{5}\beta_{ij} X_i X_j + \sum_{i=1}^{5}\beta_{ii} X_i^2$$

Coefficients	Jan.	Feb.	Mar.	Apr.	Oct.	Nov.	Dec.	Annual
β_0	-3.6626	-2.478	-2.8695	-3.1786	-2.3990	-2.7110	-3.5050	-16.5016
β_1	-1.6436	0.1871	3.8380	6.2146	4.2277	1.1837	-1.5565	29.8012
β_2	16.5835	14.4492	14.0317	11.0340	8.5517	12.2892	15.2566	125.2315
β_3	4.96E-03	6.80E-04	-0.0055	-9.78E-	-1.00E-	-1.42E-	3.07E-03	-1.98E-02
β_4	-0.1804	-0.2279	-0.3401	-0.3512	-0.2280	-0.1920	-0.1557	-2.3102
β_5	0.6017	0.4036	0.3008	0.2485	0.2493	0.3831	0.6093	2.4919
β_6	-7.5756	-6.9247	-6.9957	-5.7625	-4.1402	-5.6491	-7.0147	-55.7778
β_7	-2.73E-03	-1.86E-03	3.16E-04	1.82E-03	2.51E-03	-7.65E-	-2.56E-	-1.20E-02
β_8	-3.88E-02	5.48E-02	0.1816	0.2583	0.1456	2.72E-02	-4.81E-	1.2508
β_9	-0.1893	-0.1294	-0.1653	-0.0851	-0.1240	-0.1815	-0.1946	-1.2322
β_{10}	-1.04E-02	-3.13E-03	-1.59E-03	-1.17E-	-4.56E-	-4.83E-	-4.18E-	-0.0879
β_{11}	-1.10E-02	-1.18E-02	-1.17E-02	-3.46E-	-1.12E-	-6.46E-	-1.03E-	-7.65E-02
β_{12}	0.3209	0.3012	0.3396	0.3182	0.3753	0.3230	0.3318	3.5698
β_{13}	1.14E-04	2.19E-05	-7.09E-05	-1.29E-	-1.18E-	-1.04E-	5.65E-05	2.67E-04
β_{14}	-3.33E-05	1.08E-04	3.08E-04	3.54E-04	4.20E-04	1.80E-04	5.64E-05	-3.36E-04
β_{15}	4.61E-03	0.0027	2.86E-03	5.42E-05	-4.41E-	4.01E-03	4.75E-03	2.76E-03
β_{16}	3.3717	1.5820	-0.7049	-2.8143	-1.5719	1.2210	3.2442	-6.9433
β_{17}	-1.8771	-1.3297	-0.9485	-0.5750	-0.5940	-1.3807	-1.7929	-9.8835
β_{18}	-2.49E-06	3.82E-06	1.76E-05	3.42E-05	3.41E-05	7.23E-06	-2.15E-	2.56E-04
β_{19}	2.82E-03	2.00E-03	1.08E-03	-1.64E-	6.44E-04	1.88E-03	2.70E-03	9.73E-03
β_{20}	-5.78E-03	-2.85E-03	5.13E-03	1.45E-04	9.92E-03	1.62E-03	-6.36E-	0.1181
R^2	**0.9968**	**0.9967**	**0.9949**	**0.9912**	**0.9902**	**0.9954**	**0.9966**	**0.9935**

Once the regression models have been constructed, it is important to confirm the goodness of fit of the model and the statistical significance of the estimated parameters. Checking the goodness of fit include the R-squared, analyses of the pattern of residuals and hypothesis testing but also a particular attention of the residuals plots. The model accuracy was evaluated by the mean of coefficient of determination (R^2), the sum of residuals and the standard error of the estimate. Validation of the models was tested with 270 test cases and the mean errors observed were in the range ±7%.

RESULTS

For the case study we have analyzed a random shape building which is considered a 100 m² single-family house. The building was simulated with Trnsys16 simulation tool and the results were confronted with the data obtained using the developed energy models. A certain number of design elements were varied and the results were then compared. For this building shape a number of tests were conducted; different scenarios have been investigated where the building time constant and building envelope insulation were tested from a lower to higher level (see Table 3).

Table 3. Test case analysis - model/simulation results comparison

	Scenario 1			Scenario 2			Scenario 3		
	Simulation (kwh)	Model (kwh)	Error (%)	Simulation (kwh)	Model (kwh)	Error (%)	Simulation (kwh)	Model (kwh)	Error (%)
Jan.	3062	3046	0.51	1664	1699	-2.12	1160	1152	0.71
Feb.	2473	2459	0.58	1290	1318	-2.14	883.4	870	1.54
Mar.	2147	2151	-0.19	1026	1090	-6.27	681.1	692	-1.57
Apr.	1506	1487	1.24	673.9	707	-4.91	430.9	423	1.90
Oct.	1214	1206	0.66	555.5	581	-4.55	353.7	346	2.14
Nov.	2183	2161	1.00	1164	1177	-1.14	801.7	782	2.51
Dec.	2891	2870	0.72	1590	1611	-1.30	1109	1095	1.30
Total.	**15476**	**15381**	**0.62**	**7963.4**	**8183**	**-2.76**	**5419.8**	**5358**	**1.13**

- ***Scenario 1*** (S_f=0.795m, τ=7.69h, U_{bui}=1.18W/m^{2}K, S_{es}=7.48m^2), ***Scenario 2*** (S_f=0.795m, τ=14.34h, U_{bui}=0.54W/m^{2}K, S_{es}=6.67m^2), ***Scenario 3*** (S_f=0.795m, τ=20.19h, U_{bui}=0.3W/m^{2}K, S_{es}=5.12m^2)

The comparison showed that the models predict well the data and the relative errors have low values. Thermal renovation measures may be proposed, especially on the $U_{bui,}$ which is one of the five input parameters of the models, by an increase of the insulation level of the envelope. From Table 3 it can be seen that increasing the insulation level of the building, lower values of the U_{bui} (1.18, 0.54 and 0.3 W/m^{2}K) are obtained and a reduction in the heating demand is seen. If the proposed methodology may appear complex and heavy in calculation the implementation of such models in informatics tools [18] was already done and its use was made it easy and convenient even for non-experimented people. Different energetic strategies could be tested, like different type of insulation, inertia, glazing surface, climate or morphology.

CONCLUSIONS

In this article, the developed regression models were obtained from a database of simulations with the objective to evaluate the heating demand of residential buildings. It can be concluded that the proposed prediction models showed promising features to be easy and efficient forecast tools for comparing heating demand of residential buildings. The goals of these models are quick parametric studies in the design stage of a building project in order to find out the influence of certain elements on the energy consumption. The developed energy equations were structured in five inputs (building shape factor, building envelope mean insulation value, south equivalent surface, building time constant and climate coefficient) and one output (yearly or monthly heating demand).

The models were obtained using a multiple regression of second order polynomial functions and the final results showed that the curve fitting is accurate. The methodology that was proposed could be the start point of other models for the summer period, for colder climates or for the commercial or multi-family buildings. The regression energy equations were found to be a good way to rapidly estimate the building heating demands and their application for the design or on the thermal renovation projects is evident.

The results between the model and the dynamic simulations were in good agreement and the errors were found to be in the range of ±7%.

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