REGRESSION ANALYSIS OF ELECTRIC ENERGY CONSUMPTION OF COMMERCIAL BUILDINGS IN BRAZIL

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ABSTRACT

This paper describes a regression analysis performed over parameters related to two commercial building types and three weather files of Brazilian cities. A random sampling technique was applied to reduce the number of simulation runs needed in the parametric analysis. Equations to estimate the electric energy consumption as a function of building parameters were obtained. Despite the high coefficient of determination obtained for each equation, higher than 0.9760, the amount of data estimated with error higher than 20% is significant. The equations are presented as simplified tools to support the designer, as well the simulationist, to get a better understanding of the energy performance of the building. Such an analysis could be carried out before the incursion in a detailed simulation programme. Limitations about the equations are also discussed in the paper.

KEYWORDS

Regression analysis, sensitivity analysis, EnergyPlus

INTRODUCTION

Regression analysis of the electric energy consumption of buildings can be used as an alternative and fast way to analyze the energy performance of buildings as a function of pre-selected parameters. Regression equations are generally obtained through the simulation of several building models. Input parameters are adequately selected to represent the main building characteristics, and multivariate regression analysis is carried out to establish an equation that correlates the energy consumption (or other relevant output data) to building parameters.

Regression equations can be used for many purposes. Parametric analysis over building parameters can be performed with support of these equations. As not much input data are involved in such a tool, this kind of analysis could be made by building designers to select the most efficient alternatives in the initial design stage. Regression equations can be also applied by policy makers to set up the energy efficiency levels in the building sector.

The regression equation itself is a result of a sensitivity analysis carried out over a range of values for some building or system parameters. The linear coefficients obtained for each parameter represents its impact in the output data.

The ENVSTD program (Anon) is an example of regression equations applied in the building energy performance analysis. Thousands of simulation runs were carried out in the DOE-2.1D programme to generate the equations. Through the ENVSTD, O'Neill et al (1991) analyzed the impact of six architectural variables in the annual cooling and heating loads of commercial rooms in the USA. Sensitivity analysis was performed to obtain influence coefficients and to identify those parameters with major impact on building thermal loads.

Equations were also established by Lam et al (1997) to estimate the electric energy consumption of commercial buildings in Hong Kong. Multiple linear and non-linear regression analyses were carried out and a final equation including 12 building parameters was proposed. The coefficient of determination (R^2) obtained was 0.9880.

In a similar way, Signor et al. (2001) presented a regression analysis study where the energy consumption of buildings were correlated to 10 input parameters, for 14 Brazilian weather files. A single equation was obtained for each city, with R^2 varying from 0.986 to 0.996. Such an analysis did not cover HVAC input parameters, but included building geometry, contrary to the model proposed by Lam et al (1997), that was set up for a unique building type and weather data.

Chan and Chow (1998) applied regression analysis to determine the Overall Thermal Transfer Value (OTTV) of buildings. Information about building envelope, including window-to-wall ratio, shading coefficient of glazing systems and thermal transmittance of constructive components are considered in the OTTV calculation. Through the OTTV it was identified that different building types present significant differences in the thermal performance due to the interaction of the envelope and the exterior environment.

Multiple linear regression analysis was applied by Chung et al (2006) to evaluate the energy efficiency of commercial buildings and establish a ranking of efficiency. But energy data of real buildings were used instead of simulation results. The final regression model relates the energy consumption to parameters of the building that has significant impact in its energy performance. Such a method could be used to develop energy regulations. Policy makers could establish a constant value to some parameters, such as pattern of use, and calculate the energy level to be achieved by a specific sector.

As mentioned above, regression equations can be used to guide the engineer or architect during the initial stage of a building design. General characteristics of the building, such as window area on façades, exterior colours and building shape can be changed to assess the impact of the annual electricity consumption.

The regression analysis described in the present work is part of a methodology developed to support the calibration of building models for energy performance simulation (Westphal 2007). Such a methodology considers the use of regression equations as a first step in the modelling calibration. Sensitivity analysis over building parameters are carried out through the equations to identify significant parameters in the energy performance of the model, as a fast and simple way. This paper presents the development of the equations for three Brazilian cities and two building types.

PARAMETRIC SIMULATIONS

The simulation of several building models was performed in the EnergyPlus programme (version 1.2.3.) to obtain the regression equations. Cases for simulation were generated combining input values for each parameter listed on Table 1. This is the same list adopted in a previous research (Signor et al 2001), with additional parameters: building azimuth; coefficient of performance; thermal transmittance and capacity of walls; pattern of use; projection factor of vertical side-fins on windows; and air infiltration rate.

Two input values were considered for those parameters with linear influence on the energy consumption of the building and three input values were adopted for those parameters with non-linear influence on the energy consumption, as detected previously by Signor (1999).

Scripts routines were written in BASIC language in order to generate all building models and execute the EnergyPlus simulation automatically. Output data were processed in Excel spreadsheets, where the regression equations were obtained through the Method of Least Squares.

A first set of simulations was performed combining the first 13 parameters of Table 1. Combinatorial analysis was applied to generate 23,040 cases considering all possible combinations between these parameters. A single equation was obtained for each building type and city. A random sampling technique, Latin Hypercube Sampling (LHS), was applied to generate the second simulation batch and new equations were obtained.

Due to space limitations, modelling details about each parameter will not be address here. A brief description of the two building types and weather files will be presented only. Details about the whole set of input data is presented by Westphal (2007).

Table 1 - List of input parameters under analysis.

Parameter	Code	Input values
1- Building type	-	1-floor; 5-floors
2- Weather file	-	see Table 2
3- Coefficient of Performance	*COP*	1.82; 3.19 W/W
4- Internal Loads Density	*ILD*	20; 50 W/m²
5- Pattern of use	*PU*	8; 24 h/day
6- Thermal capacity of walls and roof	*TC*	Lightweight (≈0kJ/m².K); heavy (>100 kJ/m².K)
7- Thermal transmittance of walls and roof (W/m².K)	*U*	Lightweight: 0.50; 4.50 Heavyweight: 1.00; 2.50; 4.50
8- Solar absorptance of walls	α_{wall}	0.2; 0.9
9- Solar absorptance of the roof	α_{roof}	0.2; 0.9
10- Window-to-Wall Ratio	*WWR*	0.1; 0.9
11- Projection Factor of overhangs	PF_{oh}	0.0; 1.0
12- Projection Factor of side-fins	PF_{sf}	0.0; 1.0
13- Solar Heat Gain Coefficient	*SHGC*	0.49; 0.59; 0.81
14- Building azimuth (main façade)	*Azim*	0° (north-south); 90° (east-west)
15- Air infiltration rate	*Inf*	1.0; 5.0 ach

Building Type 1

The virtual model corresponding to building Type 1 represents a typical office building with characteristics obtained through a field survey (LABEEE 2005). The model has a rectangular shape with 27.0 m x 7.5 m, with 5 floors and floor-to-floor height equal to 2.5 m. The constructed area totalizes 1,001 m², and 874 m² are artificially conditioned. Figure 1 shows a 3D-view of the building model. Each floor was divided into three zones, as showed in the figure. The front and back zones represent office spaces and are air conditioned. The middle zone is not conditioned and represents corridors, stairs and elevator shaft. Reducing the simulation process time, the typical floor is represented by a single floor multiplied three times and positioned in a middle height between the ground and the top floors.

Building Type 2

The Type 2 corresponds to a single floor building, with total constructed area of 2,500 m², fully air conditioned. The 3D-view is presented at the right side of Figure 1. The model is a 50.0 m square shape, with floor height equal to 5.0 m. This kind of model can be adopted to represent a warehouse with little interior partitions. To achieve a better representation of the impact of the façades and windows in the region next to them, the model was divided into five zones: 1 core zone and 4 perimeter zones, with 6.0 m depth each one.

Type 1 **Type 2**

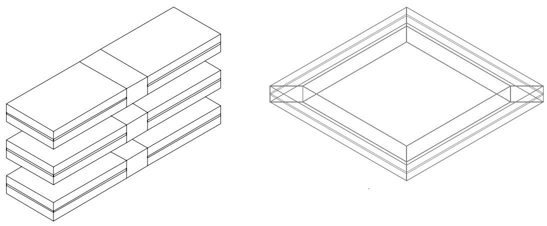

Figure 1 – 3D-view of building types.

Air-conditioning system

On both building types the air conditioning system was represented by a direct expansion packaged terminal air conditioner. The system was modelled to provide heating and cooling, with a dead-band between 18°C and 24°C. The total capacity was automatically calculated by the EnergyPlus according to the design days for each city.

Weather files

The TRY files of three Brazilian cities were used in the simulation runs. These cities were selected to represent different levels of degree-hours for cooling and heating, as showed in Table 2.

Table 2 – Cities considered in the analysis.

City:	Curitiba	Florianópolis	Salvador
Geographic coordinates			
Latitude	25°31'S	27°40'S	12°53'S
Longitude	49°10'W	48°32'W	38°19'W
Altitude	910 m	7 m	13 m
Degree-hours			
Heating (tb=18°C)	25,965	6,030	102
Cooling (tb=24°C)	1,491	4,542	15,904

REGRESSION EQUATIONS

Initially, an equation was obtained to the building Type 1 and weather file for Florianópolis. The equation was divided into two parts. The first one represents the energy consumed by non-weather dependent loads, and is calculated as a function of internal loads density and pattern of use (Eq. 1). This energy consumption was normalized by m² of total constructed area of the building. The Eq. 1 presents a coefficient of determination equal to 1, as the energy consumption of these loads is linearly dependent to the installed power and hours of use.

The second part of the equation relates the complete list of parameters (Table 1) to the energy consumption estimated to the air-conditioning system (*ConsAC*), normalized over the conditioned area, m².

Firstly, each parameter was considered as an independent variable and an equation with R^2 equal to 0.8350 was obtained (Eq. 2). In the regression analysis, each input parameter was normalized over the maximum value of the range considered for each one. Thus, the variables on Eq. 2 accept only values between 0 and 1.

$$ConsNonWeatherDep = 0.182 \times ILD \times PU \qquad (1)$$

$$\begin{aligned} ConsAC = & -78.29\times COP + 78.83\times ILD + 86.41\times PU \\ & - 2.879\times TC + 12.32\times \alpha_{wall} + 9.670\times \alpha_{roof} \\ & - 1.186\times U + 6.192\times WWR - 9.619\times PF_{oh} \\ & - 2.828\times PF_{sf} + 4.815\times SHGC + 4.097 \qquad (2) \end{aligned}$$

The graph on Figure 2 shows the correlation between the output estimated through the Eq. 2 and the output obtained through simulation.

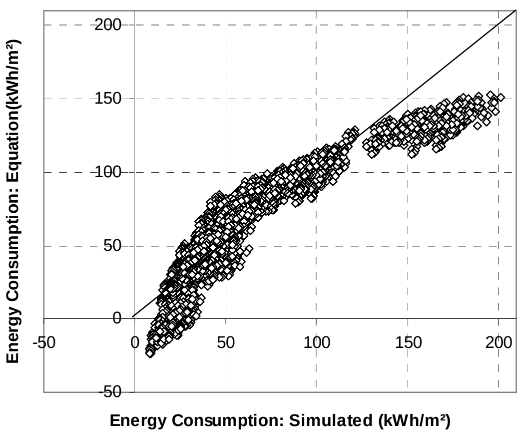

Figure 2 – Correlation between the electric energy consumption of the air-conditioning system obtained through simulation and the equation (Eq. 2) for building Type 1 and Florianópolis city.

The analysis over the cumulative frequency of errors for the results estimated by the equation shows that 45% of cases present error up to 20% (Westphal 2007). It was verified also that 20% of the points registered differences higher than 50%, which is a remarkable level of inaccuracy.

In the analysis over the effects caused by each input parameters, described in details by Westphal (2007), interaction effects were observed to some parameters. Following these tendencies, some terms of Eq. 2

were grouped together, seeking for an equation with a better coefficient of determination.

The level of impact on energy consumption caused by a variation in the *COP* will depends on the pattern of use of the HVAC system. With high level of use, higher energy saving will be obtained increasing the *COP* value. The same behavior is observed with the internal loads density (*ILD*). The impact caused by an increase in the *ILD* will depend on the daily use of these loads. Thus, the *COP* and *ILD* parameters were grouped (multiplied) with the *PU* parameter, providing an equation with better representation of the simulated data.

The Solar Heat Gain Coefficient (*SHGC*) was substituted by the sum of absorptance and transmittance to the solar radiation of the glass ($(\alpha+\tau)_{glass}$), as the effects caused by *SHGC* are non-linear. The influence of the type of glass in the building energy performance is also dependent on the window-to-wall ratio (*WWR*). With high glazing area on façades, higher impact of the glass type will be observed in the building performance. Thus, the parameters $(\alpha+\tau)_{glass}$ and *WWR* were grouped together. The same treatment was given to the PF_{oh} and the PF_{sf}.

The procedure described above was extended to the solar absorptance of walls. This parameter was grouped with the ratio of opaque area on façades, i.e., 1-WWR.

The impact of the roof absorptance depends on the thermal transmittance of this component. A dark coloured roof will influence significantly the energy performance of the building if this roof has a low thermal resistance. A well insulated roof will have little influence on the energy consumption even if painted externally with a dark colour. Hence, a new term was introduced, combining these two parameters ($\alpha_{roof}\times U_{roof}$).

Considering these new groups of parameters, a new equation was achieved (Eq. 3), with R² equal to 0.9545. The correlation between simulated and estimated data is presented in Figure 3. It can be noticed that the representation of the energy consumption by the equation was improved. The incidence of points with error up to 20% was increased from 45% to 70% of the sample. Errors higher than 50% were registered to only 5% of the points. The largest differences were observed for those cases with extreme values of energy consumption, i.e., lower than 25 kWh/m² and higher than 150 kWh/m². To use the equation, the analyst must be aware about the limitations of the method and that some sample points can not be explained accurately through the equation.

$$
\begin{aligned}
ConsAC =\ & 115.1\times COP\times PU + 113.5\times ILD\times PU + 97.34\times PU \\
& - 2.879\times TC + 21.43\times\alpha_{wall}\times(1-WWR) + \\
& 15.73\times\alpha_{wall}\times U - 10.80\times U + 7.892\times WWR \\
& -15.77\times WWR\times PF_{oh} - 5.306\times WWR\times PF_{sf} \\
& + 24.21\times(\alpha+\tau)_{glass}\times WWR - 9.287
\end{aligned}
\tag{3}
$$

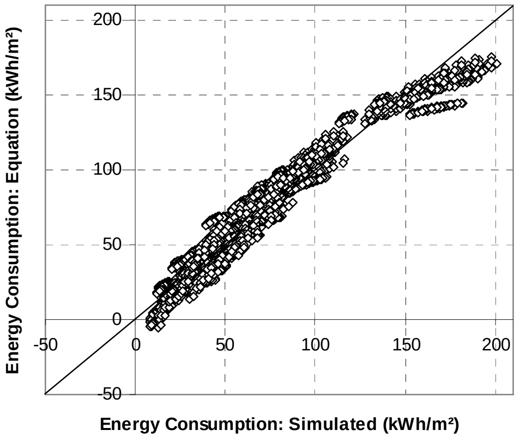

Figure 3 – Correlation between the electric energy consumption of air-conditioning system obtained through simulation and the second equation (Eq. 3) for building Type 1 and Florianópolis city.

With the equations obtained above (Eq. 1 and Eq. 3) the annual electric energy consumption (*ConsTotal*) of the building can be estimated according to Eq. 4. Where, *TotalArea* is the building constructed area and *CondArea* is the conditioned area of the building.

$$
\begin{aligned}
ConsTotal =\ & ConsNonWeatherDep \times TotalArea + \\
& + ConsAC \times CondArea
\end{aligned}
\tag{4}
$$

RANDOM SAMPLING

In the regression analysis describe above, a set of 23,040 cases was simulated. In this first analysis, two parameters of Table 1 were not changed: building azimuth and infiltration rate. In addition, the thermal transmittance of the envelope was changed simultaneously for walls and roof, and the type of floor was not changed. The inclusion of the remaining parameters and the variation of wall type independently of the roof type would demand more than 460 thousands simulation runs. The time required to perform all simulation runs and the amount of output data to be analyzed would be unfeasible. Thus, the reduction of cases to be simulated was necessary.

Statistical methods were sought so that a reduced sample of cases could be adequately selected to represent the energy consumption as a function of building parameters. From the random sampling techniques studied, the Latin Hypercube Sampling (LHS) was identified as the most adequate to this kind of analysis (McKay, 1992). In the LHS technique, each input parameter is divided into the same number of intervals. For each simulation run, the input value for each parameter is randomly selected according to its probability distribution function.

As the application of the LHS method requires the division of input values into the same number of intervals, the Table 1 was adjusted. Each parameter was divided into 3 intervals, and to simplify the modelling procedure, each one was considered as a discrete variable. Table 3 shows the new list of values.

Table 3 – Input values adopted in the LHS.

Parameter	**Code**	**Input values**
1- Coefficient of Performance	*COP*	2,50
2- Internal Loads Density	*ILD*	20; 35; 50
3- Pattern of use	*PU*	8; 16; 24
4- Thermal Capacity of walls, roof and floor	*TC*	Heavyweight (>100kJ/m².K)
5- Thermal transmittance of walls	U_{wall}	0.5; 2.5; 4.5
6- Thermal transmittance of the roof	U_{roof}	0.5; 2.5; 4.5
7- Thermal transmittance of the floor	U_{floor}	0.5; 2.5; 4.5
8- Solar absorptance of walls	α_{wall}	0.20; 0.55; 0.90
9- Solar absorptance of the roof	α_{roof}	0.20; 0.55; 0.90
10- Window-to-wall ratio	*WWR*	0.1; 0.5; 09
11- Projection Factor of overhangs	PF_{oh}	0.0; 0.5; 1.0
12- Projection Factor of side-fins	PF_{sf}	0.0; 0.5; 1.0
13- Solar Heat Gain Coefficient	*SHGC*	0.69; 0.83; 0.95
14- Building azimuth (main façade)	*Azim*	0°; 45°; 90°
15- Air infiltration rate	*Inf*	1; 3; 5

After the first set of simulation runs, it was identified that two parameters could be simulated with a single value: the *COP* and the thermal capacity (*TC*) of opaque components.

There is no need to change the *COP* value to evaluate its impact in the energy consumption through computer simulation, as the influence is linear and independent of other factors. In order to obtain the energy consumption for a different *COP*, one can just multiply the energy consumption obtained with the simulation by the ratio between the simulated *COP* and the *COP* of interest.

In the new set of simulation runs, only heavyweight walls, roofs and floors were modelled, as the difference between models with high thermal capacity and no thermal capacity was almost insignificant. In addition, Brazilian buildings are commonly constructed with heavy walls.

Uniform probability distribution function was adopted in the selection of values for each parameter. As the number of parameters (13) was much greater than the number of intervals adopted (3), the sampling procedure (LHS) was replicated to get the necessary number of cases. Bartlett et al. (2001) suggest a total of cases around 10 times the number of parameters to this kind of analysis. Following this indication, 44 replications of the LHS was applied to generate a total of 132 cases. This sample was established to each weather file and building type. As a result, 792 cases were simulated.

EQUATIONS OBTAINED THROUGH THE RANDOM SAMPLING

Electric energy consumption of fans

In this second set of simulation runs, the calculation of the energy consumption due to fans was disaggregated from the energy consumption of air-conditioning system.

As the system sizing was made automatically by the software for each case, the energy consumed by fans is directly proportional to the system capacity. As a single value of *COP* was adopted, the energy consumption of fans can be also directly calculated as a function of energy consumption for heating and cooling (compressors). The Eq. 5 presents this correlation, with R^2 equal to 1. In this equation, the energy consumption of fans (*ConsFans*) is given in kWh per m² of conditioned area.

$$ConsVent = 0.04942 \times ConsAC \tag{5}$$

Electric energy consumption for air-conditioning

A single equation was tested for each building type and weather file. A general equation, including all samples simulated was also tested. Each equation obtained will be discussed below.

Equation for building Type 1

The first equation was obtained for the sample of cases simulated with the weather file of Florianópolis. Some parameters with strong interrelationship were grouped together, as made before. The final equation (Eq. 6) was obtained with R^2 equal to 0.9916.

Figure 4 shows the correlation between simulated and estimated data. For this correlation, about 90% of the points accounted for error under 20%.

$$\begin{aligned} ConsAC = {} & 7.019\times ILD + 55.27\times ILD\times ILD\times PU + 46.60\times PU \\ & + 6.188\times\alpha_{wall} - 0.2625\times\alpha_{roof} - 8.201\times U_{wall} + \\ & 12.42\times U_{wall}\times\alpha_{pwall} - 3.644\times U_{floor} - 3.171\times U_{roof} + \\ & 14.72\times U_{roof}\times\alpha_{roof} - 10.80\times PF_{oh} - 2.367\times PF_{sf} + \\ & 12.79\times(\alpha+\tau)_{glass}\times \mathrm{WWR} - 0.1237\times Inf - 5.305\times Azim \end{aligned} \tag{6}$$

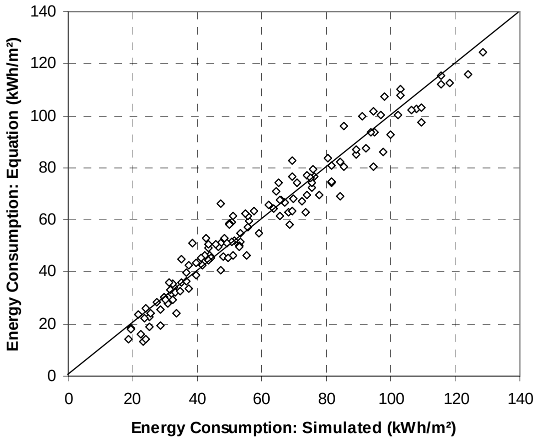

Figure 4 – Correlation between the electric energy consumption of air-conditioning system obtained through simulation and the Eq. 6 for building Type 1 and Florianópolis city.

This equation was applied to estimate the energy consumption of the first set of cases – before the random sampling – so that its efficacy could be tested. The results are showed in Figure 5. The energy consumption is reasonable represented by the equation, except for those cases with consumption higher than 120 kWh/m². Certainly, the sample did not include cases with high energy consumption and the equation did not reflect this extreme values. Nevertheless, about 70% of cases had their energy consumption estimated with error up to 20%. This representation can be considered suitable, considering the number of parameters involved in the analysis and that the cases simulated in the first step adopted only extreme input values.

This behaviour shows the limitations of such a tool. These equations should be applied carefully. They can not be employed in the energy analysis of buildings with characteristics beyond the limits simulated for the regression analysis.

The same equation form was applied in the regression analysis over the cases simulated with the other two weather files. Table 4 lists the linear coefficients for each city and the R^2 achieved. A comparison between the impacts caused by the parameters in the energy consumption in each climate can be assessed directly through this table.

The lowest R^2 was observed for Curitiba. In that climate, the degree-hours for heating is significant, compared to the other cities. Thus, some parameters may have significant influence as in the heating load as in the cooling load, but in opposite way, what can not be well represented by the equation.

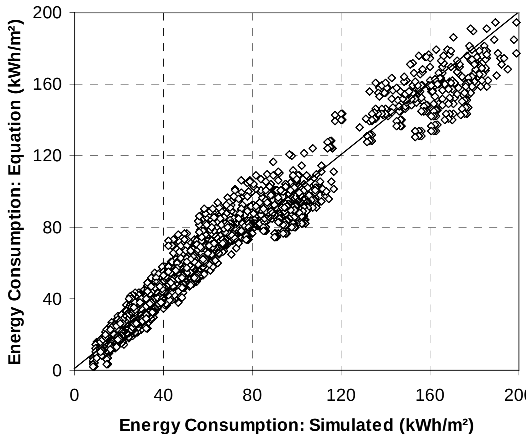

Figure 5 – Correlation between the electric energy consumption of air-conditioning system obtained through simulation and the Eq. 7 for the first set of simulation runs for Type 1 and Florianópolis city.

Table 4 – Linear regression coefficients and R² to the equations obtained for building Type 1.

Parameter	Curitiba	Florianópolis	Salvador
ILD	6.428	7.019	6.838
PU	33.71	46.60	119.2
$ILD \times ILD \times PU$	21.52	55.27	69.15
α_{wall}	1.523	6.188	-0.06211
α_{roof}	-3.505	-0.2625	-4.779
U_{wall}	-5.526	-8.201	-15.96
$U_{wall} \times \alpha_{wall}$	9.582	12.42	29.93
U_{floor}	-1.556	-3.644	-4.674
U_{roof}	-0.4308	-3.171	-11.25
$U_{roof} \times \alpha_{roof}$	14.86	14.72	27.08
PF_{oh}	-9.034	-10.80	-17.37
PF_{sf}	-1.839	-2.367	-8.128
$(\alpha + \tau)_{glass} \times WWR$	8.421	12.79	27.95
Inf	-0.1025	-0.1237	44.79
$Azim$	-5.218	-5.305	-12.31
R^2	**0.9779**	**0.9918**	**0.9941**

Some important observations can be drawn from the linear coefficients presented in Table 4.

Coefficients with absolute value very low, e.g., lower than the unit, mean that the parameter does not play an important role in the energy consumption of the cases simulated for that weather file. This is the case of the absorptance of walls (α_{wall}), when considered as an isolated term in the equation for Salvador climate, with a coefficient equal to -0.06211. This term could be eliminated from this equation, as the influence of the exterior colour of walls is already considered in the term $U_{wall} \times \alpha_{wall}$, with coefficient equal to 29.93. The same aspect is observed for the roof absorptance in Florianópolis. The single term (α_{roof}) has coefficient equal to -0.2625, but together with the thermal transmittance of the roof ($U_{roof}\times\ \alpha_{roof}$) the coefficient is 14.72.

The values of infiltration rate (*Inf*) employed as input in the simulation runs have caused almost no effects in the energy consumption in Curitiba (-0.1025) and Florianópolis (-0.1237). But for the climate of Salvador this parameter is significant, with coefficient equal to 44.79.

For the three weather files, the parameters with highest influence in the energy consumption were: internal loads density (*ILD*) and the pattern of use (terms $ILD\times ILD\times PU$ and *PU*). The architectural parameters with highest impact were those related to the windows and walls, as this building type has a large façade area.

It should be highlighted that these coefficients are representing the effects of a sample with cases generated over that building type (Type 1), and within specifics ranges of values for each parameter. These equations represent an average tendency of the sample, hence the analysis of models with significant differences to this sample should be made very carefully. In some cases the behaviour of the model can be contrary to the indication provided by a specific coefficient.

Equations to building Type 2

The same form of Eq. 6 was applied to represent the energy consumption of that sample of cases generated over building Type 2. The linear coefficients corresponding to each city are presented in Table 5.

It can be observed that, as this model has square building shape, the azimuth yields little influence over the energy consumption. The highest coefficient was achieved to this parameter for Salvador city. That is the warmest climate, where the architectural variables are significant to energy performance of the building.

Again, the parameters related to the internal loads and pattern of use had significant impact in the energy consumption in the three climates. But for this building type the major influence was caused by the roof characteristics. The parameter $Ucob\times\alpha_{cob}$ has coefficient equal to 95.82 for Curitiba, 106.1 for Florianópolis and 176.7 for Salvador.

The air infiltration rate has showed again significant influence on the energy consumption in Salvador city, but contrary to the Type 1 the impact caused in the other cities deserves special attention too.

The same form of equation was maintained from the building Type 1 to Type 2, allowing a direct comparison between the linear coefficients. But another and more adequate equation form could be tested for building Type 2.

Table 5 – Linear regression coefficients and R^2 to the equations obtained for building Type 2.

Parameter	Curitiba	Florianópolis	Salvador
ILD	19.84	13.51	9.530
PU	76.59	49.85	119.2
$ILD\times ILD\times PU$	-17.47	32.04	69.12
α_{wall}	-23.58	-1.821	-6.626
α_{roof}	-23.12	-5.637	-6.735
U_{wall}	-18.41	-5.561	-15.36
$U_{wall}\times\alpha_{wall}$	28.47	8.999	21.50
U_{floor}	-8.610	-15.47	-30.00
U_{roof}	95.82	106.1	176.7
$U_{roof}\times\alpha_{roof}$	-18.11	-24.76	-41.61
PF_{oh}	-10.69	-7.706	-10.23
PF_{sf}	-4.636	-3.429	-8.002
$(\alpha+\tau)_{glass}\times WWR$	2.929	8.858	16.88
Inf	28.24	15.02	76.91
Azim	-0.7090	-1.287	-2.593
R^2	**0.9760**	**0.9906**	**0.9926**

General equation

A general equation was obtained (Eq. 7) with R^2 equal to 0.9730, including also parameters related to the weather (DH_{cool} = degree-hours for cooling) and building type (A_{roof}; A_{facade} and Vol = roof area, façade area and volume of conditioned zones, respectively). But the accuracy obtained with this equation is very low. Only 60% of cases were located into that level of error up to 20%.

The analysis over the equations obtained above has already revealed a difficulty to represent the energy consumption of a model for different weather files in a single equation. Some parameters play an important role in some climates, but can yield no influence on energy consumption for that model in other environment.

$$\begin{aligned}ConsAC = {} & (124.2\times PU + 54.70\times Inf)\times DH_{cool} + \\ & 90.85\times U_{roof}\times\alpha_{roof}\times A_{roof}/Vol + \\ & [25.02\times U_{wall}\times\alpha_{par}\times(1\text{-}WWR) - 25.09]\times A_{fach}/Vol + \\ & [(-28.66\times PF_{oh} - 12.69\times PF_{sf} + \\ & 47.11)\times(\alpha+\tau)_{\text{glass}}\times WWR]\times A_{façade}/Vol + \\ & (49.80\times ILD\times ILD + 10.73)\times PU \\ & - 15.27\times U_{floor} - 4.294\times Azim \end{aligned} \qquad (7)$$

The influence caused by some parameters is also very different between the two building types analyzed. For example, the air infiltration rate is almost insignificant for Type 1 in two cities, but causes great impact over the energy consumption for Type 2 in the three cities.

CONCLUSIONS

This paper presented a multivariate regression analysis over the energy consumption for two building types in three Brazilian climates. In the first step, 23,040 were simulated to obtain an equation for each building type and weather file. Then the Latin Hypercube Sampling technique was applied to generate a random sample of cases to conclude the analysis covering all parameters of interest.

The equations obtained to estimate the energy consumption for different building types and weather presented R^2 from 0.9760 to 0.9941. Significant differences in the linear coefficients were detected for some parameters. This behaviour shows that simplified methods have, evidently, its limitations. A general equation, for application in any weather and building type, would hardly represent the energy performance of building accurately. Regardless of these limitations, a general equation was generated with coefficient of determination equal to 0.9730, covering 17 parameters.

This equation should be used carefully, especially for locations at latitudes different from those analyzed in this work. Furthermore, the equation does not includes parameters related to solar radiation or cloud cover, and even for cities at latitudes close to those simulated here, the energy behaviour of the building may be represented very differently through the equation.

As an example of practical application, these equations could be used to evaluate the energy performance of new buildings during the initial design stages. The influence of architectural parameters for a specific scenario of internal loads and patterns of use can be evaluated through them. The same analysis can be made preceding a detailed simulation. A better understanding about the energy performance of the building can be achieved through the equations before starting the detailed model in an hourly simulation tool, guiding the user in the definition of the most important parameters.

Simplified methods to energy analysis, as the presented here have its limitations. These equations can be used with satisfactory accuracy only within the simulated scenarios, mainly in relation to the way as the schedules were represented in the parametric simulations.

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