ANALYSIS OF DYNAMIC THERMAL SIMULATION FOR REFURBISHMENT

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ABSTRACT

This paper presents a method to analyse the impact of current refurbishment settings. Performance indicators are computed through multiple physical simulations. In the study case, the thermal comfort conditions and needs are analysed to infer relationships between them and the inputs. To reach this goal, the frequency analysis method RBD-FAST is used. For each output, a total influence ranking is produced and discussed. This study aims to help building designers take advantage of current computing power. Indeed, they could visualize the impact of each input modification and choose the best solution set.

INTRODUCTION

Refurbishment has become a major issue in the effort to decrease energy consumption in France. Indeed, the thermal regulations for new residential buildings have become more restrictive. However, the slow turnover of the building stock, about 1%, does not allow for significant improvements in energy performance, and therefore attention must be paid to the existing stock.

The refurbishment choices of house owners are often driven by return on investment. However, these improvements should focus not only on gains in energy performance but also on thermal comfort. General comfort must be improved or at least maintained, taking into account visual, acoustic and olfactory aspects.

Moreover, the old building stock is very heterogeneous and a single refurbishment solution is not feasible. Therefore, a refurbishment methodology must be developed that offers a comprehensive optimization approach to help designers.

This methodology should take into account the initial physical characteristics of the building as well as the influence of the weather and the occupants. Moreover, the constraints of the building project must also be considered: the site, the implementation and the performance and lifespan of the components in place. All these factors determine the performance guarantee for a sufficient period to justify the refurbishment, either financially or environmentally.

The building is a high-dimension system and requires a multi-physics evaluation. Thus, the problem is complex and cannot be evaluated by a single output.

Therefore, dynamic thermal simulation must be used. This powerful design tool has now become indispensable when validating solutions sets and studying summer comfort. Modern computing capabilities allow entire building models to be explored. Usually, the optimal solutions of an optimization problem may be found if the proper assessment variable is defined. However, this creates a single evaluation variable, which requires the aggregation of different kinds of temporal outputs. In order to keep the multi-criteria aspect, it is necessary to develop indicators to measure the studied phenomena. Classification methods such as ELECTRE (Ben Mena, 2000; Hatami-Marbini & Tavana, 2011) can solve this problem. Nevertheless, with these methods, the effect of a slight change in the inputs is hardly known. What happens to optimization if, in practice, a change occurs during the implementation?

This article aims at providing a better understanding of the model, keeping the multi-physical aspect. The impact of the variation of nine inputs on three performance indicators is studied during summer and winter. An evaluation of the initial state of the existing dwelling and the performance guarantee are not addressed in this paper.

DEFINITION OF INDICATORS FOR REFURBISHMENT

Assessing the quality of a building is the first step in the search for improvement solutions. Thus, weaknesses are evaluated and different solutions can be compared.

The dynamic thermal building software includes many innovative simulation capabilities. Building behaviour can be explored in detail with hourly time steps or less, and almost all variables are available in outputs. This leads to an advanced analysis of building components, such as the wall and window types, orientations, systems, etc.

To study physical phenomena related to the habitat, indicators must have a direct and understandable link to these phenomena. The method will be introduced only with regard to energy aspects without systems, for more understandable results. Thus, the study deals only with indicators related to heating, cooling and thermal comfort during the warm and cold seasons. However, this methodology is expandable to all other indicators such as system performance, detailed gains and losses, air quality, brightness, humidity, etc.

Energy Consumption

The regulatory approach (ASHRAE 90.1, EN 15217) to the calculation of energy consumption requires an annual sum. However, this information is not accurate enough for sizing. Indeed, one should be careful with the definition of scalars because aggregation induces a loss of information. Computing indicators in short periods rather than in years provides a better understanding of the building behaviour. Nevertheless, this behaviour changes during the year and indicators must be evaluated over several periods. We will see later that the influence of the inputs changes depending on the season.

Figure 1 shows the outdoor and indoor temperature progression during an annual simulation of the study case. The green line corresponds to the solicitation (outdoor temperature) and the blue line is the response of the tested case (indoor temperature).

Three main periods can be highlighted:

- Winter: An important amount of energy is needed to maintain a minimum interior temperature.
- Summer: The outside temperature is high enough to stop all the heating systems. The building temperature is strongly coupled to the outside temperature (free evolution).
- Offseason: The weather is unstable, the needs are intermittent and the two previous scenarios may occur.

Based on these rules, the need for heating or cooling was evaluated for two periods in a month. In Figure 1, the two shaded areas correspond to the months of January and July.

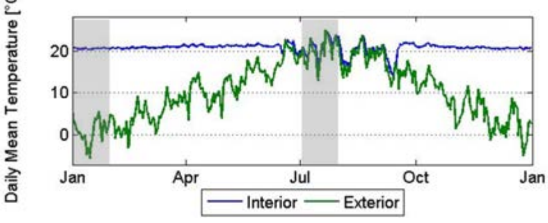

Figure 1: Annual simulation of the study case

Thermal Comfort

Assessment of comfort is a delicate task, and many methods have been developed for this. A review of the available methods is presented elsewhere Carlucci & Pagliano (2012).

The adaptive comfort theory was chosen so as not to impose occupant clothing and activity to the analysis. In practice and more particularly in residential buildings, these two values are uncertain and affect the assessment of comfort. Figure 2 presents the 90% acceptability range of adaptive comfort in prEN15251. This theory, used in regulations for summer, has also been defined for winter temperatures (Nicol & Humphreys, 2002). Indeed, correlations with user comfort are more adapted to summer but are still suitable in winter. This choice of indicator provides consistency for different seasons and maintains a clear link with the indoor temperature.

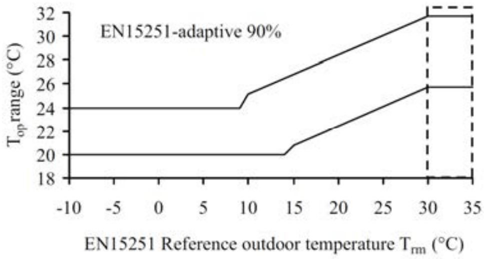

Figure 2: EN15251 optimal operative temperature from (Sourbron & Helsen, 2011)

The scalar representation of comfort will be given for each period according to the intensity of thermal discomfort (ITD) (Sicurella et al., 2011). This indicator represents the time integral of the difference between the current operative temperature and the limit of comfort expressed in [°C.day] (Figure 3). The comfort zone taken into account is defined as a Class A limit, equivalent to a satisfaction rate of 90% (DRAFT prEN 15251, 2005).

$$\mathrm{ITD}_{\mathrm{over}} = \int_P \Delta T_{over}(\tau).d\tau$$
$$\Delta T_{over}(\tau) = \begin{cases} T_{op}(\tau) - T_{over} & \text{if } T_{op}(\tau) > T_{over} \\ 0 & \end{cases} \quad (1)$$

$$\mathrm{ITD}_{\mathrm{under}} = \int_P \Delta T_{under}(\tau).d\tau$$
$$\Delta T_{under}(\tau) = \begin{cases} T_{op}(\tau) - T_{under} & \text{if } T_{op}(\tau) > T_{under} \\ 0 & \end{cases} \quad (2)$$

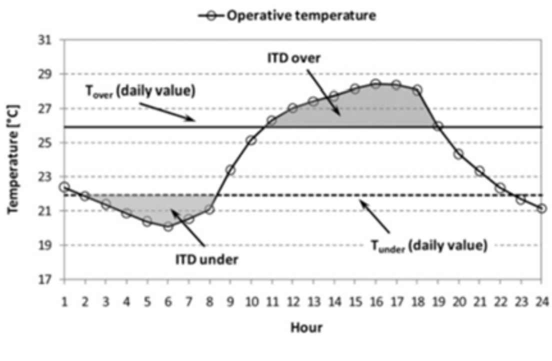

Figure 3: Definition of intensity of thermal discomfort (ITD) from (Sicurella et al., 2011).

Indicators Used in the Study Case

According to the location of the study case, a TMY2 weather file of Le-Bourget-du-Lac is used. There is a cool climate (Figure 1), thus the comfort indicator "ITD_{over}" is not displayed and has no influencing parameters. This indicator is null in winter, obviously because of the low temperature outside. In summer, the maximum observable indoor temperature stays in the comfort zone. Furthermore, this temperature peak occurs in the most unfavourable configurations. Subsequently, cooling implementation does not seem to be necessary.

Another consequence of this climate is the influence of the heating setpoint on consumption in summer. The nights are cool enough for the internal temperature to reach the heating setpoint regularly, inducing heating needs. The power required is weak, we assume that temperature is acceptable and we disable all heaters in summer.

The same conclusions can be made with the statistical results of variance (not displayed in tables). A low value indicates a weak interaction between the inputs and the observed indicator. In that case it is useless to study this indicator.

Eventually, the house is conditioned in winter and is free running in summer. The observed indicators are "ITD_{under}" summer, "ITD_{under}" winter and winter heating.

IMPACT ASSESSMENT BY SENSITIVITY ANALYSIS

The specified set of indicators allows one to define the model as a function from $\Re^m$ to $\Re^k$. Where *m* is the number of inputs and *k* the number of outputs.

$$\mathbf{Y} = \mathbf{F}(x_1, x_2, \ldots, x_m) \in \Re^k \tag{3}$$

To introduce the method, each of the six output indicators will be studied independently.

$$Y = F(x_1, x_2, \ldots, x_m) \tag{4}$$

In this case, there are nine independent and uncorrelated input variables that facilitate using sensitivity analysis methods based on the analysis of variance (ANOVA-based method). I.M. Sobol has proven that any square integrable mathematical function can be decomposed as follows (Mara & Tarantola, 2008):

$$Y = f_0 + \sum_{i=1}^{m} f_i(x_i) + \sum_{j>i}^{m} f_{ij}(x_i, x_j) + \cdots + f_{1\ldots m}(x_1, \ldots, x_m) \tag{5}$$

It can be shown that the variance of F can be decomposed into a sum of fractional variances.

$$D = \sum_{i=1}^{m} D_i + \sum_{j>i}^{m} D_{ij} + \cdots + D_{1\ldots m}$$
$$1 = \sum_{i=1}^{m} S_i + \sum_{j>i}^{m} S_{ij} + \cdots + S_{1\ldots m} \tag{6}$$

$S_i = D_i / D$ is the first-order sensitivity index that measures the amount of the response variance explained by x_i alone. To define all contributions of x_i, the total sensitivity index is evaluated by:

$$ST_i = S_i + \sum_{j \neq i}^{m} S_{ij} + \sum_{h \neq j,i}^{m} S_{hij} + \cdots + S_{1\ldots i\ldots m} \tag{7}$$

This last index is analysed according to the RBD-FAST method. The random balance design (RBD) technique was originally introduced by Satterthwaite (1959) for the design of experiments. The Fourier amplitude sensitivity test (FAST) method was introduced by Cukier et al. (1973). RBD-FAST is an extension of the RBD technique to the FAST technique developed by (Tarantola et al., 2006). T.A. Mara (Mara, 2009) improved this method to analyse effects with very low simulation costs.

According to the FAST method, inputs are sampled using different frequencies to allow an analysis of the output by Fourier transforms.

$$x_i = G_i\left(\sin(\omega_i . s)\right) \tag{8}$$

The choice of the frequency is then very important in identifying the effects and interactions between parameters in the response spectrum. With RBD, entered variables are sampled periodically and then permuted randomly and independently. The choice of the input frequency no longer has an influence and the pulse can be set to 1.

For a set of N simulation:

$$x_i^k = G_i\left(\sin\left(\omega . s_{\sigma_i^k}\right)\right) \quad k \in [1, N], \tag{9}$$

with

s a uniform crescent sampling of *N* values in $[-\pi, \pi]$,

σ_i a random permutation of the sequence 1:*N*,

G_i a transformation function according to the input.

It is then possible to see the total effect of a parameter by reorganizing the sampling according to the permutation of its sequence σ_i. The other parameters are always randomized because each sequence is independent.

The spectral analysis of the reorganized output shows the effect of a parameter in low frequencies and the effects of other inputs as a noise spread over all frequencies.

The sensitivity index of x_i is then evaluated by

$$\hat{V}_i = \sum_{1 \le n \le N_k} \left| c_{\sigma_i}^n \right|^2 \qquad \hat{V}_{tot} = \sum_{1 \le n \le N} \left| c_{\sigma_i}^n \right|^2 \qquad \hat{ST}_i = \frac{\hat{V}_i}{\hat{V}_{tot}} \tag{10}$$

with:

c_{σ_i} Fourier factor of reorganized output,

$N_k = 2M\omega$ limit of low frequencies.

The total variance $\hat{V}_{tot}$ is the sum of all Fourier coefficients. The variance $\hat{V}_i$, induced by x_i, is evaluated by the N_k first coefficients. M is the number of harmonics considered for the response. According to the literature, the six first harmonics are usually sufficient for identifying precisely the effect of the studied input parameter on each output.

To obtain an accurate representation of the index, enough simulations have to be carried out. According to the sampling theorem of Nyquist-Shannon, the number of simulation must be at least:

$$N = 2\cdot(M+L), \tag{11}$$

with L, an arbitrary positive value ($L \sim 100$).

Since the variance of unordered parameters is spread over all frequencies, it influences each Fourier coefficient, even the first ones. Therefore, the value of $\hat{V}_i$ is slightly overestimated. Tissot and Prieur (Tissot & Prieur, 2012) reduce this bias by adding a corrective term.

$$\begin{aligned} \lambda &= 2.N_k/N \\ \hat{S}_i^c &= \hat{S}_i - \frac{\lambda}{1-\lambda}\left(1-\hat{S}_i\right) \end{aligned} \tag{12}$$

The RBD-FAST method is a frequency analysis, and thus the effects should always have positive values. However, bias correction can lead to negative values, especially for the smallest effects. If there is no interaction on the studied output, the sum of all its indices must be close to 1. A value that is significantly different demonstrates the presence of interactions. A high index indicates a strong relationship between the variation of the input and the output. A low index represents a uniform noise or a constant value for the output.

To represent the behaviour of high indexes, Figures 5 to 8 show the relationship between inputs and outputs. The simulation results are organized according to the variation of a single parameter. As the glazing input is discrete, we present the results with three types of points corresponding to three glazing types. This visual analysis is qualitative. It allows one to visualize the trend and to identify a good choice following value changes.

BUILDING DESIGN & IMPROVEMENT SETTINGS

All simulations were performed on the EnergyPlus simulation software. A MatLab program was developed to automate the serial-simulation and perform various sensitivity analyses.

The building model analysed has the same geometry as the INCAS houses. It has been validated elsewhere (Spitz et al., 2012). These houses are located on the site of the National Institute of Solar Energy (INES) at Bourget-du-Lac (FRANCE). The experimental platform was designed to validate thermal dynamic simulation models by comparison with measurements. These passive buildings and their environment are well defined. Although the geometry of these buildings is kept, the thermal characteristics are degraded to allow comparisons with a housing renovation. The heated surface is 111 m². Usage and occupancy scenarios are based on French regulations (RT2005).

Figure 4: INCAS houses from www.ines-solaire.org

The degraded thermal characteristics are:

- concrete blocks and glass wool,
- ideal convective heating,
- constant air exhaust.

To test the possible impact of different solutions, the following variables are analysed:

- Glazing [single, double, triple]
- Insulation of walls [0; 40 cm]
- Insulation of crawl space [0, 40 cm]
- Insulation of attic [0; 40 cm]
- Renewal of fresh air (airtightness / ventilation) [0, 3 vol / h]
- Thickness of slab (for inertia) [0; 20 cm]
- Renewal of crawl space and attic [0, 8 vol / h]
- Setpoint of heating [15, 25 ° C]
- Setpoint of cooling [25, 35 ° C]

All samplings were generated uniformly according to the analysis method presented below. A wide range of variation was chosen so as to identify the efficiency ranges. The minimum and maximum values of previous input parameters correspond to critical cases such as old housing or recent over-insulated housing.

The first four parameters are common variables in building renovation. Other parameters were added to check the influence of secondary phenomena: ventilation of unheated spaces, interior inertia through the slab and setpoints.

The setpoints are not design parameters. Still, they are considered as a variable in this study, because of their significant differences in practice, regulation and thermal comfort.

First, all variables are analysed. Then, the most influent parameters are fixed to investigate the impact of less influential variables. In the last section, all results are summarized in a table and discussed.

General Variable Impact Analysis

According to the RBD-FAST theory, indexes of all inputs are displayed in percentage (Table 1). The last row contains the sum of all effects for each of the three outputs. In this sum, the interactions are taken into account more than once. According to Equation (7), if these interactions appear in the model, this sum is not equal to 1. However, a 10% margin of error is commonly accepted for the accuracy of each sum of indexes. Charts 1, 2 and 3 of Figure 5 present each output according to the input with the maximum index.

Table 1: RBD-FAST results with all inputs

	ITD_{under} Summer	**ITD_{under} Winter**	**Heating Winter**
Glazing	7%	-4%	0%
Walls Ins.	3%	-1%	**11%**
Crawl Ins.	0%	0%	2%
Attic Ins.	3%	-3%	1%
Air Renewal	**80%** ***(1)***	4%	**60%** ***(3)***
Inertia	-1%	0%	4%
Renewal A.&C.	2%	-1%	2%
Heating Setpoint	-1%	**97%** ***(2)***	**26%**
Sum	93%	93%	108%

The first set of results (Table 1) shows a significant difference between the effects of input parameters.

The behaviour of the housing in summer is dominated by air renewal (80%), which fits well with the condition of free evolution. This result justifies the use of overnight ventilation: the cooling increases with the flow (Figure 5: chart 1). The establishment of a system could be studied by entering an on/off schedule as input parameter.

In winter, comfort assessment depends mostly on the heating setpoint (97%). Chart 2 shows that discomfort exists with temperatures up to 21°C. Since the discomfort zone was defined with a high satisfaction value (90%), a margin is acceptable.

In the third column (heating), the percentage is less important (60%). Thus, results in chart 3 are scattered owing to the setpoints (26%) and wall insulation (11%).

Even if occupant comfort is important to guarantee a minimum performance, ventilation prevails in the internal temperature. The influence of insulation thickness comes in third position.

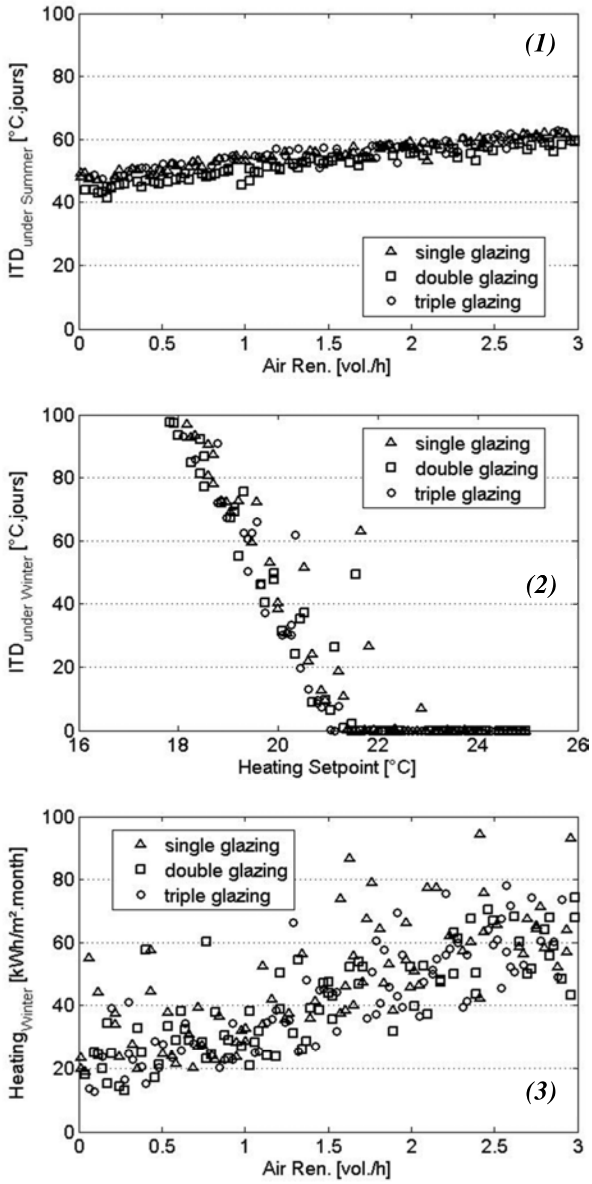

Figure 5: Results organized according to significant inputs in Table 1

It is already possible to conclude that, in the study case, only a good management of fresh air flow will allow energy losses to be cut. Upgrading of ventilation rates is a problem in refurbishment. Moreover, one should pay attention to the windows (most easily replaceable elements) because during their implementation they affect the airtightness of the building. For instance, a poor seal between the frame and the wall made during an opening refurbishment leads to a significant increase in heating consumption.

Here, parameters have highly variable effects. The next subsection presents the results of other simulations, fixing alternatively the most influential inputs.

Impact of Less Influential Variables

To analyse the other parameters accurately, three more sets of simulations are realized. Two types of conditions are added. Influential parameters are fixed for the model to correspond to a degraded building:

- A : Fresh air ren. : 2 vol./h,
- B : Heating setpoint 21 °C.

Table 2 to Table 4 present the results of, respectively, condition A, B and A+B. Each indicator according to the most influential parameter, indicated by (*), is displayed in Figure 6 to Figure 8, respectively.

Table 2: RBD-FAST results with A condition

A- Fresh air ren. : 2 vol./h	ITD_{under} Summer	ITD_{under} Winter	Heating Winter
Glazing	**52% (*)**	0%	5%
Walls Insulation	8%	2%	28%
Crawl Insulation	7%	-2%	0%
Attic Insulation	18%	0%	-1%
Inertia	4%	0%	0%
Renewal A.&C.	3%	-1%	0%
Heating Setpoint	0%	97%	60%
Sum	92%	96%	92%

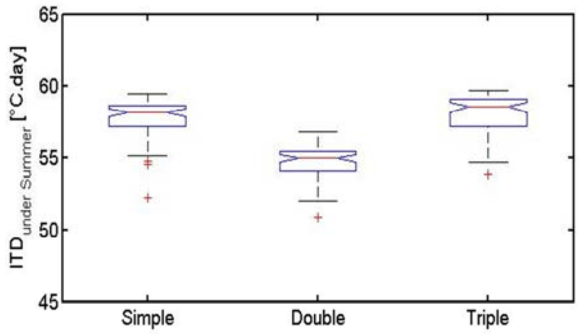

Figure 6: '$ITD_{under\ Summer}$' according to glazing type (with fresh air ren. 2 vol./h)

Table 3: RBD-FAST results with B condition

B- Heating setpoint: 21°C	ITD_{under} Summer	ITD_{under} Winter	Heating Winter
Glazing	8%	2%	-2%
Walls Insulation	8%	**71% (*)**	8%
Crawl Insulation	0%	0%	0%
Attic Insulation	4%	9%	6%
Air Ren.	79%	1%	76%
Inertia	2%	-2%	0%
Renewal A.&C.	3%	-2%	1%
Sum	103%	103%	88%

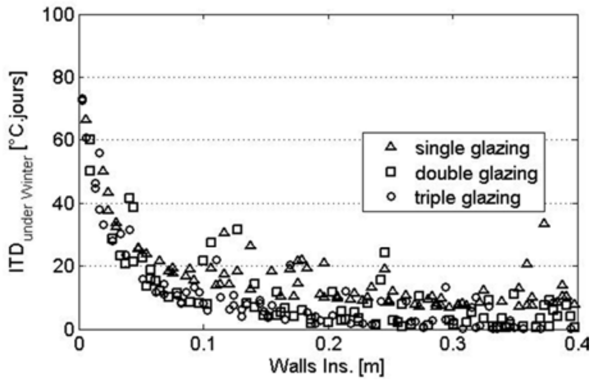

Figure 7: '$ITD_{under\ Winter}$' according to wall insulation (with heating setpoint 21 °C)

Table 4: RBD-FAST results with A&B conditions

A+B	ITD_{under} Summer	ITD_{under} Winter	Heating Winter
Glazing	48%	7%	7%
Walls Insulation	11%	71%	**70% (*)**
Crawl Insulation	5%	0%	0%
Attic Insulation	16%	16%	16%
Inertia	0%	0%	0%
Renewal A.&C.	7%	-2%	-2%
Sum	86%	91%	92%

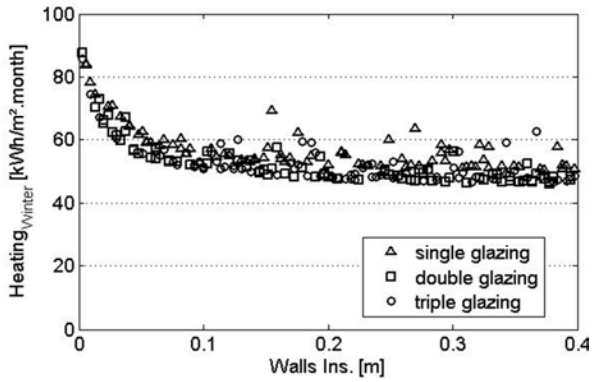

Figure 8: 'Heating Winter' according to wall insulation (with heating setpoint 21 °C and fresh air ren. 2 vol./h)

These new tests raise a few comments on the method. Between tests A and A+B, the addition of condition B (on the heating setpoint) should not have an influence on "$ITD_{under\ summer}$". It should be noted that the results are not exactly the same. This difference is due to the variability of the other inputs. In practice, the analysis is made several times so as to obtain an average effect. However, because of modelling uncertainties, we focus only on the order of magnitude of the indexes. The computing time gains will be used to perform other tests instead.

The influence of the glazing type is presented in Figure 6. The graphical representation is different because of the discrete form of this input. Boxplots were used to display each glazing influence. The five horizontal lines represent the scattering of the data: the smallest observation, lower quartile, median, upper quartile, and largest observation. With this plotting, no prior assumption of the statistical distribution is needed. The result shows a better "$ITD_{under\ summer}$" for the double-glazing.

Except for the type of glazing, which is a discrete input, the newly introduced curves are exponential (Figure 7 and 8). The outputs thus have a significant slope at the start and stabilize with increasing values. The computed effect of indexes is different if the insulation thickness is limited to low or high values. According to Figure 7 and 8, there is no interest in changing the existing insulation if the pre-existing insulation is more than 5–10 cm thick or if there is no major disorder (humidity). On the contrary, adding insulation to non-insulated housing greatly changes its behaviour. In this case, hydrothermal phenomena must be analysed in depth. Likewise, a large insulation thickness does not provide significant advantage. Here, more than 20-cm insulation does not improve the performance or comfort. The same limit is found for the other wall insulation: attic and crawl space. This maximum value obviously depends on the type of construction and the climate.

In conclusion, when the most influential parameters are fixed, the remaining heat scattering is low. For instance: the heating scattering needs changed from 10–80 to 50–60 kWh/month while fixing ventilation, setpoint, window and wall insulation. The optimization is then quasi-complete, keeping in mind that the present case is simplified. The remaining inputs are studied in the next section.

Impact of Inputs: Summary

For each table presented before, it is possible to distinguish a single influencing parameter according to output. In the following, outputs are re-investigated independently, setting the most influential parameter each time and noting its effect.

The values of fixed inputs are shown in Table 5.

Table 6 is presented column by column from top to bottom. Each cell comes from a set of tests in which all the entries listed above the cell are fixed. A significant percentage shows that the variable is highly more influential than the other inputs listed under the cell.

Table 5: Values of fixed input

INPUT	VALUE
Glazing	Double
Walls Ins.	15 cm
Crawl Ins.	10 cm
Attic Ins.	10 cm
Screed Thickness	8 cm
Ren. A.&C.	4 vol./h
Air Ren.	2 vol./h
Heating Setpoint	21 °C

Table 6 : List of parameters according to influence

ITD_{under} Summer	ITD_{under} Winter	Heating Winter
Air Ren. (80%)	Setpoint (97%)	Air Ren. (60%)
Glazing (52%)	Walls Ins. (71%)	Setpoint (60%)
Attic Ins. (40%)	Attic Ins. (36%)	Walls Ins. (70%)
Walls Ins. (32%)	Glazing (51%)	Attic Ins. (36%)
Crawl Ins. (49%)	Crawl Ins. (86%)	Glazing (53%)
Inertia (64%)	Inertia (59%)	Crawl Ins. (88%)
Ren. A.&C.	Ren. A.&C.	Ren. A.&C. (69%)
Setpoint	Air Ren.	Inertia

Optimization methods are generally based on heating needs to assess the quality of a solution. When air renewal and the heating setpoint are fixed, heating and comfort are affected by the same inputs with the same effects (Table 6). Therefore, optimizing the heating should lead to an optimization of comfort. Indeed, the two phenomena are related and so are their indexes.

The flow of fresh air due to airtightness and ventilation is difficult to measure and is highly influential. An error in the airtightness evaluation results in a poor assessment of the needs. According to the comfort model used in this study, the uncertainty generated by these parameters is significant but does not affect the occupants in winter.

The problem of the heating setpoint is different. This parameter greatly influences comfort and heating. A value that is too low leads to o discomfort for the occupants, who would then increase the temperature setpoint. In that case, the simulation achieved would no longer be representative. It is thus very important to pay attention to this value to guarantee performance.

In summer, the issue of over-heating is not a problem in this building. This may be because of the optimized solar shading of the building. The ranking of influential parameters differs completely from that in winter. Solar gains drive the building behaviour, and glazing type and attic insulation are key elements.

In summary, the percentages listed in Table 6 are rather high. In other words, there is a significant difference between each input influence. Subsequently, all the effects related to inertia or the ventilation of non-living spaces are low. However, these parameters should not be overlooked. Indeed, they may interact with more influential parameters and indirectly affect the result.

According to this method, the sum of all the effects presented in the previous tables gives an estimation of the existing interactions. Usually, its value is close to 1 with a margin of error up to 10%. Lower values, such as 0.8, indicate the presence of weak interactions. The complete study of interactions could be achieved with many additional simulations, but another type of analysis should then be implemented.

CONCLUSION

The methodology presented in this paper is based on the choice of indicators. Using sensitivity analysis, indicators allow us to analyse the impacts of inputs on the behaviours of the chosen buildings. Optimal solutions could then be defined by representing the outputs with respect to influential parameters. These solutions would take into account the characteristics of the studied building. Finally, one could choose and validate one of them, fulfilling some of the given criteria.

The results presented in this paper highlight the fact that the most influential parameters are usually badly controlled during refurbishment. For instance, if the regulatory temperature is taken as a reference, comfort conditions may not be fulfilled. Consequently, objectives could be missed by increasing consumption and return on investment time.

Moreover, this paper shows that the input ranking strongly depends on the season. Therefore, to study each parameter, the correlations with the seasons must be clearly understood. For example, it is an obvious problem in passive buildings where heating needs are strongly reduced. This often leads to summer over-heating. The refurbishment designer should choose among the influential parameters, the ones that reduce heating expenses without decreasing thermal comfort.

The next step of this study is the analysis of complete automation. Indeed, given that each parameter has a very different effect, the analysis had to be repeated, fixing influential parameters one by one. Since the computing of the analysis takes about 6 hours, generalization to the other outputs is not possible. Therefore, a reduced model will be computed using polynomial chaos (Sudret, 2008). This would yield the relationships between each variable and allow a quick estimation to be made of the solution sets.

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