STOCHASTIC OPTIMIZATION BASED APPROACH FOR EFFICIENT BUILDING DESIGN

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ABSTRACT

Facing the building related energetic and environmental issues, and heeding the thermal regulations standards, building designers have to think in a different way there design approach in order to make buildings more efficient.

Therefore, designers need a method to get information on the potential of a building program and on the optimal solution to improve visual and thermal comfort, and to reduce energy requirements and construction cost.
This paper describes a genetic algorithm based approach applied to building energy simulation tools in order to optimize building design, from the geometry to the energetic properties, while minimizing energy, discomforts and costs.

According to designer goals, two approaches were studied:

- The first way is to let designers choose the approach of optimization for the building geometry, from optimization of external and internal geometry to providing complete geometry.
- The second way is to let designers adapt the scope of the optimization.

In order to take various potential occupancies into account, several models of occupation has been integrated to the building numerical model. Models could be provided by designers according to their feedback.
To finish, this approach is tested on a basic case to assess its performances and to find the points where it needs to be improved.
Keywords: Efficient Building design, Multicriteria optimization, Genetic Algorithms, Bioclimatic architecture.

1. INTRODUCTION

Global warming and energetic crisis require us to decrease our greenhouse gases emissions and energy consumption. Facing the high impact of building field on greenhouse gases emissions (40%) and energy consumption (40%) in Europe, it clearly appear that the field of building must improve the performances of the new buildings and also renovate at efficient level existing buildings, like the future thermal regulations standard and the thermal label want to make.
However, no simple guidelines ensure to reach these outstanding levels. Therefore, it is necessary to provide designers with tools to allow them to know performances that will be expect for their buildings projects and the way to reach these outstanding levels of performances in comfort, economic cost and energy requirements for heating, cooling and lighting. This method must adapt to the

designers' projects to allow them to explore with a high accuracy their projects. In this paper, we present the method we developed and the result we obtain on a basic case.

2. PROBLEM DESCRIPTION

The aim of this method is to help designers to get information that they need to design their projects in an outstanding way facing energetic requirements, comfort and cost or only a part of this criteria according to their choice.
This method based on an optimization algorithm search cleverly in the solution space the best solutions to the designer's problem. The first part of this method is a description of the optimization problem by the designer. This first part divide into three under-parts: geometry, energetic characteristic and occupants'behaviour. For the geometry, the designer chooses a model to define his problem and then define the range or the set of values for each parameter defined in the optimization method. Next to the geometry, we define also the range or the set of values for the optimization of the energetic characteristic. The definition of the occupants'behaviour model is always difficult because it is modeled by a unique scenario and we do not know the impact of a modification of this scenario. To avoid this problem we decide to evaluate building with few occupants'behaviour scenarii, that's way also permit to take into account evolution of the family for a house for example or the refurbishment of an office building in a residential building. The definition of the optimization problem end by the description of surrounding solar shading.
Now the optimization problem is defined, we launch the optimization without designer do anything. The optimization algorithm search cleverly in the solution space and then obtain solutions.
Displaying these solutions could be difficult with more than 3 criteria. So, a tool helps the designer to visualize solutions according to his desires.

3. THE CHOICE OF A OPTIMIZATION METHOD

Nowadays, it is difficult to design outstanding building due to the energy requirements and the interactions between different physical phenomena involved in the thermal evolution of building. That is the reason why, it is necessary to use thermal dynamic simulation software. Nonetheless, the important increase of the influent factors generates an increase of design possibilities. Therefore, it is necessary to develop an optimization process to help building designers to find the solution that it feels better face to the specifications. It is necessary that the process let enough freedom to designers to adapt to their problems.

3.1. Different types of optimization methods

Optimization algorithms could be divided in 3 types: enumerative algorithms, deterministic algorithms and stochastic algorithms (Goldberg 1989), which are exposed below.

3.1.1. Enumerative algorithms

These algorithms search in a discrete space. They evaluate all the solutions and choose the best. So, these algorithms are not suitable to extended search space.

3.1.2. Deterministic algorithms

These algorithms use the gradient of the evaluation functions either by going in the direction where the gradient is the smallest or by searching solutions that have a gradient vector equal to zero.

These algorithms need that the evaluation functions have particular mathematical properties (Wetter 2004) like the continuity and the derivability.

Two examples of these algorithms are the Armijo gradient algorithm (Polak 1997) and the simplex algorithm (Nelder and Mead 1965).

3.1.3. Stochastic methods

Stochastic methods are algorithms using a probabilistic evolution of evaluated solutions. Stochastic methods have two major drawbacks: it converges slowly and we are not sure that the final solutions are optimal. Nevertheless, these algorithms need no particular characteristic on evaluation functions and works with several solutions in parallel.

Examples of these algorithms are simulated annealing (Metropolis 1953; Kirkpatrick 1983; Cerny 1985), tabu search (Glover 1990), ant colony (Dorigo 1991), particle swarm (Eberhart and Kennedy 1995) and genetic algorithms (Holland 1975; Goldberg 1989).

3.1.4. Multi-criteria optimization

Our study will be multi-criteria optimization. In this case, the definition of an optimal solution must be defined because a solution optimal for a criteria is not necessary optimal for another criteria. Criteria could also have opposite effects like energy consumption and comfort in building.

Let f(x) = [f1(x), f2(x), …, fi(x), …, fm(x)] a vector of functions

A solution x dominate a solution y (if we want to minimize functions) if:

$\forall\, i, fi(x) \leq fi(y) et\ \exists i, fi(x) < fi(y)$ with i $\in$ [1, 2, …, i, …, m] and m the number of objectives functions.

A solution is called Pareto-optimal if it is not dominated by any other solution of the search space, which means that optimum for a function is Pareto-optimal. That's also meaning that a solution is Pareto-optimal if for any solution of the search space the decrease of a function value implies at least the increase of another function value (if we want to minimize functions).

3.2. Required characteristic for our optimisation method

The algorithm will be worked with discrete and continuous variable, and run with several criteria.

The evaluation of energy needs would be done by thermal simulation software, so these softwares could involve discontinuity like demonstrate Wetter for the Energy+ software (Wetter and Wright 2004). Moreover, we do not know the mathematical definition of these evaluation functions that we do not let to use some deterministic algorithms.

Facing the dimension of the parameters vector, the possible discontinuity of some functions and the unknown mathematical expression of some functions, it is clear that the algorithm we use will be stochastic.

This stochastic algorithm will also solve constrain problem.

It is now necessary to find the most adapted stochastic algorithms to our problems. A comparison of the different algorithms could consist in a review to evaluate the using of each stochastic optimization method in building optimization problems, so these algorithms facing the same constraint as problems we want to study.

Few applications of simulated annealing, ant colony and tabu search exist whereas genetic algorithms are more developed.

In their study, (Deb 2001; Wetter 2004a; Znouda et al. 2006) show the advantages of genetic algorithms:

- GAs are robust optimization algorithms: with any parameters values, solutions obtained are good. Moreover, if algorithm use the elitist operator it exist a proof a convergence for at least one solution for a finite number of generation (Rudolph 1994).
- Using GA does not imply condition on the optimization problem structure or on the criteria functions.
- The solutions obtained by the GA are a set of good solutions that are near (or equal) to optimum. This diversity of solutions could be interesting in multi-criteria problems.
- Using probabilistic rules of transition let GA avoid local optima and go to global optimum.
- GA allows to solve constrain problems.

GA characteristic exposed in this list answer to our requests for the method we want to develop. Moreover, it exists successful examples using GAs in building.

3.3. Comparison of the different Genetic Algorithm (GA)

Many different GAs exist with different selection crossover and mutation operator. To choose the best for our problem, we can use studies of Zitzler (Zitzler et al. 2000) and Deb (Deb et al. 2002) that use many criteria functions to test different GAs.

According to these studies, the Non-dominated Sorting Genetic Algorithm II (NSGA-II) seems to be the most efficient GA.

4. DEVELOPMENT OF THE METHOD

We developed a method to help designers to get information on the potential of their project in 3 fields: energy, comfort and cost.

In the field of energy, HVAC systems have life much shorter than this of the building, so that mean that a building will have several HVAC systems before it will be refurbished. In the other hand, the efficiency of HVAC systems depends on the building and the use of it by occupants. So if we optimize building with HVAC systems, we obtain an optimized couple of building+systems but if we change HVAC systems the new couple could be suboptimal and perform less that another building with the new HVAC systems. Facing this problem, we decide to optimize building without HVAC systems and to work with energy requirements instead of energy consumption. The simplest energy to produce is that we don't need. In energy requirements, we take into account: heating, cooling and lighting.

This method based on the GA we choose and divide in 3 parts, as we see in the following figure:

- Optimization problem definition
- Optimization
- Display results

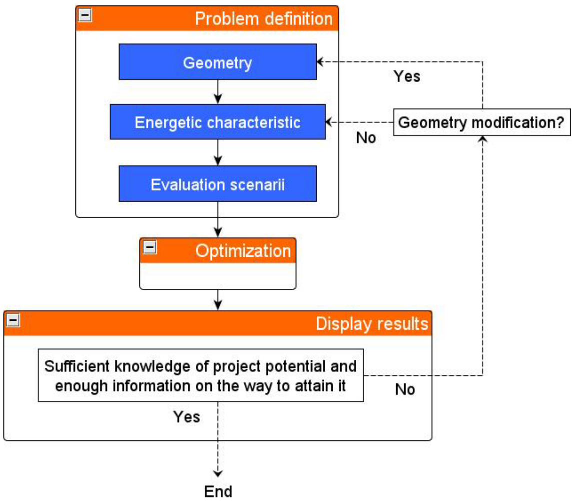

Figure 1: Macroscopic schema of the method (see the detail figure in annex1)

4.1. Optimization problem description

The first part aim to let designer choose the way to describe and optimize geometry facing to their constraints and their data. Three ways exist:

- the first uses range of rooms dimensions and building dimensions, adjacency between rooms and with exterior and windows existence on each wall
- the second expand interior geometry according to building dimensions
- in the third the designers give the complete geometry but they can optimize the window and the overhang size.

The second part is about building energetic characteristic, like the definition of range of value for the optimization of energetic characteristic of walls (thermal conductivity, inertia and, internal shortwave absorption coefficient) and windows (glazing type, frame material and shading device placement).

In the third part, we model occupants'behaviour by not only one but few scenario to take into account uncertainty in the use of buildings by occupants and let optimization be next to future use to avoid bad feedback on comfort or energetic requirements. In other hand, this artifact let test buildings in all of their life cycle with for example refurbishment of an office tower to make a residential building or the evolution of the number of member in a family (birth, growth and leave of the children).

4.1.1. Geometrical step

As said above, 3 ways for the geometry description and optimization exist. The first base on Medjdoub'study (Medjdoub, 1996), who develop a method of placement of rooms according to the building dimensions, range of value for rooms dimensions, adjacency between rooms and with exterior and floor where rooms can be placed. With these data going from specifications and designer's desire, all possible geometry are calculated and referenced by value of geometrical parameter use in each case. Then optimization calls discretely these geometries and modifies windows and overhangs size according to chromosome values for each face and window existence (defined in the rooms descriptions).

The second base on a set of internal geometry, we expand with building dimensions (depth, surface and number of floor) give by chromosome. Now, 5 geometries are implemented, they represent:

- An open space
- A floor with 2 rooms and a corridor of depth
- A floor with 3 rooms and 2 corridors of depth
- A floor with a closed patio and circular corridor between 2 lines of rooms
- A floor with a open patio and circular corridor between 2 lines of rooms

For each geometry, the windows positions are defined and their size varies with chromosomes values.

In the last description way, designers give the complete geometry. This way permit to optimize windows and overhangs sizes if they want. This way allows to work in refurbishment.

4.1.2. Energetic characteristic step

This step exists with all geometry descriptions ways. This step bases on a list of optimizable parameters choose by their impacts on criteria will be evaluated. Each optimizable parameter can be optimized or can be fixed at a value, if designers choose to optimize they can give either a set of discrete values or range of value and a discretization. Walls are referenced by type and optimize by their thermal conductivity and their inertia. Internal shortwave coefficient are optimized on the building to avoid to have walls of different colors in a same room, that could create asymmetry we can't evaluate in terms of thermal and visual comfort.

4.1.3. Definition of occupants'behaviour scenarii

The use of a building depends on occupants, so it is necessary to evaluate solutions not by only one set of parameters for occupants'behaviour (Heating and cooling temperature, ventilation flow rate, occupation, internal gains, solar shading management, window opening…) but by few to get optima most efficient not only for a type of occupants but for a maximum types of occupants.

4.2. Optimization

This part does not need any intervention of designers because the GA we choose (the NSGA-II) use only few parameters that are now given empirically. In tools will be used this method they will be calculated with the number of parameter to optimize and the mean number of value by parameter.

In this part, the NSGA-II, search in the solution space which are optimal to the given problem.

4.3. Display results

Displaying solutions for 2 or 3 criteria is easy to do and to read but if the number of criteria increase, it is impossible to do it. So a tool will be create to help designers to watch different solutions and to get needed information to make their project the more efficient that they can.

5. TEST OF THE METHOD ON A BASIC CASE

The optimization of the geometry part could be responsible of many bugs. So, we don't want to optimize geometry in the first case to work on the rest of the method and to find and correct more easily mistakes. For the same reason we start with a basic case.

After this first test, we will work with a real building by testing the method without the geometry in a first time and then test the whole method.

5.1. Test case

The test case we choose is a parallelepiped of 2.8m height, 3.6m wide and 5.5m depth with a window of 7m² on it west face, which is the only one non-adiabatic. This parallelepiped model a room within an office building. The norm EN 15265 (AFNOR, 2008) describe this model. In this study, we work on energy requirements so this model do not contain any HVAC system but has a lighting system, because it is necessary to convert lighting requirements in energy requirements to evaluate it.

The following table lists the optimization parameters.

Genes	Values
Walls thermal inertia	Low - Medium -High
Internal shortwave absorption coefficient	0,1-0,4-0,6-0,9
Window type	Double pane - Double pane low emissivity - Triple pane
Window portion of the wall	20% - 40% - 60% - 80%
Wall thermal conductivity	0,1 - 0,2 - 0,3 -0,5
Overhang dimension	0% -25% - 50% - 75% - 100% of the height of the wall
Shading device placement	Front or back to the window

Table 1: Parameter and value to optimize in the test case

As we say former, we use few scenario of occupants'behavior. The following table list the 3 scenarii we use. The scenario for the shading device and the ventilation airflow are not optimizing because it depends on the occupant's behaviour. These 3 scenarii model behaviour of 3 type of occupant from the most efficient behaviour to the less efficient.

Scénarii are different by heating and cooling temperature and solar shading management. Lighting are on for a light less than 300 lux on the floor of the room and off at more than 350 lux. The electric power for lighting is 118.8 W. Shading device are down if the mean of the temperature of the air in the zone is higher than the required value and the solar heat flux is higher than the required value. The window is never opened to avoid implementing an airflow calculation part in the model.

Scenarii	Scenario 1	Scenario 2	Scenario 3
Heating temperature	19	21	23
Cooling temperature	30	28	26
Threshold lighting	300 lux	300 lux	300 lux
Lighting hysteresis	50 lux	50 lux	50 lux
Mechanical ventilation airflow	1 V/h	1 V/h	1 V/h
Entering air temperature	Ambient temperature	Ambient temperature	Ambient temperature
Internal gain	20 W/m² in occupation	20 W/m² in occupation	20 W/m² in occupation
Occupation	8h - 18h for weekdays	8h - 18h for weekdays	8h - 18h for weekdays
Close shading device during night	Yes	Yes	No
Temperature to close shading device	Tint = 25°C	Tint = 25°C	No temperature
Solar flux to close shading device	200 W/m²	200 W/m²	500 W/m²

Table 2: Scenarii use to optimize in the test case

5.2. Results

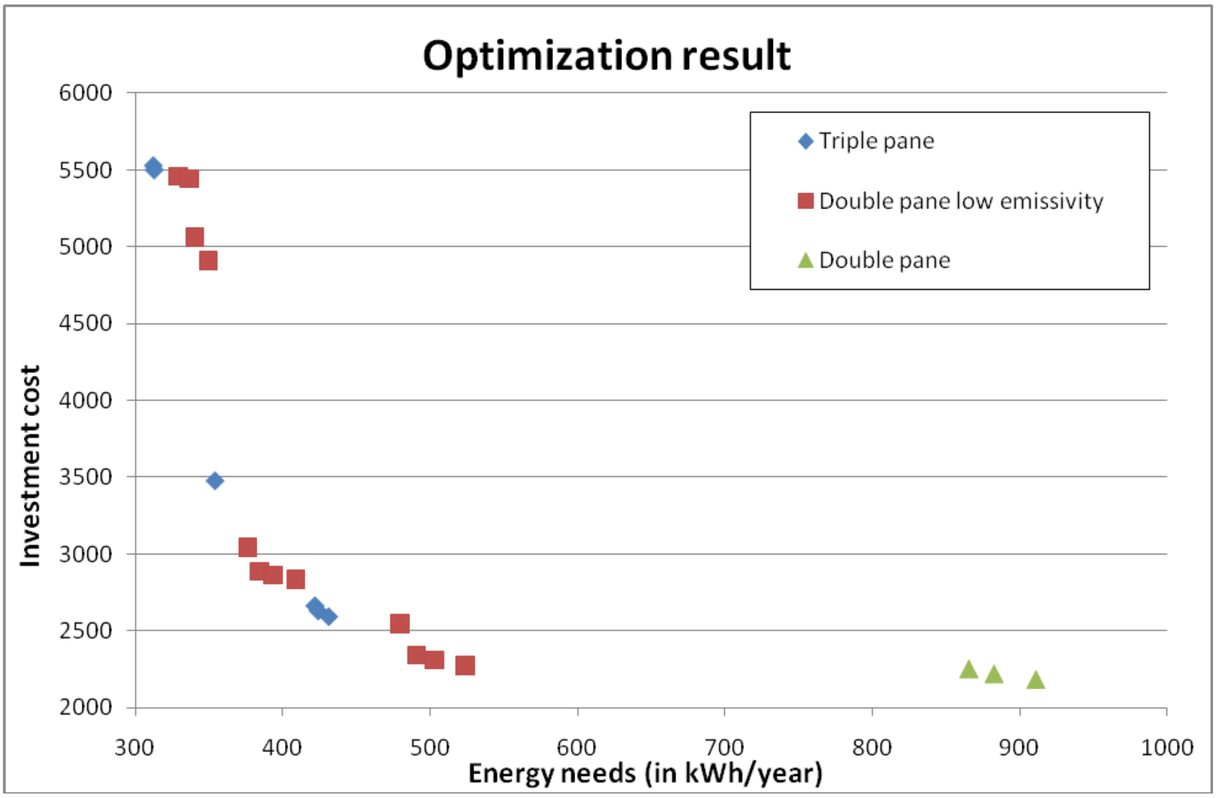

Figure 2: Optimized solutions for all optimizations with population=50

Inertia	Window	Thermal conductivity	Overhang	Window size	Energy needs (in kWh/year)	Investment Cost	Fraction of heating	Fraction of cooling	Fraction of lighting
Heavy	**Triple pane**	**0,3**	**25%**	**40%**	**312,4**	**5526**	**30,9 (10%)**	**115,4 (37%)**	**166 (53%)**
		0,5			**313,0**	**5498**	**45,9 (15%)**	**101,1 (32%)**	**166 (53%)**
Heavy	**Double pane low emissivity**	**0,2**	**25%**	**60%**	**329,0**	**5458**	**145,6 (44%)**	**67,6 (21%)**	**115,8 (35%)**
		0,3			**336,5**	**5441**	**158,5 (18%)**	**62,1 (18%)**	**115,8 (34%)**
		0,1		**40%**	**340,4**	**5062**	**146,2 (43%)**	**31,7 (9%)**	**162,5 (48%)**
		0,2			**349,5**	**4908**	**159,3 (46%)**	**27,7 (8%)**	**162,5 (46%)**
Low	**Triple pane**	**0,5**	**25%**	**40%**	**354,0**	**3478**	**53,9 (15%)**	**134,1 (38%)**	**166 (47%)**
Low	**Double pane low emissivity**	**0,1**	**25%**	**40%**	**376,1**	**3042**	**152,9 (41%)**	**60,7 (16%)**	**162,5 (43%)**
		0,2			**384,4**	**2888**	**165,6 (43%)**	**56,3 (15%)**	**162,5 (42%)**
		0,3			**393,2**	**2863**	**178,8 (45%)**	**52 (13%)**	**162,5 (41%)**
		0,5			**408,8**	**2835**	**201 (49%)**	**45,3 (11%)**	**162,5 (40%)**
Low	**Triple pane**	**0,2**	**25%**	**20%**	**421,4**	**2665**	**31,8 (8%)**	**87,8 (21%)**	**301,8 (72%)**
		0,3			**423,6**	**2632**	**41,5 (10%)**	**80,4 (19%)**	**301,8 (71%)**
		0,5			**430,7**	**2595**	**59,4 (14%)**	**69,6 (16%)**	**301,8 (70%)**
Low	**Double pane low emissivity**	**0,1**	**25%**	**20%**	**479,4**	**2548**	**164,8 (34%)**	**24 (5%)**	**290,5 (61%)**
		0,2			**490,8**	**2343**	**178,9 (36%)**	**21,5 (4%)**	**290,5 (59%)**
		0,3			**502,9**	**2310**	**193,3 (38%)**	**19 (4%)**	**290,5 (58%)**
		0,5			**523,7**	**2274**	**217,7 (42%)**	**15,5 (3%)**	**290,5 (55%)**
Low	**Double pane**	**0,2**	**25%**	**20%**	**865,3**	**2250**	**598,3 (69%)**	**0,3 (0%)**	**266,8 (31%)**
		0,3			**882,4**	**2217**	**615,4 (70%)**	**0,3 (0%)**	**266,8 (30%)**
		0,5			**910,8**	**2180**	**643,8 (71%)**	**0,2 (0%)**	**266,8 (29%)**

Table 3: Optimized solutions

All results are only for this case and are not necessarily right for other cases.
Building inertia is low for a major part of solutions except for the more efficient energetically, where it is heavy, that due to the cost we gave to inertia. That is meaning for that case, the energetic impact of inertia is not interesting compared to it cost, if we don't search very efficient building.

With all others parameters equal, the triple pane window is the more efficient but double pane low emissivity with higher window size can be energetically more efficient than solution with triple pane. Triple pane cannot have higher window to avoid risk of overheating.

Energy needs are the weighed sum of needs for heating, cooling and lighting with a factor 1 for heating and cooling and a factor 2.5 for lighting. These factors are due to the conversion factor of energy consumed to primary energy in France and to the efficiency of CVC system. The fact that solar absorption coefficient is at this low value come from the advantage to decrease lighting need instead of decrease heating needs.

Due to the little surface of external wall, insulation has a poor impact on the energy needs.

The shading device optimized position is front the window. It may due to his higher thermal resistance and his little solar transmission. The higher thermal resistance is good in heating period during night and his smaller solar transmission is good during cooling period.

The lengths of overhangs are 0.7 m but more precisely, due to the discretization, between 0.35m and 1.05 m. That is a little value for the range of value studied but relatively high in reality.

The window sizes are in a range from 2m² to 6 m². This value let got natural light and heat without have a risk of overheating.

6. ANALYSIS

This case let us to test and evaluate a part of the method on a simple case. It permits to evaluate the impact of discretization and the needed to modify this point the method to take into account this point. A solution could be to make a first optimization with a large range of value but few values and then to make a second optimization with a smaller range value. This solution could be faster that make directly only one optimisation with a large range of value with many values.

With this case, we also see the impact of the GA parameter on the result of the optimization.

Nevertheless, this case is too simple to take conclusion for this type of building. For this reason, we will study a more realist building in the next step of the development of the method.

7. FUTURE WORK

The development of the method will continue by the test of the method on a more complex building with taken into account only few geometrical variables in a first time and in second time the whole method would be tested. A test of the whole method on a third case would be done. The choice of the second building is not doing but it will be a recent existing building or a realist building.

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ANNEX A

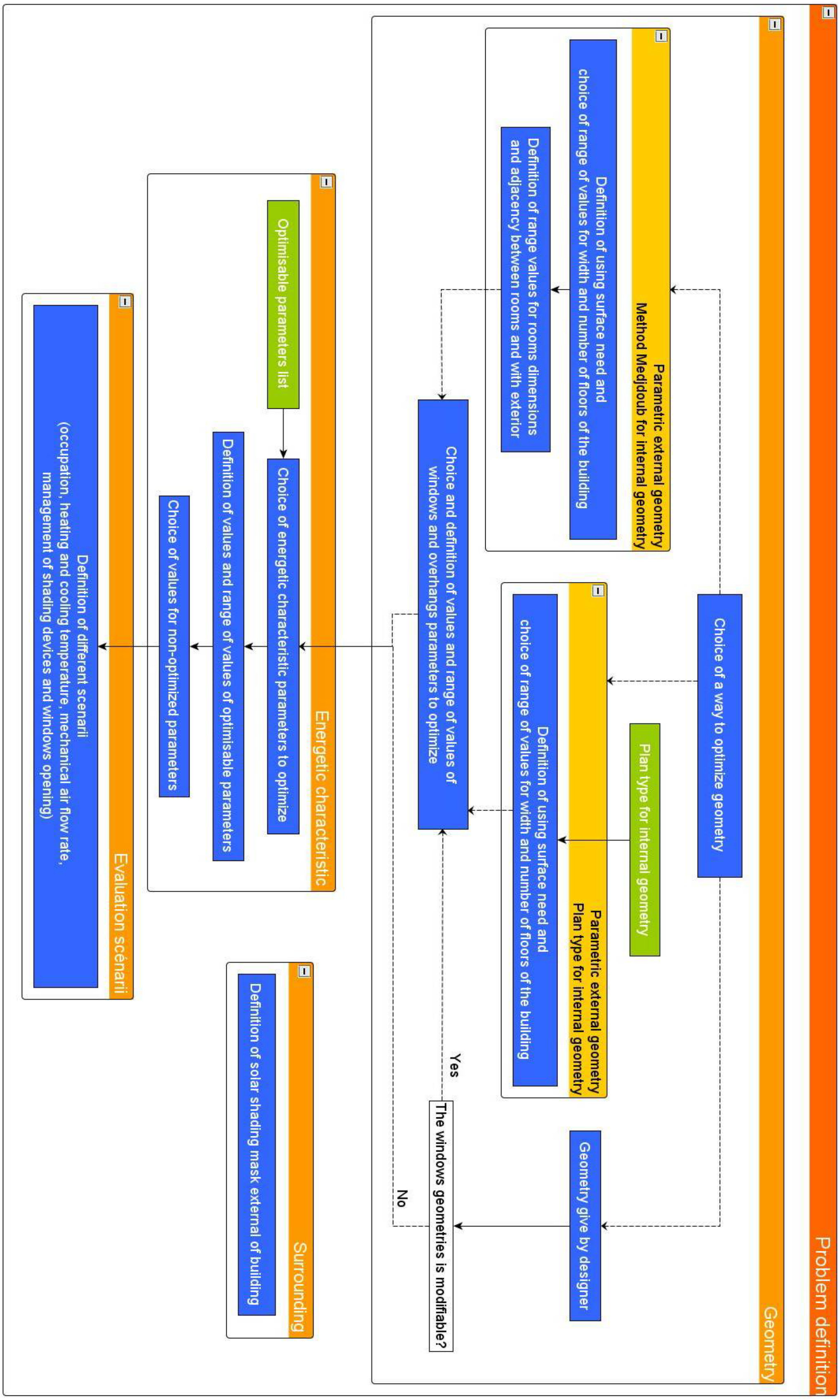

Figure 3: Detail schema of the problem definition part