A MULTI OBJECTIVE DESIGN TOOL FOR THE FRENCH DETACHED HOUSE MARKET: COST AND ENERGY PERFORMANCE OPTIMIZATION

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ABSTRACT
Considering increasing constraints from building energy performance regulations, such as EPBD for Europe, building design is bounded to become more and more of an integrated process. The dissemination of such complex approaches can be a key issue for the building sector especially for the single house market. The proposed approach aims to overcome this issue through the development of a multiobjective optimization design tool. Automated optimization could be a suitable method to help decision making in such complex problems with many variables and several design functions. The results from the implementation of an NSGA2 optimization algorithm are presented here for a building cost calculation program and the French building regulation core tool for energy performance. In the presented case study of a house design optimization, two different construction types are optimized: masonry and wooden frame houses. In these first results, some specific optimal solution typologies are highlighted. This can give design tendencies, and the use of this tool within a decision support system should allow wider and complex studies.

INTRODUCTION
With the European energy performance of building directive (EPBD) and its recast (EPBD-Recast), the level of requirement on buildings energy performance is gradually increasing for all countries of the European Union with the aim of reaching net zero energy buildings for all new construction projects by 2020. Building design is bounded to become more and more of an integrated process in order to comply with these performance constraints while insuring technical and economic feasibility.

Building computer simulation has been developed for several decades and is now widely used for helping decision making in the design phase of building projects. Although integrated design enables getting good economically and technically feasible solutions, the process is very unlikely to give optimal solutions. The number of parameters that can be changed to improve the design, also called the design space, is simply too vast to be fully explored. Instead, designers rely on their experience to improve building design with regards to their performance criteria.

Over the past two decades, automated optimization has been developed in building research to provide further help in decision making by determining optimal solutions (Evins 2013), (Nguyen, Reiter, et Rigo 2014). It has proven to give substantial help in decision making, especially when several objective functions are considered. Even though several building simulation tools have optimization modules included, it is still rarely used in the building conception industry. The reasons mentioned by experts in the fields include a lack of fully integrated optimization and building simulation tools, a time consuming process of setting both optimization algorithm and building model and a lack of awareness of the potential of optimization in building design by the building industry (Attia et al. 2013). This paper presents multiobjective optimization results obtained using an integrated cost and energy calculation tool under development (Chardon et al. 2014). Two different house construction methods are analyzed: masonry and wooden frame houses.

MATERIALS AND METHOD
Energy performance assessment
In France, the EPBD has been fully transposed and enforced in the legislation. It resulted in a new building energy regulation called RT2012 which sets energy performance and thermal comfort requirements for all new construction built after January the 1st 2013. These requirements intend to be among the most ambitious of all Member States with a primary energy consumption requirement for heating, cooling, domestic hot water, lighting and auxiliaries of 50 kWh/m².year for residential buildings and 70 kWh/m².year for office buildings (Roger et al. 2012). Contrary to simple thermal indexes from steady state calculation and building average U values, the RT2012 relies on a regulatory calculation core called TH-BCE for assessing the overall energy performance and thermal comfort of
the building. Three regulatory indexes have to be assessed:

- A building envelop energy performance indicator (BBIO) based on heating, cooling and lighting energy needs. It is a weighted aggregated index that characterizes the performance of the building envelop, disregarding the systems chosen.
- Primary energy consumption (CEP) which does include energy systems.
- Summer interior conventional temperature (TIC) which is used to characterize summer thermal comfort.

The building energy performance is evaluated using a program implementing the TH-BCE methodology provided by the authorities. In this paper, only the building envelop energy performance indicator (BBIO) is used as an objective function. It expressed without units and is defined as follow:

\[
BBIO = 2 \times \text{Heating needs} + 2 \times \text{Cooling needs} + 5 \times \text{lighting needs}
\]

Cost assessment
A cost calculation function has been developed in Python. It comprises the cost of each design variable based on a vocational cost database called “L’Annuel des Prix” (L’Annuel des Prix 2015). The database is divided in cost items (CI). Each cost item contains a number of working hours (NWH) and a material component cost (MCC). These costs are quantity based, most of the time they are expressed per square meter. The number of working hours is multiplied by the labor hourly cost (LHC) to calculate the labor cost (LC). The material components are usually divided into several element costs (EC) corresponding to various materials. A concrete block component for instance is divided into concrete blocks, sand, cement, water and lime. The element costs are expressed for an existing packaging (P), 35 kg bags for cement for instance. The elements quantities per components (EQ) are also given in the database. A discount coefficient (DC) can be applied to compute the material components costs to account for the construction size. Large construction projects imply large quantities of materials which tend to reduce material costs. Finally a coefficient (C) can be used to customize each component cost. The following equations detail the cost items calculations.

\[
CI = MCC + LC
\]

\[
MCC = \sum P \times EQ \times DC \times C
\]

\[
LC = NWH \times LHC
\]

All costs in the database are based on average values calculated by the company that maintains the database and are updated on a yearly basis. They can all be configured manually if needed be. In this study the costs were kept as they are in the database and the discount and customization coefficients were set to 1. To obtain the cost of each design variable, the cost items are multiplied by the quantity, usually the material surface. It also contains the company margin, here set to 10%. The final cost function used for this optimization case study is the following:

\[
Cost = \sum \text{Cost Item} \times \text{Quantity} \times \frac{100}{100 - 10}
\]

It is worth noticing that the cost function presented here only include the design variables cost and not the total house cost. Because the optimization case study only focuses on building envelop, all items considered are envelop materials.

Optimization algorithm
Optimization in building design has been widely studied for the past two decades. Genetic algorithms were found to perform well as compared to other algorithms for such problems (Attia et al. 2013), (Evins 2013), (Nguyen, Reiter, et Rigo 2014). Like other metaheuristics, genetic algorithms can tackle mixed integer non-linear optimization problems with black-box objective functions and constraints. These problems belong to the NP-hard problem class which can only be handled by a few groups of methods, especially for those with large design spaces (Teghem 2012). In their reviews, Evins and Attia et al. agreed on the genetic algorithms efficiency with regards to building design optimization for the following reasons:

- They do not require any specific knowledge of the objective function, contrary to many heuristic or direct search methods.
- They are faster and more robust than other metaheuristic methods (Tuhus-Dubrow et Krarti 2010), (Brownlee, Wright, et Mourshed 2011).
- They do not get trapped in local minima.
- They are relatively easy to implement.

A non-sorting genetic algorithm (NSGA-II) was hence chosen for carrying out the multi-objective optimization in this study. The algorithm, first invented in 2002 (Deb et al. 2002) has been implemented in a Python package called Deap (Fortin et al. 2012) and is used by the optimization algorithm developed in this study. Figure 1 shows a diagram of the different programs involved in the optimization tool.
Methodology and database management

This work is not intended to only be an optimization study; it is part of a process to create an integrated cost and energy performance optimization tool for house design. Consequently, a user interface has been developed to set the optimization design variables. It enables navigating in cost and products databases simultaneously to gather thermo-physical and cost information. This semi-automatic database interoperability was realized using the resource description framework (RDF) and the web ontology language (OWL) (Kadolsky, Baumgärtel, et Scherer 2014).

CASE STUDY

House

A case study was defined to show the application of the methodology developed in this paper. It consists of the optimization of a single family house of 76.34 m² of net internal area. The house is composed of a single floor as shown in Figure 2. In this case study, the optimization focuses on building envelop cost and energy performance hence no systems are described.

Design variables

The design variables comprise the envelop elements shown in Table 1. Two construction methods are investigated: masonry and wooden frame houses. The wall design variables differ in both cases. For the wooden frame house, the wall structure refers to the width of the timber frames and spacing between each timber (40 cm and 60 cm). In the masonry case, several building blocks are considered such as concrete blocks, bricks and several types of insulated building blocks. Concerning wall insulation, the materials for masonry consist of mineral wool and expanded polystyrene ranging from 6 cm to 16 cm with resistance values ranging from 1.85 m²K/W to 5 m²K/W. For the wooden frame case, only 7 insulated wall solutions were found in the cost database with resistance values ranging from 5.15 m²K/W to 6.1 m²K/W.
Table 1 - Design variables

<table>
<thead>
<tr>
<th></th>
<th>Number of possible values</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Masonry</td>
</tr>
<tr>
<td>Wall insulation</td>
<td>15</td>
</tr>
<tr>
<td>Wall structure</td>
<td>12</td>
</tr>
<tr>
<td>Top floor insulation</td>
<td>20</td>
</tr>
<tr>
<td>Top floor structure</td>
<td>2</td>
</tr>
<tr>
<td>Floor insulation</td>
<td>10</td>
</tr>
<tr>
<td>North bay window</td>
<td>10</td>
</tr>
<tr>
<td>North windows</td>
<td>10</td>
</tr>
<tr>
<td>South windows</td>
<td>10</td>
</tr>
<tr>
<td>Possible combinations</td>
<td>72,000,000</td>
</tr>
</tbody>
</table>

For the windows, 10 different types and sizes of windows were chosen, ranging from a 1.35 m x 0.8 m window to a 2.25 m x 3 m bay window. The design spaces thereby defined contain 72,000,000 (15 x 12 x 20 x 2 x 10 x 10 x 10 x 10) solutions for the masonry case and 11,200,000 for the wooden frame case. A brute force search algorithm where all solutions are evaluated would therefore not be suited here as it would be too long to complete.

Optimization algorithm settings

The optimization algorithm was run multiple times. Setting the number of generations to 300 and the number of individuals per generation to 12 seemed to be a good compromise between computation time and preciseness of approximation of the Pareto front. A higher number of generations and individuals did not significantly improve the Pareto front. The selection operator used is the one developed by Deb et al. (Deb et al. 2002). It first uses a non-dominated sorting operator which ranks the population in non-dominated fronts. The rank of the non-dominated front to which each solution belongs is assigned to each solution. A crowding distance operator is used to evaluate how densely populated the zone around each solution of the population is. Both the non-dominated front ranking and the crowding distance are used as criteria for selecting individuals by the selection operator, here a binary tournament selection operator. A uniform crossover operator is used with a crossing probability set to 0.5 meaning that approximately only half of the solutions in the parent population are selected for this operation. A mixing ratio of 0.2 is set for the crossover operation. A uniform mutation operator is also used with a mutation probability of 0.5. The mutation rate is set to 0.8 meaning that once chosen to mutate, each gene of an individual has 80% chance of mutating. All these settings are summarized in Table 2. Different settings were tried and these seemed to give the best compromise between search intensification and diversification.

Table 2 - Algorithm settings

<table>
<thead>
<tr>
<th>Type of operator</th>
<th>Selection</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Binary tournament selection using non-dominated sorting and crowding</td>
</tr>
<tr>
<td></td>
<td>distance operators (Deb et al. 2002)</td>
</tr>
<tr>
<td>Crossover</td>
<td>Uniform crossover</td>
</tr>
<tr>
<td></td>
<td>Crossover probability = 0.5</td>
</tr>
<tr>
<td></td>
<td>Mixing ratio = 0.2</td>
</tr>
<tr>
<td>Mutation</td>
<td>Uniform mutation</td>
</tr>
<tr>
<td></td>
<td>Mutation probability = 0.5</td>
</tr>
<tr>
<td></td>
<td>Mutation rate = 0.8</td>
</tr>
</tbody>
</table>

RESULTS

Masonry case

Figure 3 shows a plot of the regulatory energy performance BBIO index and cost of all solutions calculated for two different French climates. The blue crosses and dots correspond to the South West French climate (La Rochelle) while the red ones correspond to the North West French Climate (Rouen).

The optimal Pareto front for the South West climate reveals three different “zones”. In zone 1, the energy performance improves as the insulation material resistance increases either in walls, roof or floor. All solutions in this zone are characterized by small south facing windows (1.35m x 0.8m). The cost is small as compared to zone 2 and 3 because a m² of wall is cheaper than a m² of window. In zone 2 the regulatory energy performance BBIO index decreases as larger windows (up to two 2.25m x 3m bay windows) are chosen facing south. Solar gains increase for these solutions as compared to zone 1 which is thought to be the reason for this improvement in energy performance. Finally, zone 3 corresponds to the most energy efficient solutions. They are obtained by using insulated building blocks for the wall structure and large south facing windows as in zone 2. The level of insulation is therefore improved but it only leads to a small energy performance improvement while cost is significantly higher due to the expensive insulated bricks or concrete blocks.
Some design recommendations can be drawn for this particular case: increasing the level insulation materials is the priority for optimally improving the building design with regards to cost and energy performance. Then, the window surfaces facing south should be maximized. Insulated building blocks did not perform well as they are selected only in the most expensive alternatives and do not provide significantly better energy solutions.

Concerning the North West case (red), the optimal Pareto front seems shifted toward the right. Colder temperatures lead to an increase in heating demand hence in the regulatory energy performance BBIO index. For this region, the regulatory threshold value for the BBIO is also higher as it is 79.8 as compared to 67.8 for the South West case. The same three zones can be defined although some differences can be observed. Firstly, the energy performance improvement from zone 1 to zone 2 is smaller than in the previous case. This is thought to be due to a smaller solar irradiance in the northern case hence the benefits of large south facing windows are smaller. Secondly, zone 3 is wider in this case. As the climate is colder, increasing the insulation level by using insulated blocks has a more significant influence on the energy performance than in the previous case.

The design recommendations are therefore similar to the previous ones except that south facing windows are of lower importance while insulated bricks or concrete block are more relevant in this case.

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**Wooden frame house**

The results from the wooden frame house optimization are shown in Figure 4. The range cost values is much smaller than in the case of masonry as the cheapest solution has a cost of 24 173 € while the most expensive one costs around 28 100 €. This is due to a less diversified availability of wall insulation and structure products in the cost database for wooden frame houses than for masonry ones. Similarly to the previous results, two different zones can be highlighted. Zone 1 corresponds to solutions where small windows are chosen facing south while zone 2 characterizes solutions with larger ones. All optimal solutions use timber frames with a 60 cm spacing. Using a 40 cm spacing results in a higher cost and larger thermal bridges losses. The solution costs here are higher than in the masonry case for a given energy performance. This tends to show that wooden frame houses are more expensive alternatives. A more detailed cost assessment of the entire house would be needed to confirm this tendency.

The design recommendations are therefore similar to the masonry case with respect to windows and insulation. Concerning timber frame, a 60 cm spacing gives better results both in terms of energy performance and cost.
DISCUSSION
The optimization results enabled pointing out design recommendations for both the wooden frame and masonry cases. They give examples of how the final tool could be used for design purposes but are not intended to be taken as general design guidelines as they were obtained from a specific case study using a restricted amount of design variables. The application of the method to a case study with more design variables would need to be considered. Literature shows that this type of algorithm scales well when the number of objective functions and size of the design space increase (Khare, Yao, et Deb 2003). The various parameters that can be adjusted in the optimization algorithm (number of individuals per generation, number of generations, mutation, selection and crossover rates etc.) ensure the possibility of keeping a good balance between the intensification of the search and its diversification. The limitation of the method with regards to the problem size is expected to come mostly from computation time. Several strategies could be used to overcome this issue such as enabling parallel computing on several computers for instance.

Another limitation of the method in terms of cost and energy estimation is that it does not account for data variability. The method does not provide information on how the optimal Pareto front would vary with a change in input data. This could typically be the case if the design variables values are not precisely known at early design stages. Statistical method such as sensitivity analyses could be coupled to the tool to provide such information.

CONCLUSION
Preliminary results from a house cost and energy performance optimization tool under development were presented in this paper. The results seem promising as it enabled solving optimization problems with design spaces containing 72,000,000 possible solutions in 30 minutes on a desktop computer. Examples of recommendations for cost and energy performance optimal designs were obtained for a given case study using two different types of construction: masonry and timber frame houses. The use of a regulatory building energy performance program enables respecting the building regulation but lacks of indicators such as solar gains for instance to fully understand the buildings behavior. Perspectives of this work include reassessing automatically the solutions located on the Pareto front with a building energy simulation tool to get more detailed results, add energy systems to calculate primary energy consumption and thermal comfort and develop the cost function in order to compute the total house construction cost.

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REFERENCES


