Towards holistic building optimization using a computing environment that enable interoperability between numerical tools

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Abstract:

Performance optimization has become a standard approach for the design and control of energy systems. The building sector doesn't escape this trend with very dynamic research activity on the subject. This allows designing more and more efficient buildings that contributes to limit the climate change's effects. Design of buildings is usually based on a sequential approach: reduction of demand improvement of energy efficiency and finally use of renewable energies. A holistic building design approach is more efficient since the optimum of a system can be different from the one obtained by separating its components. It is thus necessary to optimize the design by considering the building as a whole (envelope, system, occupants, and environment) and over its lifetime, particularly in the perspective of the climate change.

In this context, there are significant difficulties linked to calculation time, dynamic simulations of the building (envelope and systems), taking into account the climate change, combinatorial explosion related to the decision parameters during the optimization, and inclusion of uncertainties ... It is therefore necessary to use specific methodologies such as the use of surrogate models or parallel computing. The optimization is obviously multi-criteria and the overall optimum must be obtained with a reasonable computing time for an engineering office for example. The performance functions (environment, financial, comfort, reliability ...) can be evaluated with different tools that must be interoperable.

In this context, we present a methodology and an environment for the holistic optimization of buildings. This environment allows the interoperability of numerical tools used by engineering offices. Finally, two optimized multi-criteria design case studies (2 test functions and the real building "Les Roches Blanche" in Chambéry) are presented to illustrate the approach and the developed environment.

Keywords:
Global optimization, Surrogate model, Interoperability, Building, Life cycle Analysis.

1. Introduction

The pronounced advances in computational techniques and optimization methods lead to applications of simulations for studying the complex engineering systems. Building performance optimization is a complex dynamic phenomenon where researcher generally used dynamic simulation model for the desired goals e.g. lowering energy consumption, reducing environmental impact, cost optimization, thermal comfort etc. [1]. The decision parameters having the largest influence on performance correspond generally to early design phases, e.g. the architectural sketch including geometrical and structural choices. But other parameters defined in detailed design may be optimized as well. Environmental performance is evaluated using life cycle analysis (LCA) [2], which integrates several indicators: primary energy consumption and CO_2 emissions, but also other

criteria related to e.g. human health and biodiversity. Accounting for such a broad set of criteria is not common. Dynamic LCA [3] seems more appropriate than the standard static approach to evaluate impacts building on dynamic energy simulation results.

The main phases of building optimization studies are pre-processing (formulation of the optimization problem), running optimization (monitoring, control and error detection) and post processing (interpretation of the results) [4]. Most of the building optimization researches used the single-objective approach [5] but the real world building design optimization problems have opposite criteria simultaneously e.g. minimum energy consumption vs maximum thermal comfort; investment and operational cost etc. [6]. Therefore authors optimize energy systems and building envelop with multi-objective optimization. The best alternative solution were identified for least environmental impact of building using life cycle analysis principle considering the many economic and environmental criteria [7]. Multi-objective optimization model was used by Carreras et al. [8] who simultaneously minimize the cost and the environmental impact linked with energy consumption in operational and construction phase. Using multi-objective optimization model Wu et al. [9] minimizes life cycle cost and greenhouse gas emission by simultaneous optimization of building energy system and retrofitting with heat pumps and renewable energy systems. With more than two objective functions Penna et al. [10] considers energy saving, cost and thermal comfort as three objective functions to estimate the optimal total energy on a building including energy systems and envelope.

In building energy efficient design optimization the commonly used algorithms can be divided into three categories, viz. gradient-based search algorithms, evolutionary algorithms, and hybrid algorithms [11]. The computational optimization methods applied to sustainable building design were reviewed in [5]. Machairas et al. [12] presented the review about the algorithms used in performance-based building design optimization. However Attia et al. [13] addresses the gaps and needs for integrating building performance optimization tools in Nearly Zero Energy Building design.

The dynamic variables such as energy price, investment cost and climate change over the whole life span of building introduce the uncertainty. This leads to the robust optimization that increases the number of simulations to be performed and enhances the computational time. Therefore the aim of energy building design, now a day are to reduce the computational time using in particular surrogate model. Carreras et al. [14] minimize cost and environmental impact using surrogate model based on a cubic spline interpolation. They showed that the implementation of surrogate model took around 1 day, which is approximately 8 times less as compared to the time consuming original SIMMOD model in Energy+ (more than 7 days).

A surrogate model includes majorly the sampling of input individuals and computes the reference model response to construct a data base for training the surrogate model, construction of surrogate model using suitable method e.g. radial basis function [15], Kriging [16-18], support vector machine (SVM) [19], artificial neural network (ANN) [20] and validation of surrogate model. In literature the Kriging model has been used with efficient global optimization (EGO) technique in single objective optimization problems [21-22] as well as for multi-objective problems by generating a surrogate model for each objective function [23-24]. Panão et al. [25] presented a method based on genetic algorithm to optimize the urban forms for mid lattitude climates and concluded that lattitude dependent radiation conditions based optimization results in better thermal performance. The Artificial neural network (ANN) with multi-objective NSGA II genetic algorithm is used for optimization of thermal comfort and energy consumption in a residential house [20]. ANN significantly reduces the optimization cost (3 weeks) compared to the the optimzation cost without ANN (10 years). A multivariative optimization using a nonlinear optimization scheme with building modeling based on physical, tecnhnical and economical interactions was presented in [26]

to find the economic optimum. Kriging model is used in multi-objective optimization problems of many fields such as magnetics [27], aerodynamic [28] and railways [29]. In building design optimization problems the Kriging model has been majorly utilized in multi-objective building design. A non-dominated sorting-based particle swarm optimization (NSPSO) algorithm together with the Kriging method with adaptive sampling procedure has been used to perform the multi-objective optimization of typical office room [30]. In this study, up to 46.6% reduction of computaional time has been reported. A recent study on building design optimization [31] reported that Kriging based fitness approximation slightly improve the NSGA II ; however authors in this study recommend that more research required to test this method for complex problems of building design optimization. Aijazi [32] compared several common surrogate modeling techniques and reveal that parametric radial basis functions and Kriging are highly accurate regression techniques for predicting building energy consumption with about five orders of magnitude faster than the detailed Energy+ simulations. Authors conncluded that the impact of climate change on a building depends on its location and type.

In present optimization study, we have used the Kriging surrogate model for two cases namely (i) optimization using Camel and Rosenbrock test functions and (ii) a case study of building simulation using Energy+ software. The adaptive metamodel-based optimization approach has been considered by performing a series of multiple optimization processes using the Kriging model. The sampling process is done following design of experiment approach, and NSGA-II algorithm has been considered for the optimization process. We propose to implement the approach in an existing framework, called CADES dedicated to design and optimization [33]. This framework is based on a software component approach allowing the connection of models with optimization algorithms and pre or post-processing solution for setting, solving, and analyzing optimization problems. The approach is based on a software component approach offering a solution for inter-operability with the main simulation software of the field [34] and is compliant with the emerging software component standard FMU[1]. The originality of this environment is to offer a proposal of integrating, in the same environment, inter-operability, multi-objective optimization and connection with Kriging surrogate models and parallel computing. The goal is to simplify the use of those technics, so that they can be used by final users in design offices.

2. Methodology

2.1. Kriging model

The Kriging method is defined as optimal interpolation based on the regression against observed values of surrounding data points, weighted according to spatial covariance values. The random field of Kriging is composed of residual and trend components. The residual component has a stationary mean of zero and has a constant covariance [35]. There are three Kriging types namely the Simple Kriging (trend component is constant over entire domain and mean is known); the Ordinary Kriging (the trend component is constant in the local neighbourhood of each estimation point and mean is unknown); and Universal Kriging (composed of non-random trend function and a real valued residual function).

The optimization tool has been developed in CADES following Openturns documentation. The set of initial sample input data (individuals) with uniform distribution between minimum and maximum bound is generated following random weighted design of experiment with latin hypercube sampling (LHS) technique. The Kriging model approximates the reference model using the array of input (learning) individuals and produces the array of learning performance (output)

[1] See also following reference for description of the software component approach used for inter-operability http://muse-component.org/

corresponding to the learning individuals. We compute the metamodel on array of learning individuals and compute the relative errors on learning points. The covariance between two samples $(s,t) \in R^n$ is defined as following

$$Cov(s,t) = E\left[(X_s - m(s)).(X_t - m(t))^t\right] \quad (1)$$

To obtain the covariance matrix, we discretize the stationary covariance function with 50x50 meshes. In optimization with NSGA II, we minimize the covariance for the accurate prediction from the Kriging metamodel.

The output of Kriging metamodel is Gaussian random vector with stationary covariance function defined as following

$$Y(x) = f(x)^T.\beta + Z(x) \quad (2)$$

Where $f(x)^T.\beta$ is generalized linear model and $Z(x)$ is a zero mean Gaussian process with stationary auto correlation function C^{stat} :

$$E\left[Z(x)_s Z(\tilde{x})\right] = \sigma^2.C_\theta^{stat}(x - \tilde{x}) \quad (3)$$

This output is given as the input argument for the calculation of Gaussian random vector at new point.

2.2. The adaptive design of experiment (DoE)

The adaptive design of experiment allows to both fitting the Kriging model in the global space and near the optimal individuals (Pareto frontier). The schematic for the methodology is given in Fig. 1.

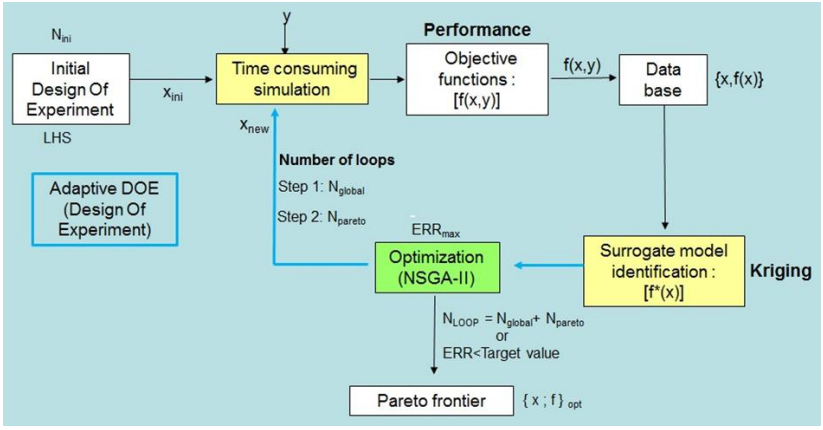

Fig. 1. Methodology adopted for the optimization using Kriging metamodel

The algorithm starts by sampling the initial data points using the Latin Hypercube Sampling technique (LHS). The set of points is then evaluated using the reference time consuming model. The Kriging surrogate model is identified for all objective functions. In step 1, the individual with maximum covariance is selected using NSGAII algorithm and added to the data base. The aim of step I is to explore the whole (global) design space. In step 2, the identified Kriging model is then trained to run the multi-criteria optimization process using also NSGA-II algorithm to find the optimal solutions (Pareto frontier). The new individual with maximum covariance in the Pareto

frontier is added to the data base for further iteration in the Kriging model identification. The optimization process ends with the maximum number of loops not greater than the sum of number of individuals in each steps ($N=N_{LHS} + N_{global} + N_{pareto}$) or if the minimum error target is achieved.

2.3. Implementation of the Design of Experiment in a user friendly environment

The previous described DoE methodology has been implemented and integrated in the CADES framework [33]. Fig. 2 gives a view of how a connection can be easily made with a TRNSYS model, demonstrating the interoperability possibilities implemented that must be simple as possible for the final designer in the design office (toward a "plug and play" approach). Similar solutions will be available for connection to Energy+ model, or FMU software components.

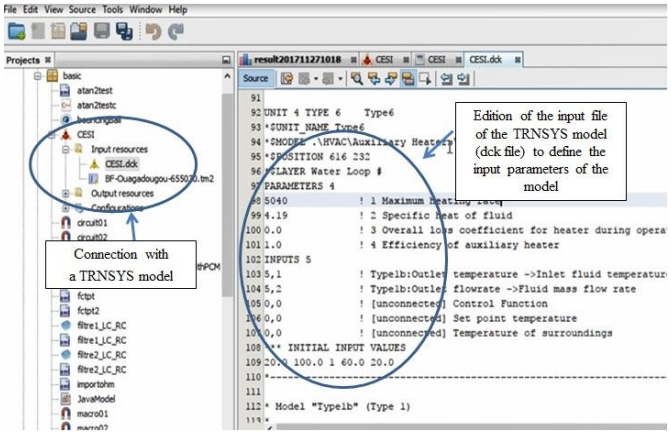

Fig. 2 Connection with a TRNSYS Black-Box model (Time consuming model) – Inter-operability in the proposed tool

In DoE approach, initial individuals correspond to the number of individuals (N_{LHS}) that are allowed to be evaluated in the first LHS sampling of the design space. The number of points for surface improvement (N_{global}) corresponds to the maximum number of individuals that can be tested on the time consuming model in the first improvement loop of the methodology, when new sample are added for minimizing the maximum covariance of the Kriging surface (step I of the methodology). The number of points for Pareto improvement (N_{pareto}) corresponds to the number of individuals that can be tested on the time consuming model in the second improvement loop of the methodology when new samples are added to improve the Pareto front of the defined optimization problem (step II of the methodology). This allows controlling the maximum number of calls for the time consuming model, which cannot be greater than the sum of the 3 previous parameters $N=N_{LHS} + N_{global} + N_{pareto}$. The user must also define two additional parameters: "Surface acceptable relative error" corresponds to the required error in step I: if the error is lower than this value, for the point having the maximum covariance, the sampling on the time consuming models stops for step I. "Pareto acceptable relative error" corresponds to the required error in step II: if the error is lower than this value, for the point having the maximum covariance, the sampling on the time consuming models stops for step II. For reaching this, a connection has been made with the Kriging library implemented in Openturns[2]. An option allows also parallelizing the computing on the time consuming models on multi-core computers (not presented in this paper).

[2] See : http://www.openturns.org/

3. Results and discussion

In this section we present the results for the test functions and for the building case study.

3.1. Case study n°1: test functions

The Camel and Rosenbrock functions are selected as test function for the present multi-objective optimization study. We know the Pareto frontier of these test functions and also these reference test functions are fast. Both test functions are minimized in the interval (-2, 2) for x_1 and x_2 (decision parameters). The acceptable relative errors in step I and step II are kept equal to 10^{-4} and 10^{-5} respectively.

- **Camel and Rosenbrock functions**

The camel and Rosenbrock functions are given by Eq. (3) and (4) respectively

$$f_1(x_1, x_2) = \left(4 - 2.1x_1^2 + \frac{x_1^4}{3}\right)x_1^2 + x_1x_2 + 4x_2^2\left(x_2^2 - 1\right) \quad (3)$$

$$f_2(x_1, x_2) = (1 - x_1)^2 + 100.0 * \left(x_2 - x_1^2\right)^2 \quad (4)$$

- **Responses surfaces at the end of the design of experiment**

The response surfaces of reference model and Kriging model along with the number of individuals in LHS phase, after step I (global phase) and after step II (Pareto phase) for camel and Rosenbrock functions is shown in Fig. 3.

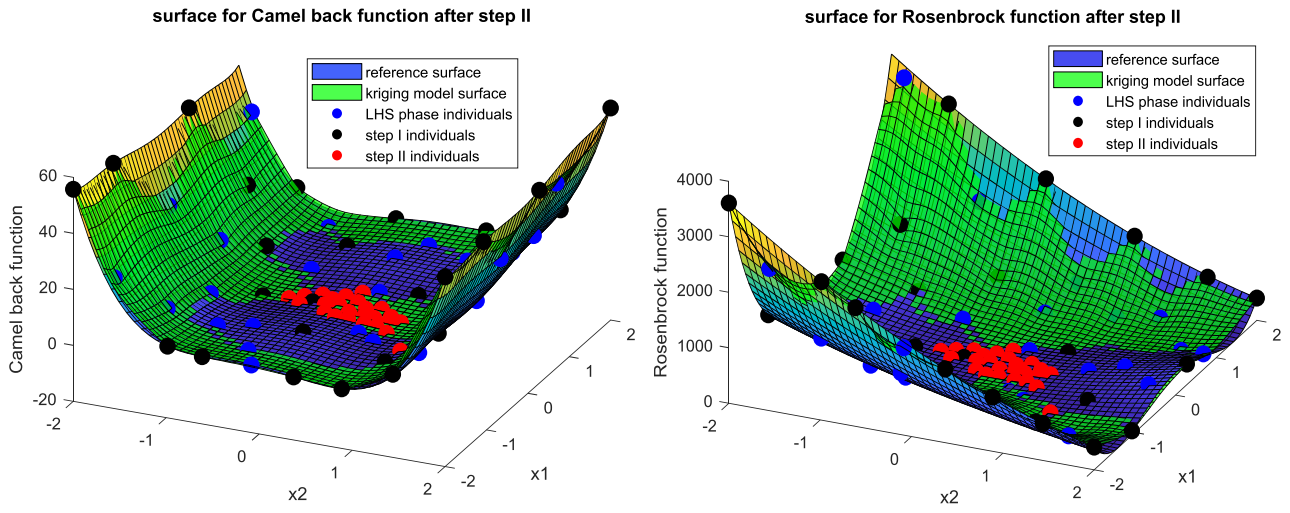

Fig. 3. Surfaces for test functions and Kriging model after step II

These surfaces have been obtained for N=75 variables distributed as 25 individuals in each step. It can be observed from these surfaces that the individuals are distributed over whole space in LHS phase and step I (with many points on the boundaries for step I) but during step II the individuals are near to Pareto frontier.

- **Comparison of the Pareto frontiers in the design or objective spaces**

The Pareto frontier in design space and objective space for reference and after each step are obtained and depicted in Fig. 4. It can be observed that the Pareto frontiers after step I is far from the reference function but after step II the Pareto frontiers is closer to the reference Pareto.

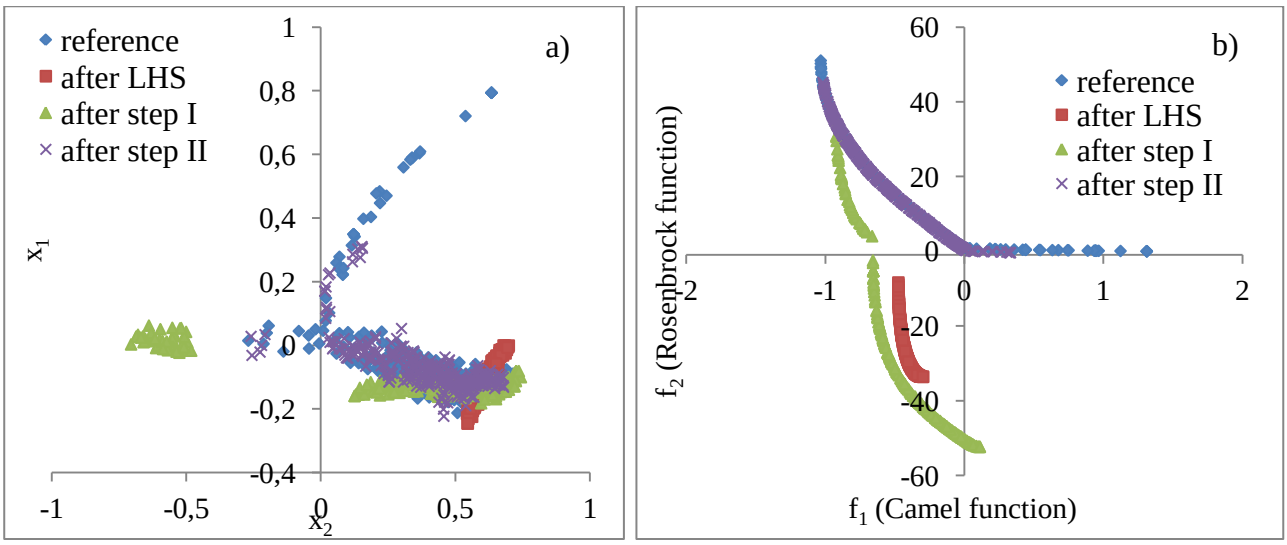

Fig. 4. Pareto frontier reference and after each step a) with decision parameters (x_1, x_2) and b) with objective functions (f_1, f_2)

- **Kriging model accuracy**

The coefficient of determination R^2 is calculated between the individuals for reference model and the individuals obtained with the metamodel. R^2 value has been calculated for each new individual obtained in steps I and II.

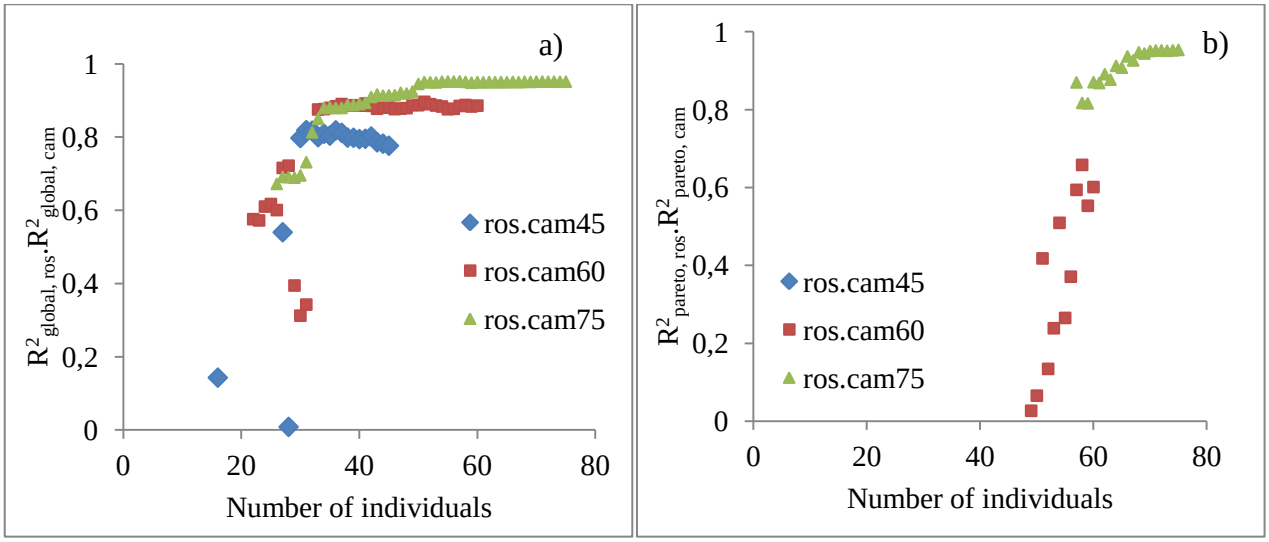

Fig. 5. Variation of a) R^2_{global} and b) R^2_{pareto} with number N=45/60/75 during step I and II

To assess the accuracy of the metamodel, we calculate the R^2_{global} (step I) values with a 50x50 mesh for design variables x_1 and x_2. The values product of R^2 for camel and Rosenbrock functions are calculated for both global space ($R^2_{global,ros}.R^2_{global,cam}$) and individuals of the Pareto frontier ($R^2_{pareto,ros}.R^2_{pareto,cam}$). As we increase the number of individuals N, the R^2 product approaches to 1 indicating the accuracy of the metamodel with respect to reference for both the global space and the Pareto area (Fig. 5(a) and 5(b)). A number of individuals, N=75 is the best choice for our case study (compared with N=45/60).

3.2. Case study n°2: building

The building studied has four levels. It has a living area of about 1200m² (Fig. 6). The building is composed of 17 apartments, a landing, a garage / crawl space and attic. Each of these areas has been simulated as a thermal zone. The model has 20 thermal zones in total. It is located in Chambery (Savoie, France) at an altitude of 235m.

Fig. 6 South and East views of the building "Les Roches Blanches"

The buildings walls, intermediate floor, partitions and floor are made of concrete. Walls have gypsum plaster board and exterior insulation. Floor on crawl space has Polystyrene insulation; however the Flat roof and Floor under attic have polyurethane insulation and glass wool insulation respectively. The windows in rooms are PVC double glazed windows with overall heat transfer coefficient U_w = 1.3 W/(m².K). The number of occupants in an apartment kept equal to the number of room in the apartment. The occupancy for different hours during weekdays and weekend are varied from 25% - 50% - 100%. The internal heat gains of housing (related to cooking, electrical appliances, etc.) are taken into account on hourly basis and vary between 1.5 W/m² to 7.68 W/m². The cooling and natural ventilations have been taken into account from 15 July to 15 August. The infiltration was considered 0.15vol.h^{-1}. The mechanical ventilation varies with size of the apartment.

Dynamic thermal simulations were run in Energy+ 8.5 software. This software models the thermal comfort, ventilation, infiltrations, internal heat gains, and the heating and cooling loads of the building. The weather file (Meteonorm) used is a typical year weather of the city of Chambéry (Savoie, France).

- **Decision parameters and objective functions**

In order to optimize the building, decision parameters and objective functions have been defined. The decision parameters used to test the tool and their range of variation are presented in Table 1.

Table 1. Decision parameters

Decision parameters	Range of variation	Area (m^2)
The thickness of insulation in the exterior walls	0.1 to 0.4m	906
The thickness of the slab of the intermediate floor	0.1 to 0.25m	869
The thickness of insulation in the floor on the outside	0.1 to 0.4m	216
The thickness of insulation in the flat roof	0.1 to 0.4m	243
The U_w value of the windows	0.9 to 1.5 W/(m².K)	207
The building orientation	0 to 270 °	-

The functions used to evaluate the decision parameters are the sum of heating and cooling loads supplied by the system to the building and the cost related to the changes. The heating and cooling loads are directly calculated by Energy+. They represent the energy demand of the building. The

cost equations include the price of the material and the installation. Costs are expressed in €/m^2 excluding Tax:

- Insulation thickness variation cost of the wall $= 520.1x + 73.602$
- Insulation thickness variation cost of the floor on the outside $= 53 + (50 \times (x - 0.1))$
- Insulation thickness variation cost of the roof terrace $= 40.585e^{4.4882x}$
- Insulation thickness variation cost of the intermediate floor $= 663.25y + 57.49$
- Variation cost of the U_w of the windows $= 110 \times \left(1 - \frac{1}{1 + e^{-30(z-1.15)}}\right) + 455$

where, x is insulation thickness (m), y is concrete slab thickness (m) and z is U_w (W/m^2K)

The objective is to find the optimum between the sum of heating and cooling loads which must be the lowest possible, and the cost of the operation which must also be minimized.

- **Results**

We run the optimization with N=75 individuals as in case of test functions but the Pareto frontier obtained after step II was not closer to the reference Pareto frontier (obtained directly with NSGA II and Energy+). This may be due to the 4 decision parameters instead of 2 decision parameters for test functions. Therefore we run the optimization for 105 individuals. The Pareto frontiers for reference model and after each step are given in Fig. 7. It can be observe that the Pareto frontier is not smooth as the case of test function which reflects the complexity of the case study problem which can be credited to increased number of decision parameters. For the reference model with NSGA II, 1321 simulation are required to run the optimization. The time needed for one simulation is approximately 7.5 minutes. Therefore the time required to run the optimization with Energy+ is approximately 7 days. With Kriging model we have run the optimization with 105 individuals, therefore the time required to run the optimization with Kriging model is 13 hours which is approximately 13 times faster.

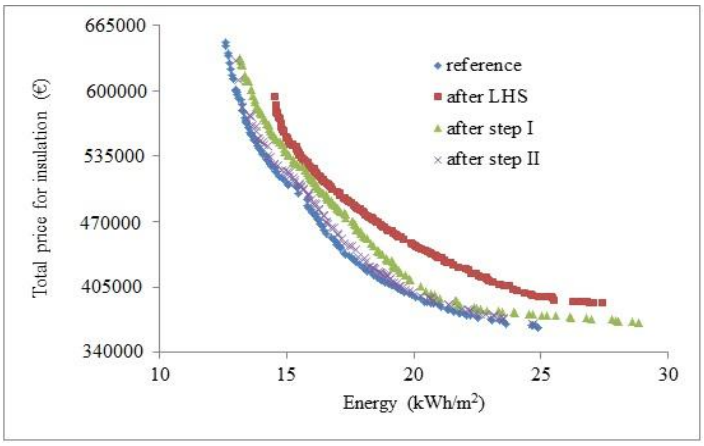

Fig. 7 Pareto frontier for energy need and total price of insulation for the building (case study)

In this work, our main objective was to validate the approach developed in CADES. Of course further work is necessary to precisely analyze the optimal solution as in [36]

4. Conclusions and outlooks

A global strategy for making a Design of Experiment on time consuming models has been proposed in this paper. The deployment of such an approach can be a complex task for final users in design offices. That is why the approach has been implemented in a framework in which the complex

computer science aspects, like interoperability or connection with the Kriging libraries is encapsulated. The idea is to offer, for the final user, an approach as closed as possible from a "plug&play" approach. The perspective is now, to work on tutorials and illustrations of the use of the methodology and the software on real examples. By this way, we hope that future users will not only be able to use the approach, but also to understand, how they must configure and use it to go towards an efficient design process.

For the test functions we observe that, with increasing number of individuals the R^2 values approaches to 1 which justify the accuracy of the Kriging model. The number of individuals which gives the R^2 value near unity depends on the complexity of the reference function. As observed from the case study n°2, with increased decision parameters, the number of individuals N needed to predict the model accurately is increased (from N=75 to 105). Therefore further study is required with different test functions and increasing complexity to find the minimum number of individuals to predict the reference accurately, particularly in the Pareto area.

In this first step, LCA has been performed in a separate computer platform including also energy simulation and optimization [37]. The considered decision parameters were the insulation thickness in walls, roofs and floors, glazing type (double or triple), ventilation system (with or without heat recovery). According to optimization results shown in Fig. 8, a limited supplementary cost of 40 € per m^2 floor area would allow CO_2 emissions, over the life cycle of the building, to be reduced by 23% compared to the base case.

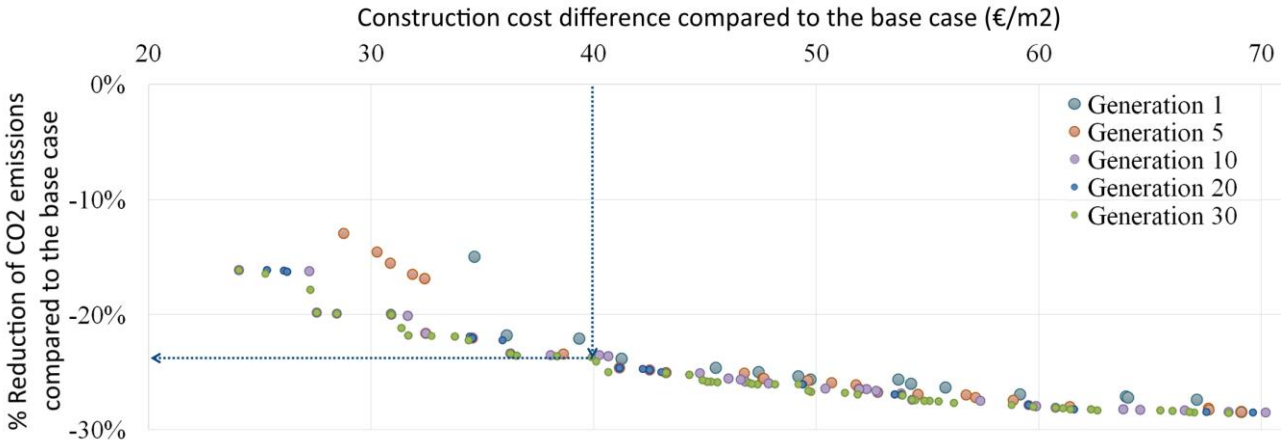

Fig. 8 Pareto frontier for CO_2 emissions and construction cost (case study)

Corresponding technical solutions have been identified, e.g. 85% of the Pareto front solutions include heat recovery on ventilation air, but only 40% use triple glazing. Integrating LCA in the tool presented above would therefore bring new possibilities for eco-design.

Acknowledgments

This study has been supported and funded by the French National Research Agency (ANR), under grant agreement N° ANR-13-VBDU-0003-01, Acronym INTENSE. Partners: LOCIE, LGCB, ARMINES, G2ELAB, CEA-INES, ALBEDO, FAURE, VESTA SYSTEM

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