Optimization method using genetic algorithms for designing high performance building

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SUMMARY

In the framework of the OPTISOL project, funded by the French Agency for Energy and Environment (ADEME), a methodology for life cycle optimization during sketch or refurbishment has been developed for professional building actors: architects, building owners, designers, HVAC engineers… First, a French typology of tertiary buildings has been created: partitioned and open space offices, hospitals, schools and nursing homes. Once done, a proposal list of systems related to each building was developed. To minimise the number of simulations and to establish a 15 parameters function providing energy consumptions for each building with each system, in each climate, simulation experimental designs were used. The methodology developed was implemented in a software tool to facilitate its use. Two options are proposed to users: to perform the calculation of energy consumption, CO_2 emission and investment for chosen solutions or to perform different optimization calculations resulting in technical proposals.

INTRODUCTION

In France, the total consumption of the tertiary sector represented by 839 millions of m² was estimated in 2004 to 218.5 TWh splited as follows: 88.1 TWh for electricity, 70.6 TWh for gas and 59.7 TWh for other uses [1]. The typical consumption per sector is presented in the table below.

Table 1: Energy consumption for tertiary sector in France [1]

Sector	Surface	Consumption	Average consumption
	millions of m²	TWh	kWh/m²
Offices	179.7	52.4	283
Schools	169.9	26.2	131
Hospitals and social buildings	97.3	26.2	221
Total	839.2	218.5	222

Improving the energy efficiency of the existing buildings stock must be tackled urgently to deal with climate change, energy security, economic crisis and peak oil. To reach this objective, decision makers have to take into account energy, environment and economic

aspects. In most of cases, designers are experts in one field and they need a simple and a global approach tool to make a multicriteria optimization at the very beginning of the project.
In order to propose an optimization methodology without simulation, we were interested in experiments designs and genetic algorithms. In this article we will present the two methods and discuss results obtained for an air conditioned small suburban office.

METHODS

1. Typology

Under the project "office building consumption less than 100 kWh/m²/year" interested on air-conditioned solutions for office buildings, five types of buildings have been selected: large open space, large partionned offices, small open space, refurbished building and small suburban office [2].
From plans of these buildings and databases of existing building, a table characteristic of a small suburban office was established (Table.2).

Table 2: Characteristics of a small suburban office

<table>
<tr><td colspan="2">Number of floors</td><td colspan="4">2</td></tr>
<tr><td colspan="2">Surface (Floor area)</td><td colspan="4">1000</td></tr>
<tr><td colspan="2">Floor Ceiling Height (m)</td><td colspan="4">2.7</td></tr>
<tr><td colspan="2">U_{wall} (W/m².K)</td><td colspan="4">0.6</td></tr>
<tr><td colspan="2">U_{roof} (W/m².K)</td><td colspan="4">0.3</td></tr>
<tr><td colspan="2">U_w (W/m².K)</td><td colspan="4">3</td></tr>
<tr><td colspan="2">Solar factor without Solar Protection /with SP</td><td colspan="4">0.7/0.2</td></tr>
<tr><td colspan="2">Light transmission without Solar Protection/with SP</td><td colspan="4">0.7/0.2</td></tr>
<tr><td colspan="2">Air tightness ($m^3/h/m^2$ under 4 Pa)</td><td colspan="4">1.2</td></tr>
<tr><td colspan="2">Losses Surface (areas)/floor</td><td colspan="4">1.02</td></tr>
<tr><td colspan="2">Windows surface/floor area</td><td colspan="4">0.2</td></tr>
<tr><td colspan="2">Inertia</td><td colspan="4">Medium</td></tr>
<tr><td></td><td>Percentage of surfaces per use (%)</td><td>Lighting (W/m²)</td><td>Internal loads (W/m²)</td><td>Occupation</td><td>Air flow</td></tr>
<tr><td>Offices</td><td>0.54</td><td>18</td><td>15</td><td>1 p / 12m²</td><td>25 $m^3/h/p$</td></tr>
<tr><td>Conference room</td><td>0.18</td><td>18</td><td></td><td>1 p/ 3.5 m²</td><td>30 $m^3/h/p$</td></tr>
<tr><td>Sanitary</td><td>0.03</td><td>6</td><td>0</td><td>0</td><td>Extraction zone</td></tr>
<tr><td>Corridors</td><td>0.25</td><td>12</td><td>0</td><td>0</td><td>Extraction zone</td></tr>
</table>

2. Simulation tool

To determine the consumptions for each building with each solution, we used a methodology studied in thesis of Filfli [3] and Chlela [4] consisting of using numerical simulation tools and experiment designs (DOE) to develop polynomials allowing to evaluate the energy consumption of buildings.

To establish polynomials, ConsoClim was selected as a simulation tool. It was developed by CSTB and Center for Energy and Processes of MINES Paris Tech in 1999. ConsoClim

calculates the energy consumption of air-conditioned buildings. It is composed of a series of algorithms which make it possible to assemble different air-conditioning systems: fan coil units with or without integrated fresh-air inflow, air handling units with constant and variable flow, reversible water-loop units, rooftop units, variable refrigerant volume systems.
The various parts of a building are grouped into homogeneous units and are connected to a central hot and/or cold fluid-production station, as required.
ConsoClim is therefore designed to be simple and precise. Its building model [5] is based on a simplification of the heat transfer between internal and external environments. A R5-C1 equivalent electric configuration of building components is implemented in this software. The main advantage of the model is its simplicity. Inputs are easy to define and include variable solar protection. The building is described by three temperatures: T_a, indoor temperature, T_m, mass temperature and T_s mean temperature from indoor temperature and mean radiant temperature.
Three outdoor temperatures allow to define heat exchange (Figure.2) T_e, outdoor temperature, T_{es}, solar equivalent temperature for light external components, T_{em}, solar equivalent temperature for heavy external components. T_e is an input and T_{es} and T_{em} are calculated from T_e, direct solar radiation, long wave sky radiation and wall characteristics.

R_{ei} [K/W]: New air flow rate thermal resistance
R_{es}, R_{em} [K/W]: Thermal resistances between indoor and outdoor of light and heavy components
R_{is},R_{ms} [K/W]: Thermal resistances between internal surfaces of light and heavy components and air thermal resistances
R_{is}, R_{ms} and R_{em}: Constants characterizing the building
R_{ei} : Resistance related to ventilation and airtighness
R_{es}: Resistance related to solar protections management

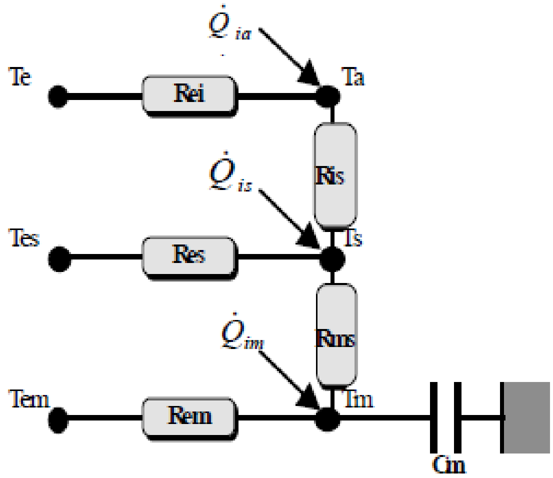

Figure 1: Building model [6]

Heat flux Q_{ia}, Q_{is} and Q_{im} represent heat flux on indoor air, light components and heavy components due to internal gains and solar radiation. Internal gains and solar radiation are split into a convective part and a radiative part.

Thanks to Tagushi tables [7] functions of 15 main variables were established: wall insulation, roof insulation, windows thermal resistance, solar factor of windows, natural lighting transmission of glasses, percentage of windows, internal gains, artificial lighting power, artificial lighting management, solar protections, inertia, air tightness, exhaust air recovery efficiency, boiler efficiency or heat pump COP, cooling EER.

The factorial design depends on the number of levels chosen for each parameter and on the evolution of the answers (2 levels if it is a linear and more than 2 if it is not linear). As an example, the factorial design for heating consumption is presented below.

As the transmittances of walls, of windows, of roof and the boiler efficiency represent the most influencing parameters on heating consumption, the model will be as follows:

$$C_{ch}(kWh/m^2) = C_0 + U_{wall} + U_w + U_{roof} + \eta_{ch} + \eta_{ch}.U_{wall} + \eta_{ch}.U_{roof} + \eta_{ch}.U_w \quad (1)$$

η_{ch}: efficiency of the boiler ; C_0 : constant value; C_{ch} (kWh/m^2) : heating consumption

In this example, we have 4 factors, 3 interactions and one constant. The design experiments level must be higher than 8. So, in Tagushi tables, the table $L_8(2^7)$ was selected (Table.3).

Table 3: Tagushi table $L_8(2^7)$ [7]

n°	η_{ch}	U_{wall}	$\eta_{ch}.U_{wall}$	U_w	$\eta_{ch}.U_w$	$\eta_{ch}.U_{roof}$	U_{roof}
1	-1	-1	-1	-1	-1	-1	-1
2	-1	-1	-1	1	1	1	1
3	-1	1	1	-1	-1	1	1
4	-1	1	1	1	1	-1	-1
5	1	-1	1	-1	1	-1	1
6	1	-1	1	1	-1	1	-1
7	1	1	-1	-1	1	1	-1
8	1	1	-1	1	-1	-1	1

The range of variation between the low and high levels was defined following the existing solutions and the best products on the market (Table.4).

Table 4: range variation of values

N°	Variable	Units	Low level	High level
1	Thermal transmittance of the walls : U_{wall}	(W/m^2.K)	0.15	1.6
2	Glazing ratio (glazing area / façade area)	-	25 %	75 %
3	Thermal transmittance of the windows : U_w	(W/m^2.K)	1.2	4.5
4	Thermal transmittance of the roof : U_{roof}	(W/m^2.K)	0.1	1.3
5	Air tightness	m^3/h/m^2 under 4 Pa	1.2	3
6	Inertia		C_m = 110 A_m = 2.5 => low	C_m = 260 A_m = 3 => heavy
7	Presence of solar protection : PS	-	0	1
8	Solar factor	-	0.1	0.9
9	Light transission	-	0.1	0.9
10	Internal loads : IG (without occupants)	(W/m^2)	5	25
11	Artificiel lighting power	(W/m^2)	8	20
12	Lighting management	-	Dimmer +presence detector	Switch
13	Cooling efficiency : EER	-	1.5	4.5
14	Efficiency of boiler η_{ch} COP	-	0.55 2	0.978 5.7
15	Efficiency of heat recovery : η_{exch}	-	0.5	0.9

After multiple simulations, the heating consumption model can be written as below:

$$C_{ch}\,(kWh\,/\,m^2) = 49 + \begin{bmatrix}-1.75 & 1.75\end{bmatrix}\begin{bmatrix}U_{wall}\end{bmatrix} + \begin{bmatrix}-10.09 & 10.09\end{bmatrix}\begin{bmatrix}U_{w}\end{bmatrix} + \tag{2}$$

$$\begin{bmatrix}-2.81 & 2.81\end{bmatrix}\begin{bmatrix}U_{roof}\end{bmatrix} + \begin{bmatrix}-7.28 & 7.28\end{bmatrix}\begin{bmatrix}\eta_{ch}\end{bmatrix} + {}^{t}\begin{bmatrix}\eta_{ch}\end{bmatrix}\begin{bmatrix}0.52 & -0.52\\ -0.52 & 0.52\end{bmatrix}\begin{bmatrix}U_{wall}\end{bmatrix} +$$

$${}^{t}\begin{bmatrix}\eta_{ch}\end{bmatrix}\begin{bmatrix}1.68 & -1.68\\ -1.68 & 1.68\end{bmatrix}\begin{bmatrix}U_{w}\end{bmatrix} + {}^{t}\begin{bmatrix}\eta_{ch}\end{bmatrix}\begin{bmatrix}-0.61 & 0.61\\ 0.61 & -0.61\end{bmatrix}\begin{bmatrix}U_{roof}\end{bmatrix}$$

The accuracy of the results obtained has been carefully studied. The difference between results obtained with simulation and polynomial are generally around the range of ± 1% and does not exceed 3%.

3. Optimization method

In order to develop the optimization method, the existing methods and applications presented in the literature were compared. Goldberg [8] classifies optimization methods under three groups: enumerative, calculus based and random.

- Enumerative methods

The principle of this method is simple. Within a finite search space, or a discretised infinite search space, the algorithm assesses the fitness function at every point in the space, one at a time. In spite of its simplicity of implementation, this method is not considered efficient. Consequently, this method is not convenient for our problem.

- Systematic methods

Those methods are called systematic [9] or exact methods [10] and are based on a rigorous mathematical expression of the objective function or of its gradient.
There are two classes of systematic search methods: direct and indirect. Indirect methods try to find local optimal by solving the set of equations resulting from setting the gradient of the objective function equal to zero. Direct search methods seek local extremum by hooping on the function and moving in a direction related to the local gradient [8].

Several authors Göktun [11], Kilkis [12] and Bouchlaghem [9] selected these methods to optimize heating or cooling systems and to improve the efficiency of low energy buildings.

As the convergence of these methods depends on regularity hypotheses of the objective function, on the starting point and on the convex validation of the explicit function these methods become not adapted to our problem.

- Random methods

The random or stochastic methods are based on a random evolution of solutions. These methods have often been developed by analogy to other phenomena. We can list several methods: simulated annealing, taboo search, ant colony algorithm, genetic algorithm…
Genetic algorithms remind the most popular random methods. It is based on mechanisms of genetic concepts [8]. The method uses a population of solutions. Each iteration involves a competitive selection to remove poor solutions. After several iterations, the final population consists of improved solutions.
In building area, genetic algorithms are applied to optimize various aspects. Lu [13] used genetic algorithms to minimize energy consumption of a set of HVAC systems and Chow

[14] carried on a detailed optimization of an absorption chiller system. In architectural design, Caldas [15] used them to define an optimal sizing of the windows. Some recent research works use genetic algorithms for the energy design of the building. This method was selected to solve our problem.
Initially many individual solutions are randomly generated to form an initial population (Figure.2). During each successive generation, a proportion of the existing population is selected to breed a new generation. After a chromosomal recombination: crossover and mutation, a new generation is obtained. This one in assessed. Individuals with the highest fitness are selected as parents for the next round of recombination. The process stops after a fixed number of generations proposing the optimized solutions.

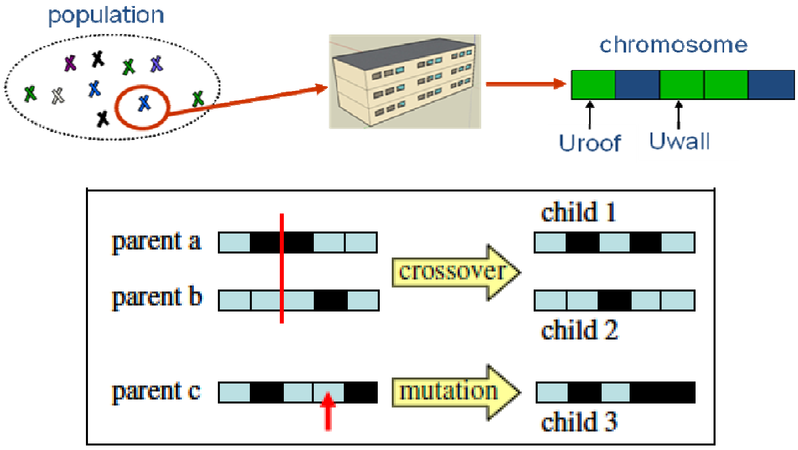

Figure 2: Principle of genetic algorithm

To provide different optimization models, three objective functions were proposed: energy consumption, investment and overall cost. Objective functions are summarized below.

Overall cost optimization : $FO = overall\cos t(x)$ (3)

Fixed investment optimization : $FO = conso(x) + 10^{80} * (invest(x) - investfixed)^2$ (4)

Fixed energy consumption optimization : $FO = invest(x) + 10^{80} * (conso(x) - consofixed)^2$ (5)

Where:

$$conso = \sum conso\_i \quad (6)$$

$$invest = \sum P_i \quad (7)$$

i : heating, cooling, electricity
P_i : price of walls, roof, windows, solar protection, systems (heating, cooling, ventilation)

RESULTS

In this article, we study the refurbishment of a small suburban office located in Nice with an annual energy consumption target corresponding to 50 kWh final energy/m². This type of optimization corresponds to the fixed energy consumption optimization.

Initially, the office was equipped with a gas boiler for heating, a chiller for cooling and ventilation with mechanical extraction to guarantee the indoor air quality. Solar factors and light transmission were 0.7 and air tightness 1.2 under 4 Pa. The initial characteristics of the office are presented in the column “initial” in Table 5.

Before the refurbishment, the annual energy consumptions of the office was 104.8 kWh (final energy)/m². A set of optimization objectives were performed (Table.5). In optimization A, the objective is to keep the same installations facilities and replace existing systems by efficient ones. In optimization B, the ventilation system is changed to balanced system with a heat exchanger.
In optimization C, the cooling and heating systems are changed to a heat pump. In a second series (D,E,F), before running the optimization following optimization ways A,B and C, solar protections are added and light switches replaced by dimmers and presence detectors.

Table 5: Optimization results

	Initial	Opt. A	Opt. B	Opt. C	Opt. D	Opt. E	Opt. F
U_{wall}(W/m^2.K)	0.6	1.6	1.6	1	0.15	0.15	0.9
U_{roof}(W/m^2.K)	0.3	0.1	0.1	0.8	0.1	0.1	0.6
U_w(W/m^2.K)	3	1.2	1.2	3.2	1.2	1.2	3.2
Internal loads(W/m^2)	15	5	5	5	5	5	7
Lighting power (W/m^2)	15	8	8	8	8	8	8
Inertia	Average	Heavy	Heavy	Lower	Heavy	Heavy	Heavy
Solar protections	No	No	No	No	Yes	Yes	Yes
EER or COP		4.5	4.5	2.7	4.5	4.5	2.8
η_{ch}	0.8	0.978	0.978		0.978	0.978	
η_{exch}			0.576	0.522		0.5	0.508
Heating power (kW)		54	54	38	74	73	54
Cooling power (kW)		24	22	74	16	11	34
Investment (€)		242 209	259 322	181 905	312 498	332 402	202705

Results presented above, present possibilities provided by the tool developed but also some limits. The first refurbishment step with the slightest cost following optimizations A, B, D, E propose to improve the insulation of the roof, the replacement of the windows and an increase of the building inertia. For optimization A and B, a degradation of the insulation of the walls is proposed. Second step, consists on the replacement of the existing systems providing heating and cooling by efficient ones.
In Opt. D and E, solar protections and efficient lighting are installed before looking for an optimized package. The solutions obtained are more expensive than A and B but more efficient for summer comfort. This type of information is not provided. To take this information into account, a comfort evaluation function would be added.
The optimization C and F represent the cheaper proposed packages based on a new heating and cooling systems and a degradation of the envelope.
Through the results proposed, U_w is strongly reduced to 1.2 while the solar factors remained at a fixed high value of 0.7. These results do not take into account the fact that, for a given glazing, a decrease of a transmittance tends to lead to a decrease of the solar factor. To solve this type of problem, it could be interesting to consider discrete variable parameters corresponding to existing products or coherent systems rather than to use continuous variables.

Following optimization C and F, the package proposed for refurbishment consists on a degradation of the walls, roof and windows insulations and, a selection of a low efficient heat pump. It corresponds to the limits of the developed tool. Solutions proposed must be efficient than existing.

CONCLUSION

In this article, we present the development of a simple optimization method based on experiments methods and genetic algorithms. It allows decision makers to establish refurbishment scenarios or to compare different possibilities for a new building.

However, the proposed functions are adapted to a specific typology in a given climate and with specific systems. To study a building with a different shape and systems needs to establish new functions with a new experiment designs. Through this assessment and results presented in this article, some improvements were identified: use discrete solutions, add functions related to environmental evaluations, to comfort and use a dynamic tool.

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