MODELLING AND SIMULATION TO DESIGN MULTI-STOREY TIMBER BUILDING USING MULTI-OBJECTIVE PARTICLE SWARM OPTIMISATION

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ABSTRACT

In order to promote multi-storey timber building projects, a preliminary design methodology with optimisation step and decision-making support is proposed. The objective is to optimise building envelope composition taking into account trade-off between heating needs, summer thermal comfort, floor vibration comfort, global warming potential and embodied energy objectives. These objectives, that are conflicting and can implement in the same time continuous and discrete variables, will be then modelled as objective functions to be optimised in multi-objective manner. To obtain thermal objectives, a time consuming option is to couple an optimiser with a detailed simulation models. Another alternative is to generate meta-models and implement them directly to the optimiser as objective-functions. The multi-objective optimisation will be achieved using the metaheuristic Particle Swarm Optimisation (PSO) to determine the Pareto front of optimised solutions. A case-study is explored using two thermal meta-models. A Pareto front is obtained and analysed.

Keywords: Multi-objective optimisation, Energy simulation, Meta-model, Particle Swarm Optimisation

1. INTRODUCTION

Wood is a low environmental impacts material with a dry and rapid implementation in the building process, facilitated by a potential high prefabrication level. However in France, timber building is still underdeveloped with a building incorporation rate of 10% against 15% in Germany and 35% in Scandinavia and North America (Gabenisch et al. 2012). Furthermore, a lack of knowledge in timber building, especially for multi-storey slows its development (FCBA and CSTB 2009). To expand multi-storey timber building there is a need to develop design methods and tools with regulatory constraints consideration.

Building is a complex system, subject of multidisciplinary design studies generally considered by technological fields. In order to design preliminarily optimised building envelope and structure composition considering thermal, structural and environmental objectives, it is necessary to increase design understanding trade-offs involved. This makes it a challenging multi-objective optimisation problem.

To promote multi-story timber buildings with multidisciplinary design, a multi-objective optimisation method is under development. The objectives are to optimise the envelope and the structure composition of a building. Architectural geometry, location and use are fixed parameters. The minimising of energy needs, thermal discomfort, CO2-eq emission and embodied energy of the building and the maximizing of floor vibration comfort are considered objectives. Regulatory structural constraints are considered by preliminary design calculations to ensure the safety of the structure. In longer-term the objective functions will be completed by adding acoustic insulation, lighting autonomous and structural cost to the multi-objective optimisation process.

The preliminary design methodology couples multi-objective optimisation to multi-criteria decision. First, the overall approach is to perform a search process through the multi-objective optimization for the calculation of the Pareto front of optimal compromises between the different objectives to be optimised. Then, a decision process is implemented through a multi-criteria analysis to help decision in choosing the optimal compromise, from the Pareto front, to be implemented. Objectives and significant variables are initially selected. Relationships between them are then established and represented as influence graph. Next, explanation of links between variables and objectives which consists in assembling knowledge and implementing necessary research to explain the relationships between variables and objectives is done. Objective functions are then designed as explicit qualitative function or algorithm. Optimisation and multicriteria analysis process are then implemented consecutively.

To explicit thermal objectives use of dynamic simulation model is required. However such detailed model easily requires more than ten minutes estimating thermal performance. Total simulation time may quickly become important especially when several iterations are necessary to find a set of optimal solutions. Efficient methods of searching the design space became necessary. One promising method is the use of stochastic algorithms to optimise discontinuous and multi-objective building design problems (Attia et al. 2013). However, many hundreds or even thousands of design samples can still be necessary to converge to an optimum design or Pareto front. Optimisation processes still lead to a large computational burden, especially when detailed simulation models are used.

On this work, to save valuable time during the optimisation process and its implementation, detailed simulation models are replaced by surrogate models. Surrogate models or meta-models express the outputs in terms of decision variables as an analytic function. Such functions represent the explanation of links between variables and objectives for thermal objectives. First, they are easy to implement into the optimisation process and may facilitate sensitivity analysis on decision variables. Finally, they may be used to perform many objective function evaluations without running full simulations each time. Such approach has already been used by (Eisenhower et al. 2012) that developed a methodology for the use of meta-models in building optimisation problem with over 1000 parameters. They optimised thermal comfort and energy use with a gradient based optimiser that used the derivatives available from the meta-model. (Tresidder et al. 2012) fitted a Kriging meta-model to simulation results, which was then optimised using a Genetic Algorithm.

This article presents the calculation methodology employed to optimise the building envelope composition taking into account trade-off between heating needs, summer thermal comfort, floor vibration comfort, global warming potential and embodied energy objectives. Firstly, the thermal, mechanical and environmental objectives are presented. Secondly, explanation of links between variables and thermal objectives by using a surrogate model would be explained. Third, the optimisation process and implementation would be detailed and the compliance to the problem clarified. Finally a case study is presented and first results are discussed.

2. OBJECTIVES OF THE DESIGN OF MULTI-STOREY TIMBER BUILDING

The objective is to optimise building envelope composition taking into account trade-off between heating needs, summer thermal comfort, floor vibration comfort, global warming potential and embodied energy objectives.

2.1. Thermal objectives

Two thermal objectives to optimise have been selected: Heating needs and summer comfort.

2.1.1. Heating needs:

It is the energy demand to keep the building at a setpoint temperature T_{set} during the winter. The objective F_1 is to minimize the gap between the desired H_d and obtained heating needs H_n as (1). If the objective is simply to minimize the needs for heating while $H_d=0$. H_n must be less or equal to a fixed value for maximum heating needs, H_{max}.

$$F_1 : \min(abs(H_n - H_d)) \text{ subject to } H_n \le H_{\max} \qquad (1)$$

2.1.2. Summer comfort:

The degree-hour *DH*, expressed in the EN15251 version, measure the accumulation of the temperature offset from a comfort threshold per each hour (Figure 1). It is the building thermal zone integral operative temperature degrees T_o higher than a comfort temperature T_c during an hourly simulation period with occupancy *pocc* (2). The comfort temperature depends on the type of building. The objective F_2 is to minimize *DH*. *DH* must be less or equal to a fixed value for maximum degree-hour, DH_{max} (3).

$$DH = \sum \left(\int_{pocc} (T_o - T_c) dt \right) \text{ with } T_o > T_c \qquad (2)$$

$$F_2 : \min(DH) \text{ subject to } DH \le DH_{\max} \qquad (3)$$

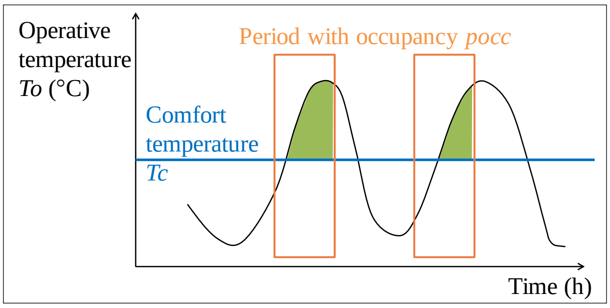

Figure 1: Summer comfort objective calculation

To predict energy needs and thermal comfort dynamic thermal simulation using detailed models are necessary. Such models take into account all of the variables input at the building stage, such as the thermal performance of the materials, yearly weather information, occupation periods of the building and occupant use. Hn and hourly thermal zone operative temperature are computed directly by using *EnergyPlus* 7.2 (DOE: U.S. Department of Energy) software. For a large scale building, as a multi-storey office building, the calculation time required to compute both, Hn and hourly thermal zone operative temperature necessary to compute DH, is about few minutes to hour. An important task is to reduce computation time required to get the optimal solutions from days, weeks, even months to less than one hour. When detailed simulation models are used, the issue may be addressed by meta-modelling techniques, which approximate a simplified function relationship between the simulation results and the input variables. Such functions represent the explanation of links between variables and objectives for thermal objectives and their generation would be detailed later.

Meta-models may be used instead of main model for the optimisation procedure: more calculations can be made in the available time using a meta-model than a main simulation model that is more detailed. Nevertheless, to surrogate main simulation model, meta-model has to be accurate.

In (Merheb 2013), while the main model requires 200 second to evaluate H_n, use of meta-models allows to evaluate 2056 alternatives in one second. These figures confirm the effectiveness and interest to calculate a meta-model to surrogate a computationally expensive detailed model.

2.2. Mechanical objective and constraints

Structural and environmental objectives, F_3, F_4 and F_5, may be described as follow:

2.2.1. Floor vibration comfort:

Three comfort levels 1, 2, 3 and 4 respectively, very good, good, acceptable and unacceptable are fixed. Comfort level, F_v, have to be minimized.

$$F_3 : \min(F_v) \text{ and } F_v \neq 4 \tag{4}$$

2.2.2. Mechanical constraints

Structural and sizing constraints are:

- **Floor height:**

The floor height is limited to a maximum value defined by the variables.

- **Wall thickness:**

The wall thickness is limited to a maximum value defined by the variables.

- **Structural constraints:**

Solutions must meet the normative requirements of Eurocode 5 (AFNOR 2005a; AFNOR. 2005b) or, for CLT as the recommendations of FPInnovations (FPInnovations 2011). Preliminary design calculations will be performed to check the viability of solutions regarding to the ultimate limit state (ULS) and the serviceability limit state (SLS).

2.3. Environmental objectives

2.3.1. Global warming potential (GWP):

The objective is to minimize de *GWP* related to the envelope during the building life cycle (Pre-Use, Use, Replacement and End of Life). The pre use and replacement emissions of the raw material extraction and materials manufacturing are calculated based on the mass of each material in the building construction. The end of life emission related to the demolition and disposal transportation to landfill and recycling centre are also calculated based on the mass of each material in the building construction. Finally the use emission related to the envelope is determined by first calculating the heating needs during the building life cycle.

Then heating needs are multiplied by the efficiency of the heating system and the local electricity emissions factor.

$$F_4 : \min(GWP) \tag{5}$$

2.3.2. Embodied energy:

The objective is to minimize embodied energy E_m of the envelope during the building life cycle. It is determined similarly to the *GWP*.

$$F_5 : \min(E_m) \tag{6}$$

3. META-MODELLING OF THERMAL FUNCTIONS

3.1. Meta-model generation

To generate a meta-model, three steps are required:

1. Generation of an initial sampling of the dynamic simulation model (the main model)
2. Meta-model calculation
3. Meta-model validation

To define the sampling it is necessary to define its size, parameters, and their range and distribution law for their variation (e.g. Gaussian, Uniform, Log-normal). Then the sampling is carried out by varying the parameters of the model within a range around their baseline value using Monte Carlo method, which randomly selects these samples. Corresponding models are realized and simulated preferably using parallel computation.

From this sample, meta-model based on polynomial chaos (PC) (Wiener 1938) is build. Use of PC from an *EnergyPlus* model was done in (Merheb 2013) to evaluate the spread of uncertainties by coupling with the *OpenTURNS©* tool, which integrate a PC toolbox (Dutka-Malen et al. 2009).

Let a numerical model, *f*, having *n* input parameters gathered in an input vector $\underline{X} = (x_1, x_2, \ldots x_n)$, and a scalar output *Y*:

$$Y = f(\underline{X}) \tag{7}$$

$\underline{X}$ follows the joint probability density function. The polynomial chaos expansion enables to approximate the output random variable of interest *Y* by the new output random variable of interest $\tilde{Y}$. A truncated polynomial chaos to order k_h is as follows

$$Y \approx \tilde{Y} = \sum_{k=0}^{k_h} \alpha_k \Psi_k \circ T(\underline{X}) \tag{8}$$

where *T* is an isoprobabilistic transformation which maps the multivariate distribution of $\underline{X}$ into the multivariate distribution μ, and Ψ_k is a multivariate polynomial basis which is orthonormal according to the distribution μ and α_k are the polynomial coefficients to compute in order to minimize the difference between the variable of interest Y and its polynomial approximation using least squares strategy.

Two main parameters characterise PC meta-models:

- The order k_h *of* the polynomial
- The sampling size

To determine the best order the sample is divided into two parts according to learning theory: learning base (90% of the sample) and validation base (10%). The meta-model calculation is done with the learning base and validated or rejected with the validation base.

Mean-squared and relative errors are determined with the validation based, respectively (6) and (7). The order k_h *of* the polynomial is gradually increased until mean squared decrease which means that the sample size is not enough to build higher polynomial order.

$$L^2 = \sqrt{\frac{1}{n_v}\sum_{i=1}^{n_v}\left[f(\underline{X}_i) - \tilde{f}(\underline{X}_i) \right]^2} \tag{9}$$

$$L^\infty = \sup \frac{\left| f(\underline{X}_i) - \tilde{f}(\underline{X}_i) \right|}{f(\underline{X}_i)} \tag{10}$$

After meta-model generation, it is checked on the main model according to the mean-squared error, relative error and residual which is calculated on the learning base (8). If errors and residual are satisfactory according to the designer, the sample size is adequate. Otherwise, sample size has to be increase to obtain a higher order polynomial.

$$r = \sqrt{\frac{1}{n_l}\sum_{i=1}^{n_l}\left[f(\underline{\tilde{X}}_i) - \tilde{f}(\underline{\tilde{X}}_i) \right]^2} \tag{11}$$

3.2. Sensitivity analysis

Meta-models based on polynomial chaos (PC) (Wiener 1938) have the advantage to deduct Sobol indices (Sobol 1993) of the output from its coefficients with almost no additional cost (Crestaux et al. 2009). The Sobol indices are used in global sensitivity analysis as a tool for ranking the input random variables of a model according to their weight in the variance of the model response.

The determination of the Sobol decomposition and sensitivity indices is immediate as soon as the PC expansion of f is known. The Sobol indices S_u of f are approximated by (Crestaux et al. 2009):

$$S_u \approx \tilde{S}_u = \frac{\sum_{k \in k_u} \alpha_k^2 \left\langle \Psi_k, \Psi_k \right\rangle}{\sum_{k \in k_h} \alpha_k^2 \left\langle \Psi_k, \Psi_k \right\rangle} \tag{12}$$

When generating meta-models, it is possible to extract the total Sobol indices *STi* (10). *STi* express the responsibility of each parameter in its range of variation correlated with the others on the output variation.

$$S_{T_i} = \sum_{u \ni i} S_u \tag{13}$$

Non influent parameters would be fixed according to the designer.

4. MULTI-OBJECTIVE OPTIMISATION

4.1. A mixed integer non linear programming problem (MINLP)

The design of building envelope composition taking into account trade-off between thermal, structural and environmental objectives is a non-linear optimisation problem. Many variables interact with each other and influence several common objectives simultaneously. The optimum value for a variable depends strongly to the value taking by other variables. Two kinds of variables are considered in this optimisation model: continuous variables as insulation thickness and discrete variables as kind of floor. Continuous variables are box constraints with boundary values and discrete variables give a predefined set of alternatives. Each additional variable makes the set of all possible alternatives (the design space) exponentially large.

Metaheuristic algorithms are well adapted to carry out the global optimisation for multi-objective mixed-integer non-linear programming (MINLP) problems, especially when the design space is large.

Developed by Eberhart and Kennedy (1995), PSO, like other metaheuristic methods, finds a set of optimal solutions to a difficult optimisation problem. This method, motivated by the simulation of social behaviour, has proved to be very efficient in hard optimisation problems. The system is initialized with population and searches for optima by updating generations. Kennedy and Eberhart (1997) have introduced a discrete binary version of PSO (DPSO) that operates on binary variables (bit, symbol or string) rather than real number. Thus, they extend the use of PSO optimisation to discrete binary functions as well as to functions of continuous and discrete binary variables at the same time. Michaud et al. (2009) have generalized the discrete binary version of PSO to a discrete n-ary of PSO. Finally, the mixed-integer PSO (MIPSO) technique is especially and fully suitable for our problem where non linear functions have to be optimised with both, continuous and discrete decision variables.

4.2. Multi-Objective Particle Swarm Optimisation algorithm

The original procedure for implementing PSO is simple and easy to implement six steps algorithm (Ndiaye et al. 2009):

1. Initialize a population of particles with random positions and velocities on *n* dimensions in the problem space
2. For each particles calculate the fitness (the function to optimise in *n* variables)
3. Compare particle's fitness with the fitness of its best position ever visited (*pbest*). If current value is better than *pbest*, then it becomes *pbest*.
4. Identify the particle in the neighbourhood with the best fitness; it becomes the leader of the neighbourhood.
5. Change the velocity and position of particles according to velocity and position updating rules (16) and (17).
6. Loop to step 2. Until the end condition is met, usually a sufficiently good fitness or a maximum number of iteration.

For a search in an *n*-dimensional search space where the particles movements are synchronized, at the *t*th iteration, for the *i*th particle, the position and position change (*velocity*) vectors are respectively represented as (14) (15) (Eberhart and Kennedy 1995):

$$X_i^t = (x_{i,1}^t, x_{i,2}^t, ..., x_{i,n}^t) \tag{14}$$

$$V_i^t = (v_{i,1}^t, v_{i,2}^t, ..., v_{i,n}^t) \tag{15}$$

The position and position change (*velocity*) $v_{i,j}^{t+1}$ updating rules are given as below:

$$x_{i,j}^{t+1} = x_{i,j}^t + v_{i,j}^{t+1} \tag{16}$$

$$v_{i,j}^{t+1} = w.v_{i,j}^t + c_1 r_1 (p_{i,j}^t - x_{i,j}^t) + c_2 r_2 (g_j^t - x_{i,j}^t) \tag{17}$$

Where $i = 1,2,\ldots p$, $j = 1,2,\ldots,n$, p is the number of particles (the size of swarm), and n is the dimension of search space; $x_{i,1}^{t+1}$ is the position of the particle i and $v_{i,j}^{t+1}$ its velocity; w is called inertia weight, it is used to control the impact of the previous history of velocity on the current one; r_1 and r_2 are uniformly distributed random numbers between 0 and 1; c_1 and c_2 are positive acceleration constants; $p_{i,j}$ is the value of *j*th dimension of the best position ever visited by *i*th particle; g_j is the value of *j*th dimension of global best position ever visited by all particle in the swarm.

For discrete n-ary variables the difference is in the definitions of velocity updating rules where the position updating rule is based on logistic function as below (Michaud et al. 2009):

$$\begin{aligned} x_{i,j}^{t+1} &= n_k \text{ if } \varphi_{k-1} < S(v_{i,j}^{t+1}) \\ x_{i,j}^{t+1} &= n_l \text{ if } \varphi_{l-1} < S(v_{i,j}^{t+1}) \le \varphi_l \text{ with } 1 < l \le k-1 \\ x_{i,j}^{t+1} &= n_1 \text{ if } \varphi_1 \ge S(v_{i,j}^{t+1}) \end{aligned} \tag{18}$$

where

$S(v_{i,j}^{t+1}) = \dfrac{1}{1+e^{-v_{i,j}^{t+1}}}$ and $\varphi_1,...,\varphi_{k-1}$ are strictly ordered uniformly distributed random numbers between 0 and 1.

With the PSO algorithm, the leader determining that influences the updating of a particle position depends on the established neighbourhood topology. In a multi-objective optimisation problem it is function of the set of leaders already founded in the search space. Set of leaders are stored in a specific memory called extended memory (Hu et al. 2003). When a particle dominates some leaders in the extended memory, it is added to the leaders set and the dominated ones are discarded from the extended memory. The set of leader is reported as the final Pareto optimal set or Pareto front.

4.3. Multi-objective optimisation implementation

Attia et al. (2013), Evins (2013) and Stevanović (2013) underline and conclude on the necessity to develop tools, for sustainable building design, that integrate both, building physic simulation and optimisation process. Such tools have to reduce computation time, to be accurate, and to support decision-making. However, optimisation process can lead to a large computational burden especially when detailed simulation models are used (Wang et al. 2005).

Based on this observation, the optimisation framework consists to a preliminary design tool incorporating thermal meta-models generation, and optimisation process.

The flowchart of optimisation solution toolbox used in this work is illustrated in the figure 2 and is divided into five steps:

1. A multi-storey timber building is defined: architectural geometry, location and use are fixed parameters; constraints and decision variables are identified.
2. Thermal objectives are then modelled on *EnergyPlus* 7.2 for energy and comfort simulation; and corresponding meta-models are generated and used as objective functions
3. A sensitivity analysis is carried out on thermal objectives and non-influent parameters are fixed according to the designer.
4. Structural and environmental objectives are modelled using analytic functions and then implemented in *Ted*© tool (Tool for Ecodesign).
5. The PSO multi-objective optimisation process is then performed using the *Ted*© tool.

5. CASE-STUDY

The case-study building model was made in order to keep calculation time as short as possible. It is a simple rectangular office building without sun protection.

5.1. Description

The case-study (Figure 3) is a three-storey office building with as objective the optimisation of the building envelope composition. Architectural geometry, location and use are fixed parameters. The surface area is about 168 m² and ceiling height about 2,6m. Variables concern the building envelope such as insulation level, glazing, cross laminated timber (CLT) section and panels' thickness.

The building model was built using *OpenStudio* and exported to run in *EnergyPlus*. Each analysis of the model took around 40 seconds to run in *EnergyPlus*. Using such a simple model was judged to be beneficial because the aim of the paper was to set up an optimisation solution toolbox rather than to answer specific building-design questions. Twenty-four decision variables were selected (Table 1).

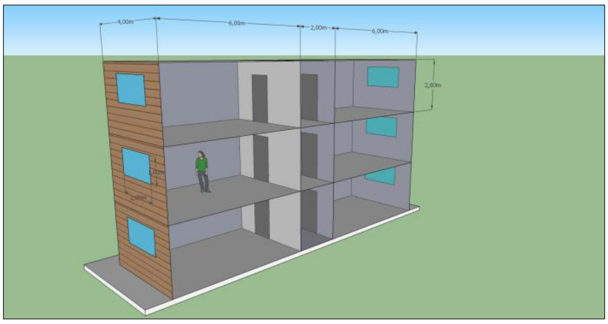

Figure 3: Case-study building

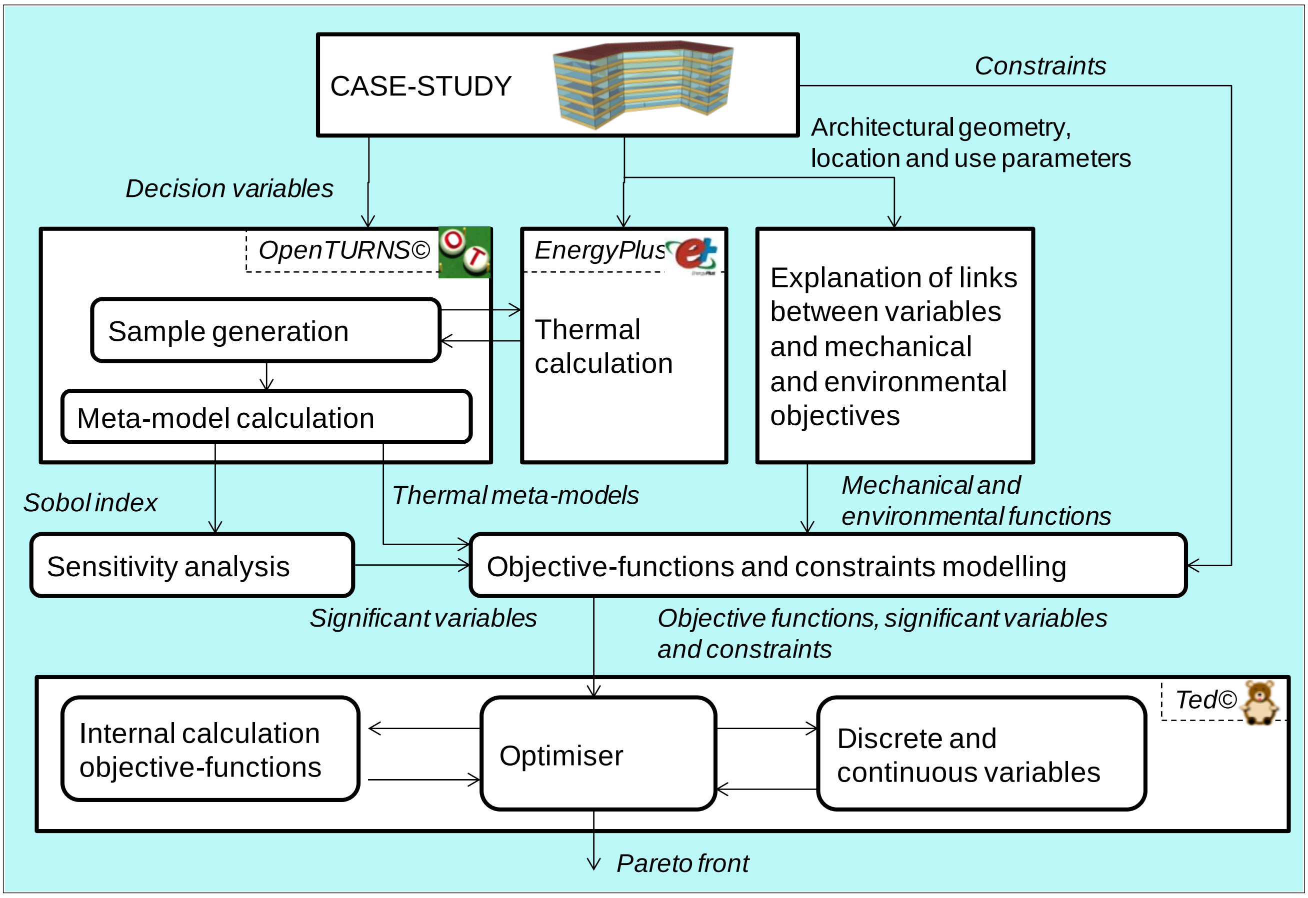

Figure 2: Summer comfort objective calculation

Table 1: Parameters description

xj	Description	Unit	Main relations
x0	Wall insulation thickness	m	$0.04 \leq x0 \leq 0.3$
x1	Wall CLT layers number	-	Discrete variable x1 = {3,5,7,9}
x2	Wall CLT thickness of longitudinal layers	mm	Discrete variable x2 = {20,30,40,50,60,70,80}
x3	Wall CLT thickness of transversal layers	mm	Discrete variable x3 = {20,30,40} and $x3 \leq x2$
x4	Wall CLT thickness	m	$0.06 \leq x4 \leq 0.2$ and $x4 = ((x1+1)*x2+(x1-1)*x3)/2000$
x5	Wall insulation conductivity	W/(m.K)	$0.03 \leq x5 \leq 0.04$
x6	Wall cover panels thickness	m	$0 \leq x6 \leq 0.04$
x7	Cover and ceiling panels density	kg/m^3	Discrete variable x7 = {800,2200}
x8	North windows U-value	W/(m².K)	$0.6 \leq x8 \leq 2$
x9	South windows U-value	W/(m².K)	$0.6 \leq x9 \leq 2$
x10	North windows solar factor	-	$0.35 \leq x10 \leq 0.6$
x11	South windows solar factor	-	$0.35 \leq x11 \leq 0.6$
x12	Floor insulation thickness	m	Constant x12 = 0.1
x13	CLT density	kg/m^3	$350 \leq x13 \leq 700$
x14	Floor concrete cover density	kg/m^3	Constant x14 = 2300
x15	Roof insulation thickness	m	Constant x15 = 0.2
x16	Roof CLT thickness	m	Constant x16 = 0.5
x17	Roof insulation conductivity	W/(m.K)	Constant x17 = 0.038
x18	Ceiling panels thickness	m	$0.006 \leq x18 \leq 0.04$
x19	Floor CLT layers number	-	Discrete variable x19 = {3,5,7,9,11}
x20	Floor CLT thickness of longitudinal layers	mm	Discrete variable x20 = {20,30,40,50,60,70,80}
x21	Floor CLT thickness of transversal layers	mm	Discrete variable x21 = {20,30,40} and $x21 \leq x20$
x22	Floor CLT thickness	m	$0.2 \leq x22 \leq 0.4$ and $x22 = ((x19 + 1) * x20 + (x19 - 1) * x21) / 2000$
x23	Floor concrete cover thickness	m	$0 \leq x23 \leq 0.06$
x24	Natural ventilation rate	vol/h	$0 \leq x18 \leq 4$

Table 2: Meta-models characterisation

Meta-model	Sample size	L²	Linf	r
H_n 2^d order	600	0.5 kWh/(m².year)	9%	0.2 kWh/(m².year)
DH 2^d order	600	12 °C	7%	5 °C

5.2. Results and discussion

Meta-models have been first calculated with *OpenTURNS®* tool. *DH* was calculated only for the warmer zone during the warmer week of the year. H_n and *DH* meta-models have been based on a sampling of 600 data sets that were enough to obtain acceptable second order precision (Table 2). Simulation execution times of 23,1s and 7,7s were necessary to respectively calculate H_n and *DH*; total times of 5 hours and 7 minutes were required for establishing the two meta-models using personal computer (Windows® 8, 2.53 GHz Intel® Core™ processor, 4.00 Go RAM).

Then, a sensitivity analysis has been done using Sobol indices. They where oriented according to meta-model coefficients (Figure 4). Wall insulation thickness, windows U-value and windows solar factor influence both H_n and *DH*. The variations of certain parameters, as roof insulation thickness, do not influence the optimisation process and were implemented as constants (Table 1).

The PSO' parameters *w*, c_1 and c_2 have been respectively settled to 0.63, 1.45 and 1.45. With 300 particles and 100 iterations 38 minutes were necessary to the PSO' program Ted© to calculate a Pareto front of 52 solutions (Figure 5). With this simple case-study, 257 days would have been required to execute the same calculation using the detailed simulation models of the thermal objectives instead of meta-models.

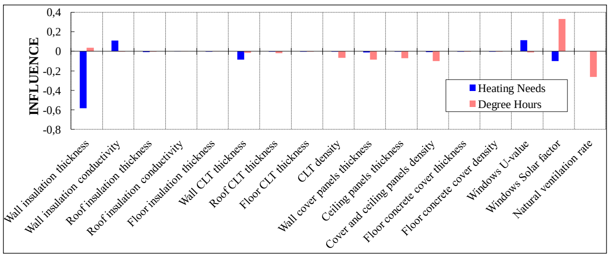

Figure 4: The influences of decision variable on H_n and *DH*

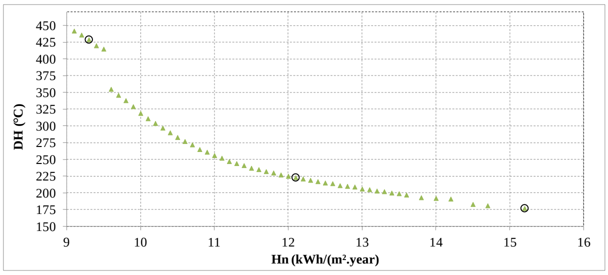

Figure 5: Pareto front for H_n and *DH objectives*

With a Pareto front made from two thermal objectives some parameters as wall insulation conductivity, wall cover panels' thickness and ceiling panels' thickness are constants. By integrating others objectives these parameters would have taken several values.
Table 3 illustrates three solutions in the Pareto front. When windows solar factor is low, insulation and CLT thickness are high; this compensates the deficit of solar gain by a best insulation. On the contrary when solar factor is high, insulation is lower and windows U-value is very low. Solutions on the Pareto front represent the best compromises between insulation and penetration of solar rays.

Table 3: Example of solutions in the Pareto front

Solution	*x0*	*x4*	*x10*	*x12*	*x14*	*x23*	H_n	*DH*
a	0.3	0.2	2200	1.4	0.35	0.03	15.2	177
b	0.25	0.18	2200	0.6	0.37	0.04	12.1	223
c	0.22	0.14	800	0.6	0.58	0.06	9.3	429

6. CONCLUSION

In this paper a methodology to optimise building envelope composition taking into account trade-off between heating needs, summer thermal comfort, floor vibration comfort, global warming potential and embodied energy objectives have been presented.

The optimisation framework which is a preliminary design tool incorporating thermal meta-models generation and optimisation process has been developed. The use of meta-models in state of detailed thermal simulation modelled saves time (from several months to less than one day) and reduces computing resources.

The multi-objective particle swarm optimisation (MOPSO) algorithm enables to calculate a Pareto front for both thermal objective functions. These functions use in the same time continuous and discrete variables.

On-going work on environmental and structural objectives will complete the optimisation process. Also integration of discrete variables concerning the structure type has to be performed.

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