USE OF GENETIC ALGORITHMS FOR MULTICRITERIA OPTIMIZATION OF BUILDING REFURBISHMENT

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ABSTRACT

In the current context of energy crisis and with the debate on climate change, low-energy buildings are required. Designers have to come to a compromise between the energy consumption, the economic cost, the comfort and the environmental impact of the building.

In this article, we focus on the development of an optimization method dealing with these objectives. The method, based on genetic algorithms, takes into account the multicriteria aspect of the building refurbishment.

We discuss the pertinence of the method, its robustness and the part of simulations through its application on the refurbishment of school building in France. We suggest improvements for the optimization method.

INTRODUCTION

In the current context of energy crisis and with the debate on climate change, low energy buildings are required. Designers have to deal with heating but also with air conditioning and specific uses of electricity. The weight of these spending categories increases strongly. Designing low energy buildings is not enough: it is necessary to take into account the economic and environmental aspects of building and also the thermal and visual comfort.

In our work, we choose a global approach to optimize the building. This article presents the development of a multicriteria optimization method for tertiary building. We use genetic algorithms to reach an optimized choice for building refurbishment.

There are three parts in this article. In the first one, we review the existing optimization methods and we explain the reasons why we choose genetic algorithms. In the second part, we describe the method we develope. In the last part of the article, we focus on the implementation of the method and on the results obtained.

CHOICE OF OPTIMIZATION METHOD

In order to develop our optimization method, we were interested in various existing methods and applications found in the literature.

Vocabulary

This type of method permits to solve an "optimization problem", it allows finding at least one solution that minimizes or maximizes a particular criterion. This criterion is often represented by an objective function or a fitness function (Barichard, 2003). This fitness function depends on variable parameters that describe the solutions. The variable parameters can be continuous or discrete (Nielsen, 2002).

The distinction between monocriteria optimization and multicriteria optimization is based on the nature of the objective function: when it corresponds to a unique criterion, we speak of monocriteria optimization, when it deals with several objectives, we speak of multicriteria optimization (Mansilla-Pellen, 2006).

In our case, the problem is to optimize refurbishment scenarios: the variable parameters are the characteristics of the measures included in the refurbishment scenarios and the objective functions are linked with energetic consumption, environmental impact of the building, economics and comfort.

Various optimization methods

Optimization methods can be classified into three groups (Goldberg, 1989): enumerative, calculus-based, and random.

- Enumerative methods

The principle of enumerative search method is simple. Within a finite search space, or a discretized 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 suffers from a lack of efficiency. This method cannot be used with large search spaces. Consequently, this method is not convenient for our problem.

- Calculus-based methods

The calculus-based methods are sometimes called systematic (Nielsen, 2002) or exact methods (Bourazza, 2006). These methods 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

optima by solving the set of equations resulting from setting the gradient of the objective function equal to zero. Direct search methods seek local extrema by hooping on the function and moving in a direction related to the local gradient (Goldberg, 1989).
Several authors (Göktun et al., 2001; Kilkis, 2006) used these methods to optimize heating and cooling systems. Bouchlaghem (Bouchlaghem et al., 1990) used a calculus-based method called simplex to improve the efficiency of low energy buildings.
These methods have two main limits. First of all the convergence of these methods depends on regularity hypotheses of the objective function. We have to know an explicit expression of the function and sometimes, the function must be continuous or admit derivatives. Furthermore, these methods are local search methods. They converge on the global optimum only if the starting point of the algorithm is in the neighbourhood of this optimum. In the case of objective function with several local optima, the implementation of theses methods become laborious.

- Random methods

The random or stochastic methods are based on a random evolution of the 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…
Simulated annealing is based on thermodynamics and can be compared to the physical annealing process where a molten material with a high temperature is slowly cooled and forms crystals. The objective function is represented by the internal energy and the algorithm seeks minimal energy state. Nielsen (Nielsen, 2002) developed his own optimization method based on simulated annealing. With this method, he tried to design building with optimized life cycle analysis.
Taboo search uses a memory of past moves to diversify the search and avoid becoming trapped in local minima (Barichard, 2003).
The ant colony algorithm permits to solve problems that can be reduced to finding good paths through graphs. It works like a colony of insect looking for food and is based on collective intelligence (Dietz, 2004).
Genetics algorithms are evolutionary algorithms, using an analogy with the mechanisms of natural selection and genetic concepts (Goldberg, 1989). 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.
Genetic algorithms are used to optimize various aspects of the building. Lu (Lu et al, 2005) uses genetic algorithms to minimize energy consumption of a set of HVAC systems and Chow (Chow et al. 2002) carries on a detailed optimization of an absorption chiller system. In the field of architectural design, genetic algorithms help sometimes the choice of building shape. For instance, Caldas (Caldas and Norford, 2002) uses them to define an optimal sizing of the windows, through the study of the thermal and visual performances. Some recent research works use genetic algorithms for the energy design of the building. Wang (Wang et al, 2005) uses them to optimize the design of “Green Buildings” and Charron (Charron et al, 2006) improves the energy consumption of “net-zero energy solar homes”.

Multicriteria optimization

In the previous paragraphs, we attempted to describe monocriterion problems of optimization. However, in most of the real cases, we have to optimize simultaneously several objective functions. Moreover, these functions are often contradictory.
At the end of the XIXth century, an economist named Pareto developed a optimum concept for multi-objective problems (Dietz, 2004). This concept treats all objectives independently of others during the optimization and deduces the compromise between objectives by determining the non-dominated solutions.
A solution is non-dominated or “Pareto optimal” when no other feasible solution exists that decreases one objective without causing simultaneously an increase in at least one other objective. When the problem treats two objectives (for example financial cost and energy consumption), the result of the optimization is a curve of non-dominated solutions, called the Pareto curve (Wang et al, 2005; Verbeeck, 2007).
Figure 1 presents an example of Pareto curve for an optimization problem with two objectives.

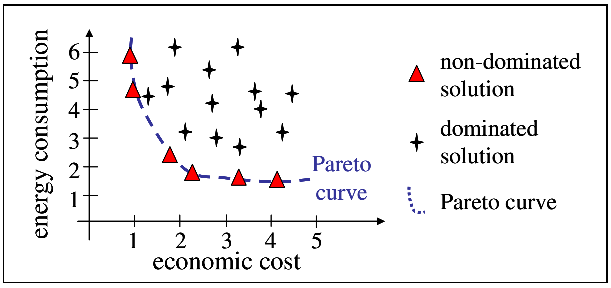

Figure 1 – An example of Pareto curve

For an optimization with three objectives, the result consists of a Pareto surface. For more than three objectives, Pareto optimization can be done but no direct visualization is possible..
With the Pareto method, the objectives are treated independently during the optimization. The different objectives are identified as independent fitness functions. Some methods by-pass the multi-objective aspect of the problem and consider an objective as a constraint. In other methods, like the aggregation method, the balanced sum of the different objective functions is defined as the new objective function. The Pareto concept allows to obtain a set of improved solutions among which we can establish preferences.

Characteristics of our optimization method

We try to optimize refurbishment scenarios of buildings, dealing with energy consumption, economic cost, comfort or environmental impact. The problem we consider is multi-objective.
The nature of the objective functions can guide the choice of optimization method. To assess the energy consumption of a building, we can use a simplified method or dynamic thermal simulations. When we use dynamic simulations, we do not have any rigorous and explicit expression of the objective function. We have no idea about the regularity of the function. Consequently, in order to preserve our choice of tools for the assessment of energy consumption or comfort, the optimization method must admit irregular objective functions.
The variable parameters of the problem represent the characteristics of the refurbishment scenarios. These parameters may be continuous like a U-value or discrete like a type of isolation material. Therefore, the optimization method has to deal with several types of variable parameters.
The problem we consider is complex. The objectives are sometimes contradictory and many local optima could exist. Thus, the optimization method must conduct global search.
Considering the previous remarks, we can already direct our choice of optimization method. Our search domain corresponds to the refurbishment scenario possibilities. This search domain is too large for using enumerative methods. We have no idea about the form of objective functions; it seems difficult to implement calculus-based methods. We choose consequently to work with random methods.
Among the stochastic methods, the genetic algorithms seem to be the most used for the optimization in the building sector. According to literature (Dietz, 2004; Wright et al., 2005; Bourazza, 2006; Znouda et al., 2006), this method has several advantages:

- It is very robust; the choice of the algorithm parameters does not influence the quality of the solutions;
- The implementation of this method requires no knowledge on the mathematical structure of the problem;
- The genetic algorithms seek solutions in the whole search domain and random transition rules permit to find global optimum;
- At the end of the optimization process, we obtain a population constituted by good optimized solutions. This variety of solutions seems more interesting than a unique solution, especially within the framework of a multicriteria optimization.

The advantages of the genetic algorithms seem to correspond to our expectations and to the specificities of our problem. We thus choose to use genetic algorithms to optimize the refurbishment scenarios of buildings.

SIMULATIONS – IMPLEMENTATION OF THE OPTIMIZATION METHOD

In this part, we describe an example of the implementation of genetic algorithms for the optimization of refurbishment scenarios.

Principles

As explained previously, the use of genetic algorithms is based on the evolution of a population of individuals, each individual being a solution of the optimization problem. In our case, an individual corresponds to a building on which a refurbishment scenario was implemented.
A chromosome represents every individual. The genes of this chromosome corresponding to characteristics of the individual. When a scenario deals with wall insulation or heater efficiency, the chromosome contains genes related to each of these characteristics. The figure below (Figure 2) presents this principle.

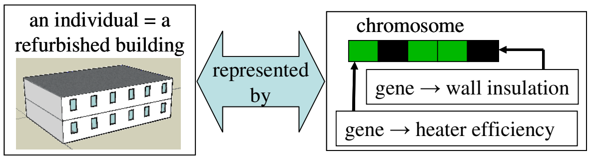

Figure 2 – A solution represented by a chromosome

In this article, we study the implementation of the method on the refurbishment of school building in France. Consequently, we define variable parameters and objective functions adapted to our example.

Initial characteristics of the building

In this example, we consider the refurbishment of a particular type of school. The plan of this school was defined from a typology of the French building stock (OPTISOL, 2008). It is thus representative of existing school buildings. The figure below (Figure 3) presents a simplified plan of the studied school.

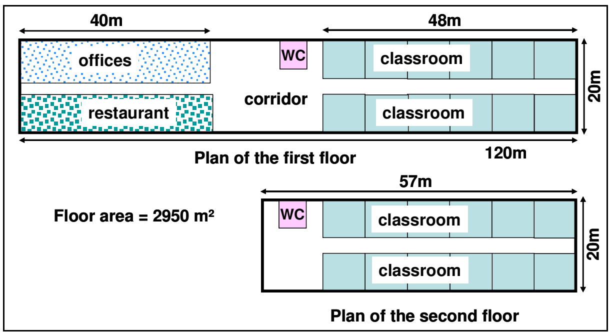

Figure 3 – Simplified plan of the school

From this building model and with the optimization tool (OPTISOL, 2008), we are able to give leads for the refurbishment of this type of school.

Definition of the variable parameters

For this example, we consider the following variable parameters. The last one is a discrete parameter. The others are continuous; they can vary in their definition domain. For instance, U_{wall} can take all values between 0,15 W/m².K and 1,6 W/m².K

- U_{wall}, thermal transmittance of the walls (W/m².K) [0,15 ; 1,6];
- U_{wind}, thermal transmittance of the windows (W/m².K) [1,2 ; 4,5];
- GR, glazing ratio (glazing area / façade area) [25% ; 75%];
- SF, solar factor of the windows [0,1 ; 0,9];
- U_{roof}, thermal transmittance of the roof (W/m².K) [0,1 ; 1,3];
- AT, air tightness of the building envelope (m^3/h.m² under 4 Pa) [1,2 ; 3];
- LP, artificial lighting power W [8 ; 20];
- LS, lighting regulation [switch, occupancy sensor, daylight sensor].

Definition of the objective functions

From the variable parameters defined above, we can form an initial population of solutions. To estimate these solutions and keep those that have high fitness, we define objective functions.
For this example, we consider three objective functions. The first one is linked with energy through the energy consumption, the others are linked with the financial costs : the financial investment and the economic global cost.

- Objective function linked with energy

The first objective function "*energy*" deals with the global yearly energy consumption of the building: heating, ventilation, lighting, other use of electricity…These consumptions are estimated in kWh of final energy per m².
The objective function representing the energy consumptions is a polynomial function drawn up with the design of experiments method (Filfli, 2006, Chlela, 2008, OPTISOL, 2008). The function "energy" depends on the parameters defined previously. With this polynomial function, we can estimate the consumption without using dynamic thermal simulation. On the other hand, a polynomial function is adapted to one unique building in a specific climate.

- Objective functions linked with financial costs

The second objective function "*invest*" represents the investment cost linked with the refurbishment of the building. This function is drawn up using prices databases (OPTISOL, 2008). This function depends on the parameter defined for the scenarios: U_{wall}, AT...etc.
The third objective function assesses the economic global cost "GC". It is the sum of the initial investment cost, the yearly energy cost and the yearly maintenance cost. The estimation of these costs is done with prices databases and hypotheses on the energy cost, the inflation rate and the discount rate.

Optimization process

Thanks to the objective functions, we can assess the initial population and determine the best solutions according to energy and economic aspects of the problem. The best solutions are the "parents" of the following generation.
The "children" are defined by recombination of the parents' chromosomes. We use two genetic operators: crossover and mutation. Chromosomal crossover is the process by which two chromosomes pair up and swap part of their genes. Mutation is a random alteration of a gene. Figure 4 presents these genetic operators.

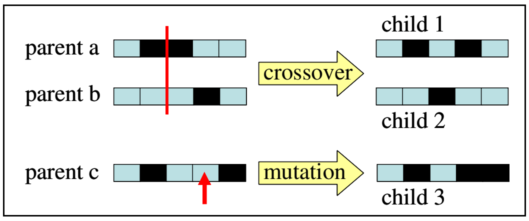

Figure 4 – Crossover and mutation operators

After the chromosomal recombination, we obtain "children" solutions that form a new generation, which is assessed. Individuals with the highest fitness are selected as parents for the next round of recombination. This process is iterative and stops after a fixed number of generations. The final population contains optimized solutions.

Three types of optimization

With the objective functions defined above, we can imagine three types of optimization:

- An optimization with an energetic target: the fitness function is the investment cost and we consider a requirement in term of energy consumption;
- An optimization with an investment target: the fitness function is the energy consumption and we consider a requirement in term of investment;
- A global optimization: we minimize the economic global cost.

The optimization with a target is a method for bypassing the multicriteria aspect of the problem: one of the two objective functions becomes a constraint. There is only one function to optimize.
In the global optimization, we use the "aggregation method". The objective function is the balanced sum of two functions: energy consumption and investment.
For this example, at the end of the optimization, the optimization tool suggests then a unique optimized scenario. Indeed, with a monocriteria objective function, the optimum concept has a real sense.

The parameters of the optimization method

The tool used for this example has been developed based on the algorithm proposed by Turkkan "Real-Coded Genetic Algorithm, GenetikSolver V4.1" (Turkkan, 2006).

In this example, we chose parameters for the implementation of genetic algorithms:

- the number of individuals in a population is fixed and equal to 200;
- the crossover probability is 0,85;
- the mutation probability is 0,05;
- the algorithm stops after 3000 generations.

For this example, we set the inflation rate at 0,03 and the discount rate at 0,06. For the evaluation of the economic global cost, the time period used for calculation is 15 years.

For the simulations of this example, certain variable parameters are fixed: the glazing ratio is 50 %, the power installed for artificial lighting is 8 W/m² and the lighting is regulated through switches.

RESULTS, ANALYSIS, DISCUSSIONS

In this article, we present the results of the implementation of the optimization method. We study the refurbishment of a school. In the first series of simulations, we focus on the leads given for school refurbishment: how good they seem and the problems we discover. In the second series of simulations, we focus on the three different types of optimization and the multicriteria aspect of the problem.

First series of simulations – Leads for school refurbishment

- Presentation

In the first series of simulations, we seek leads for school refurbishment and we study the robustness of the method. We consider the school described above and located in Trappes, a town near Paris (Figure 5).

Figure 5 – Map of France

A gas boiler and radiators provide the heating. Ventilation with mechanical extraction guarantees the indoor air quality and there is no cooling system.

The initial characteristics of the school are presented in the column "initial" in Table 1. Before the refurbishment, the energy consumptions of the school are 86,1 kWh(final energy)/m² or 132 kWh(primary energy)/m².

- Results

The optimization method we choose is optimization with energy target. We seek a scenario for which the energy consumption of the refurbished building will not exceed an energy target. We choose three nearby energy targets around 70 kWh*(fe)*/m². These targets correspond to the global yearly energy consumption of the refurbished building and represent a decrease of 20% according to initial consumption.

We compare the optimized solutions. As the energy targets are nearby, if the solutions tally, it allows underlining interesting actions. The incoherences emphasize the limits of the method developed. Table 1 presents the optimization results.

Table 1
Optimized results for a school in Trappes

	initial	opt. A	opt. B	opt. C
Energy target (kWh*fe*/m²)	-	68	70	72
Uwall (W/m².K)	0,57	0,37	0,69	0,81
Uwind (W/m².K)	3,55	1,2	1,38	1,99
SF	0,6	0,86	0,75	0,80
Uroof (W/m².K)	0,35	0,12	0,15	0,21
AT (m^3/h/m² under 4 Pa)	1,7	1,2	1,2	1,2
Investment (k€)	-	809	703	571
Global cost (k€)	-	954	853	723

These results give leads for the refurbishment of the scholar building stock. First, we can notice that for the three optimisations, the optimized scenario contains a significant improvement of the parameters U_{wind} and U_{roof}. The thermal transmittance of the windows and of the roof is in average divided by two with regard to the initial situation. The air tightness of the building envelope is improved too: from 1,7 m^3/h.m² under 4 Pa to 1,2 m^3/h.m² under 4 Pa. The results show an increase of the solar factor for the optimized scenarios. On the other hand, except for the optimization A that corresponds to the most demanding energy target, the thermal properties of the walls are not improved.

We can thus consider that for schools similar to the example studied (similar shape, similar climate), the first refurbishment steps to limit the energy consumptions with the slightest cost are the insulation of the roof and the replacement of the windows. For more ambitious energy objectives, then it will be necessary to increase the insulation of the walls.

Finally, we can note that the investment bound to the refurbishment scenarios evolves in inverse proportion to the energy target: the weaker the energy target is, the more important the investment necessary for the refurbishment is.

- Discussion

Through this example of implementation of the optimization method, we discover the possibilities offered by this tool but also some of its limits.

The results obtained allowed us to answer our initial problem: the definition of refurbishment scenarios

reducing the energy consumptions with a controlled investment. This method suggests steps and could help building stock administrators to implement building refurbishment.
To use this method for a specific project, we have to go further in the results analysis to suggest products for the refurbishment. For instance, in the optimization B, the final thermal transmittance of the windows is 1,38 W/m² and the solar factor is 0,75. A double glazing window in PVC with a low-energy layer has a U-value of 1,4 W/m².K. On the other hand, the solar factor of this type of window is close to 0,42, which does not correspond to the value obtained with the optimization B.
Thus, the optimization method does not supply results corresponding to existing products. It can even end up in incoherence when the characteristics of a product influence parameters distributed on several genes.
For instance, in the optimization A, B and C, the U_{wind}-values are strongly reduced while the solar factors increase. These results do not take into account the fact that, for a given glazing, a decrease of U-value tends to lead to a decrease of the solar factor and not to a strong increase. This incoherence underlines a lack of robustness of the optimization method.
To limit 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.
With this example, we can study one aspect of the refurbishment of building: the envelope. The variable parameters correspond indeed to the characteristics of the building envelope. To take into account other characteristics of the building, we have to add new variable parameters. For instance, we can consider the type of heating or the set temperature for the cooling.
Through the application example of the optimization method, we evaluate the scenarios from the point of view of the investment and the energy consumptions. Without cooling system, the result analysis of the energy consumptions does not give any information about the possible overheating of the building. To this aspect into account, it would be necessary to add a new objective function dealing with the thermal comfort.
Moreover, to carry on a systemic vision of the building and to suggest pertinent refurbishment, it would be necessary to introduce objective functions related to the environmental impact or to the visual comfort
To estimate the environmental impact of a refurbishment, we can base our study on the life cycle analysis of the products suggested by the scenario. The life cycle analysis is standard for existing product but it is more difficult for product described by thermal properties like the U-value. Consequently, the introduction of new objective functions gives new arguments for the discrete variable parameters representing existing products.
As mentioned previously, the objective function “energy” arises from the design of experiments method. This method allows establishing polynomial functions estimating a given criterion depending on a fixed number of parameters. The interest of this method is the speed of the calculations once the function is established.
However, the obtained function is adapted to a specific building in a given climate. To study a building with a different shape or in an other climate, it is necessary to establish a new function adapted to this new case. The design of experiments method requires an expertise and its implementation leans on hypotheses. The generalization of an optimization method based on the design of experiments method is thus not simple.
To avoid these difficulties and allow a generalization of the developed method for any type of building, it can be interesting to associate the optimization algorithm with software of dynamic thermal simulation like TRNSYS (Klein, 2005).
The optimization method would then be applicable to any type of building and all the climates without supplementary development and without taking into account new hypotheses. Furthermore, when the optimization method uses software of dynamic thermal simulation rather than a simplified method, it is not necessary to verify the thermal calculations.

Second series of simulations – Optimization methodology

- Presentation

In the second series of simulations, we focus on the different types of optimization and on the multicriteria aspect of our optimization problem.
For these simulations, we consider a school located in Agen (Figure 5). The heating and ventilation systems and the initial characteristics are the same than in the previous simulations
Before the refurbishment, the energy consumptions of the school are 65,3 kWh(final energy)/m² or 109,3 kWh(primary energy)/m².

- Results

We want to compare the results obtained with the three types of optimization. We consider five optimization processes:

- Opt. D is an optimization with an energy target of 54 kWh *final energy*/m²;
- Opt. E is an optimization with an investment target of 551 k€, this target corresponds to the investment linked with opt. D;
- Opt. F is a global optimization, the objective function is the economic global cost;
- Opt. G is an optimization with an energy target of 69,4 kWh*fe*/m², this target corresponds to the energy consumption found with opt. F;

- Opt. H is an optimization with an investment target of 336 k€, this target corresponds to the investment found with opt. F.

Table 2 displays the results.

Table 2
Optimized results for a school in Agen

	opt.D	opt.E	opt.F	opt.G	opt.H
Optimization type*	"en"	"inv"	GC	"en"	"inv"
Target	54,0 kWh /m²	551 k€	-	69,4 kWh/ m²	336 k€
U_{wall} (W/m².K)	0,74	1,25	1,53	1,03	1,58
U_{wind} (W/m².K)	2,08	1,98	4,50	2,26	4,49
SF	0,86	0,51	0,90	0,53	0,68
U_{roof} (W/m².K)	0,23	0,23	1,30	0,57	1,30
AT (m^3/h/m² under 4 Pa)	1,2	2,2	1,2	1,2	1,9
Investment (k€)	551	551	336	429	336
Global cost (k€)	672	685	482	579	491
Energy consumption (kWh/m²)	54,0	59,6	69,4	69,4	73,7

*"en": optimization with an energy target
"inv": optimization with an investment target
"GC": optimization with the global economic cost as objective function

- Comparison between opt. D and opt. E

Opt. D and opt. E lead to the same investment by two different ways. In opt. D, the investment is an objective function and in opt. E, it is a constraint.

Opt. D leads to better results than opt. E for the energy consumption and the economic global cost. The optimized scenarios present some similar items like the decrease of U_{wind} and U_{roof}. There are also differences between the two refurbishment scenarios. The U_{wall}-value and the air tightness for opt. D are smaller than for opt. F. Moreover, the solar factors are different.

- Comparison between opt. F, G and H

Opt. F and opt. G lead to the same energy consumptions and opt. F and opt. H lead to the same investment. The objective function of opt. F is like a balanced sum of the objective functions of opt. G and opt. H.

The scenarios obtained for the same investment (opt. F and H) present similar refurbishment steps but we can notice a difference between the energy consumptions. This result reveals the predominance of the investment over the energy consumption in the economic global cost. Even if the energy consumptions change, with a fixed investment, the scenarios do not vary so much.

With the same energy consumptions, opt. F and opt. G lead to two different optimized scenarios. The refurbishment steps change a lot between the scenarios and the costs are high in opt. G.

- Discussion

The three types of optimization methods implemented in this example try to deal with multicriteria problem through monocriterion objective functions. They use objective functions with penalty or constraint or balanced sum of objective functions.

With the simulations (opt. D and E) we can notice that the obtained results differ, depending whether a criterion is considered as an objective or as a constraint. The optimization method with target is thus not very robust, since with the same investment, a variation in the nature of the target involves an important change in the optimized scenario. In this case, it is difficult to validate the optimization methodology.

The simulations F, G and H underline an other limit of the implemented methodology. The definition of an objective function that depends on the other functions (aggregation method) does not seem to report the reality of the treated problems. Indeed, we saw that the scenarios obtained at the end of the optimization (F, G and H) differ. Nevertheless, the opt. F should report the two different objectives: energy and investment.

The validation of this methodology is all the more difficult that the studied optimization process leads to a unique solution. It would be easier to discuss the robustness of the method when it suggests a set of good solutions. It is more relevant to compare two groups of solutions than two isolated solutions.

In order to by-pass these difficulties and to deal with the multicriteria aspect of the problem, the Pareto concept seems to be a solution. This concept allows to treat equally the different objectives during the whole optimisation process. With genetic algorithm, it could lead to a set of optimized solutions.

Moreover, a set of optimized solutions suits better the problem of the building refurbishment. Indeed, today the actors of the project work on several variants. With this optimization method, they can discuss some optimized solutions.

It does not seem relevant to develop a method suggesting a unique solution. We consider too many and varied objectives. The compromise is difficult to achieve, and especially since certain preferences are difficult to quantify as the aesthetics or the integration of the building in a town.

CONCLUSION

In this article, we present the development of an optimization method on the refurbishment of tertiary buildings. The method is based on genetic algorithms. It deals with the steps that constitute a refurbishment scenario. We have a global approach of the building.

The implementation example presented in this article constitutes a first stage in the development of the optimization method. It allows underlining the advantages and the limits of the method. Through the results of the two simulations series, we can already list some possible improvements for the optimization method:

- consider discrete parameters representing existing products or coherent systems;
- consider parameters that characterize the building envelope, the HVAC systems and the regulation strategies;
- introduce objective functions linked with environmental impact, financial costs, energy, visual and thermal comfort;
- use dynamic thermal simulation instead of simplified method to evaluate the energy consumption and the thermal comfort;
- use the Pareto concept to classify the solutions;
- present a set of optimized refurbishment scenarios as final solution.

To carry on our research, we will improve the optimization methodology and test it on an effective refurbishment project.

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