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BENCHMARK OF OPTIMIZATION TECHNIQUES FOR IDENTIFICATION OF BUILDINGS THERMAL PARAMETERS

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ABSTRACT

This article presents an ongoing work aiming at the development of an optimization tool for the assessment of building intrinsic performances. The objective is to enable for the reliable calculation of as-built envelope thermal parameters (resistance and capacitance) based on measurements collected over a limited period of time. The tool is based on the combination of a basic physical model and of optimization algorithms that automatically calibrate the model from measures. This paper presents a benchmarking study lead as part of this work to select an inverse optimization methodology, which is intended to identify a set of thermal parameters. Three methods have been tested for the building thermal inversion. The first method is based on a simple greedy resolution (Particle Swarm Optimization) whereas the other two are based on substitution model (Support Vector Regression and Metamodels). The study has been validated on a basic use case (monozonal building) and relied on a comparison between the predictions obtained from calibrated models and those obtained from the Energy Plus simulation environment. The study shows that metamodels coupled with a cross-validation method (kriging) lead to the best results.

INTRODUCTION

Energy is a valuable asset and the basis of economic growth and societal well-being. Gradually, energy conservation has become a recognized priority for environment preservation and energy efficiency a prominent concern. The building sector is known to be one of the main contributors to energy consumption. It represents for instance 40% of energy consumption and 36% of CO₂ emissions in the European Union (EU)¹. Therefore, in order to reach the ambitious targets set by recent environmental policies (e.g. the EU 2020 climate and energy package²), energy performances of buildings have to be significantly improved. In this respect, one major challenge is to enable for reliable and cost-effective assessment of as-built, intrinsic performances. Significant gaps are actually often observed, between “as-designed” and “as-built” building performances (P.De.Wilde 2014). Enabling for the reliable assessment of as-built intrinsic performances would help to identify

the causes of possible deviations and, gradually, to tackle their root causes. The good thing is that a significant number of tools for thermal modeling are available. These models are generally gathered into three categories: *white box*, *black box* and *gray box* models (A. Fouquier 2013a). White box models describe in details the physical behavior of the system modeled. They include numerous equations, parameters and variables and therefore are usually complex. Black box models, based on statistical models, may provide reliable predictions but do not allow for any physical analysis. Gray box models are hybrid: they rely on simpler physical modeling approaches, but can be calibrated from measures using optimization and statistical learning techniques. They allow for inverse modeling (calculation of actual thermal parameters from measures) with few building information and limited data collection. Gray box models could therefore be a good trade-off between ease of implementation and reliability for the implementation of intrinsic performances assessment solutions. However, to unfold their full potential, the following aspects have to be considered with proper attention: (i) the modeling approach shall be simple to use but shall as well allow for the calculation of the main thermal parameters; (ii) the optimization algorithms have both to be reliable and to require reasonable processing time; (iii) the process for collecting the data (building and measurements) shall be swift and simple.

With respect to (i), we presented in a previous paper (A.Fouquier 2013b) a modeling approach based on a thermal-electric analogy that gave a sound foundation to our solution. This paper gives the outcomes of a study lead on the second issue (ii), i.e. the selection and the prototyping of the optimization algorithms.

We specifically focused on the evaluation and testing of three optimization methods: Particle swarm optimization (PSO); the coupling of the PSO method with a regression model based on polynomial support vector regression (SVR); Metamodels validated with a cross-validation method (kriging). The proposed methods are interesting because they can be used both for calibration of a white box model or for the regression of a black box model. In this paper, these methods were used for the calibration of physical model (white box) and in the same time to identify the thermal parameter of single-zonal building. Seven thermal parameters were identified and the predictions from

¹ <http://ec.europa.eu/energy/en/topics/energy-efficiency/buildings>, accessed April 2014.

² http://ec.europa.eu/clima/policies/package/index_en.htm, accessed April 2014.

calibrated were compared to predictions from the EnergyPlus environment.

The paper is structured as follows. A first section introduces the case study and the related model. The subsequent section presents the mathematical foundations of the particle swarm optimization method. The third section illustrates the two substitution models (support vector method and kriging). These two types of models will be compared with a basic theoretical example in the same section and the associated algorithms will be presented. The last section discusses the results obtained on the case study, before giving a conclusion.

CASE STUDY, MODEL PRESENTATION AND PROPOSED SOLUTIONS

In this section, we present the case study. The first sub-section describes the targeted building. Then, the electrical analogy based on Resistance Capacitances (RC)-modeling of the building is described. At last, some considerations about model simplification are given, before highlighting the thermal parameters considered in the optimization phase.

Case study

The geometric information (building, openings) is supposed to be known and is used as an input to the optimization process. We have considered a mono-zone building of dimension 7.5x6.5x2.5 m³ as shown in *Figure 1*. This building includes 7 openings distributed on the 4 façades. Table 1 summarizes the geometrical characteristics of these openings.

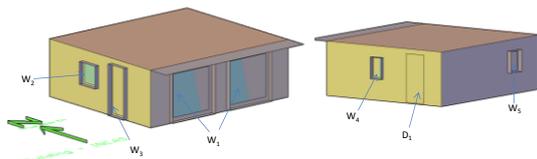


Figure 1 Case study geometry

Table 1

Geometric parameters of the openings

DESIGNATION OF THE OPENING	W ₁	W ₂	W ₃	W ₄	W ₅	D ₁
HEIGHT (M)	2.15	9.5	2.15	1.05	1.05	2.24
WIDTH (M)	2.3	1	1	0.8	0.8	1

RC-network modeling (A. Fouquier 2013a)

The building topology is determined by an undirected weighted graph $G = (\aleph, \mathcal{E}, W)$ (K. Deng 2010). $\aleph := \{1, 2, \dots, n\}$ denotes the set of nodes of the graph, $\mathcal{E} \subset \aleph \times \aleph$ denotes the set of edges and W is the set of edges belonging to the same element (same wall or zone or opening). A node represents a point measuring temperature and an edge is the segment that connects two adjacent nodes. Each node $i \in \aleph$ is assigned by a temperature T_i and a capacitance C_i and each edge $a = (i \in \aleph, j \in \aleph) \in \mathcal{E}$ is assigned by a resistance $R_{i,j}$ that satisfies $R_{i,j} = R_{j,i}$. Since the thermal model is an RC-network, its dynamics is described by a system of coupled first order linear differential equations of the form:

$$\vec{C} \cdot \frac{\partial \vec{T}}{\partial t}(t) = \mathbf{A} \vec{T}(t) + \vec{\Phi}(t) \quad (1)$$

where $\vec{T}(t) = [T_1(t), T_2(t), \dots, T_n(t)]'$ denotes the column temperatures vector at the time t for the set of building nodes mesh, $\vec{C} = [C_1, C_2, \dots, C_n]'$ is the column vector of nodes capacitance and $\vec{\Phi} = [\phi_1, \phi_2, \dots, \phi_n]'$ is the column vector of radiative, solar and net flux. The entries of the transition-rate matrix $\mathbf{A} = (A_{ij}, i, j \in \aleph)$ are given by:

$$A_{ij} = \begin{cases} 0 & \text{if } i \neq j \text{ and } (i, j) \notin \mathcal{E} \\ \frac{1}{R_{ij}} & \text{if } i \neq j \text{ and } (i, j) \in \mathcal{E} \\ -\sum_{j \neq i} A_{ij} & \text{if } i = j \end{cases} \quad (2)$$

The initial temperature is denoted by $T(0)$.

Model simplification

In order to reduce the size of the optimization search space and keep computation time within reasonable boundaries, it is necessary to simplify the geometry. The approach of geometric simplification and its impact on fitness resolution is presented in (A.Fouquier 2013b). This study shows that merging walls and openings has few impact on reliability and improves significantly the performances. *Figure 2* shows the model resulting from the application of this simplification approach to our use case. The six walls have been merged into a single wall and the seven openings into a single opening. As can be seen, the wall is supposed a monolayer one and is modeled by a 2R3C (2 resistances, 3 capacitances) configuration.

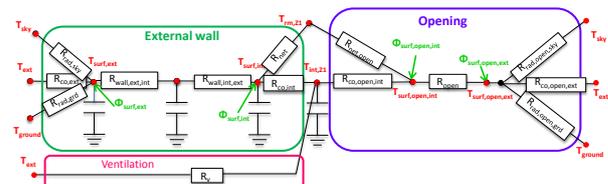


Figure 2 Simplified RC model of the use case

As a consequence, the number of parameters that will be identified by the optimization algorithms is reduced to 7. These are:

- The overall heat transfer coefficient and capacitance of the wall ($U = \frac{1}{RS}, C$), where R is the wall's resistance and S is his surface.
- The distribution coefficient of U in the wall ($Coef_{rep,U}$),
- The net flow resistance h_{net} of the wall,
- The overall heat transfer coefficient (U) of the opening ,
- The radiative distribution coefficient of the zone ($Coef_{rep,Rad}$),
- The ventilation rate for the zone (ACH_{Ventil}),

Proposed algorithms presentation

The problem studied does not fit mathematical requirements, it could not be properly solved by classical mathematic and required then a greedy resolution. A grid search resolution is based on building a solution incrementally by adding an item at every step regarding a greedy criterion. In this context a reference method (called particle swarm optimization) was tested for the resolution of our problem. Despite the simplicity of the implementation of this method, obtaining optimal solution requires a large number of samples which goes up the run time and do not guarantee that a global minimum of the objective function. Considering that one simulation of a set of parameters needs at least one minute, one have to decrease the number of iterations in order to keep the computation time realistic.

To minimize the number of tests required to obtain the optimal, using a surrogate model can be very interesting. The key of such model is to estimate the overall shape of the cost function in order to guide the convergence procedure. In this context two substitution models have been tested: Support vector machine and kriging models.

The two next sections are devoted to the presentation of the three optimization algorithms. Firstly, we present an optimization tool based on population of random solutions updating for the search of optima. This method is named particles swarm optimization. Secondly, two algorithms based on substitution model are presented. To this end, we first describe the two regression models used (Support vector machine and kriging models). These models are then compared thanks to a basic theoretical test case. At last, the algorithms associated are explained in detail.

GRID SEARCH METHOD: PARTICULES SWARM OPIMISATION (PSO)

This is an optimization method developed by Russell Eberhart and James Kennedy (R. Eberhart 1996) which is based on the simulation of the movement of a particles group. Through displacement rules of each particle, the particles converge towards an optimal model in the sense of the objective function. This method does not require the calculation of the gradient and therefore can be used for black box models.

Each sample is mapped to a particle. The principle of the PSO method is to use simultaneously multiple particles that explore the solution space by sharing their experience in order to converge to a global minimum. The future position of a particle depends on its velocity and an attraction to the most interesting position met both by each lonely particle and by the group. The PSO algorithm (Y.Cheng 2015) controls the movement of the n particles in space is as follows. At each iteration k, each particle i is defined by:

- Curent position X_i^k
- Current velocity V_i^k
- Best position encountered during travel P_i
- The best position of the set of particles at the kth iteration P_g .

At each iteration, the velocity of the ith particle is calculated as follows:

$$V_i^{k+1} = \omega . V_i^k + c_1 . rand . (P_i - X_i^k) + c_2 . rand (P_g - X_i^k) \quad (3)$$

Where ω, c_1, c_2 are fixed values, and rand are random numbers in the [0, 1] interval. The position of each particle is defined by:

$$X_i^{k+1} = X_i^k + V_i^{k+1} . dt \quad (4)$$

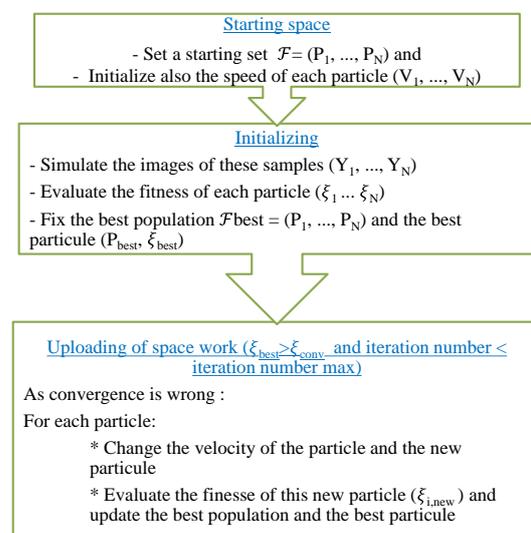


Figure 3 The three steps of the PSO algorithm

The movement of the group of particles is evaluated until the algorithm converges or until the maximum number of iterations is reached. **Figure 3** outlines the three steps of the algorithm.

METHODS BASED ON SUBSTITUTION MODEL

In an optimization process, using a simple analytical and differentiable model is preferable. Substitution models have the advantage to give a good approximation of the system response, in a simpler and more manageable way. Such models can be a simple mathematical representation of a numerical model, a black box model, or a behavioral model (related to experimental data). There are a variety of mathematical models classified under this category. These methods are commonly used for the benefits they provide:

- An understanding of the relationship between the governing inputs and outputs of the model
- A quick analysis tool for optimization
- A quick and easy coupling between dependent fields and disciplines.

This approximation via mathematical models involves three requirements classified and characterized in (T. Simpson 2001)

- The choice of experiments points,
- The choice of the type of model best suited to the representation of data,
- The experiments approximation (fitting), i.e. the determination of the unknown parameters of the model equations.

In this study, two algorithms based on substitution model have been used: SVR and kriging metamodel.

Substitution models

Support vector method (SVM)

Support vector machines (SVMs) are a set of related supervised learning methods that analyze data and recognize patterns, used for classification (machine learning) and regression analysis. The original SVM algorithm was invented by Vladimir Vapnik (V.Vapnik 1995).

Suppose a set of observational data (samples) $(X_1, Y_1), (X_2, Y_2), \dots, (X_k, Y_k)$ such as $X_i \in \mathbb{R}^n$ and associated value $Y_i \in \mathbb{R} \forall i \in \{1, \dots, k\}$. For the regression problem based on the SVM, the objective is to find a function f that minimizes the difference between $f(X_i)$ and $Y_i, \forall i \in \{1, \dots, k\}$. The function that was used in this work is polynomial of order 2 and the quadratic optimization problem was solved with the interior point method. This function is named the SVM regression function and can be written as:

$$f(X) = \sum_{1 \leq i \leq n} w_i K(X, X_i) + b \quad (5)$$

where K is a 2-order polynomial kernel function

$$K(X, X_i) = (\langle X, X_i \rangle + 1)^2 \quad (6)$$

Kriging metamodel

Kriging is an approximation or modeling method based on a statistical model (J. Sacks 1989). The typical use of this approximation is to construct a prediction model based on experimental data.

Given a set of m samples $S = [X_1, \dots, X_M]$ with $X_i \in \mathbb{R}^n$ and the answers $Y = [Y_1, \dots, Y_M]$ with $Y_i \in \mathbb{R}$. The data are assumed to satisfy the normalization conditions:

$$\begin{cases} \mu[S(:, j)] = 0, V[S(:, j), S(:, j)] = 1, j = 1, \dots, n \\ \mu[Y] = 0, V[Y, Y] = 1, \end{cases} \quad (7)$$

μ, V denote the mean and covariance respectively.

We assume a model \hat{y} which approximates the response $y(x) \in \mathbb{R}$, for an n -dimensional input $x \in D \subset \mathbb{R}^n$, based on a regression model \mathcal{F} and a random function (stochastic process) z such as :

$$\hat{y}(x) = \mathcal{F}(\beta, x) + z(x) \quad (8)$$

Validation and comparison of the substitution models

This paragraph illustrates the validation of the two substitution model thanks to a simplified, theoretical use case. The aim is to compare the resulting model obtained with SVR and kriging with a theoretical model that has been analytically defined.

Validation case:

We studied an RC model consisting of two nodes to represent the behavior of a homogeneous single layer wall that separates two adjacent areas z_1 and z_2 (**Figure 4**).

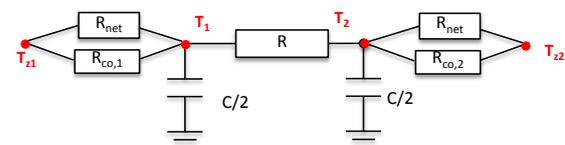


Figure 4 modelling of heat transfer between two zone by a 1R2C network wall

This network can be translated to the following system of equations:

$$\begin{aligned}
 & \begin{pmatrix} C/2 \\ C/2 \end{pmatrix} \begin{pmatrix} \frac{\partial T_1}{\partial t} \\ \frac{\partial T_2}{\partial t} \end{pmatrix} \\
 &= \begin{pmatrix} -\frac{1}{R} - \frac{1}{R_{co,1}} - \frac{1}{R_{net}} & \frac{1}{R} \\ \frac{1}{R} & -\frac{1}{R} - \frac{1}{R_{co,2}} - \frac{1}{R_{net}} \end{pmatrix} \begin{pmatrix} T_1 \\ T_2 \end{pmatrix} \quad (9) \\
 &+ \begin{pmatrix} \frac{1}{R_{co,1}} + \frac{1}{R_{net}} & 0 \\ 0 & \frac{1}{R_{co,2}} + \frac{1}{R_{net}} \end{pmatrix} \begin{pmatrix} T_{z1} \\ T_{z2} \end{pmatrix}
 \end{aligned}$$

With:

- T_{z1}, T_{z2} : Temperature of the two adjacent zone z_1 and z_2 [°C]
- T_1, T_2 : Temperature of the two surfaces of the wall [°C]
- S : Surface of the wall [m²]
- R : Resistance of the wall [K/W]
- C : Heat capacity of the wall [J/K]
- $R_{co,1}, R_{co,2}$: the two convection resistances of the wall [W/(m².K)]
- R_{net} : net resistance of the wall

The parameters to be determined are the thermal resistance R of the wall, and its heat capacity C . The other variables are either measured or pre-determined. We consider the wall that separates the ground floor and the subsoil in the I-MA house of the INCAS experimental platform of the French National Institute of Solar Energy (INES) in Le-Bourget-du-Lac. The values of the other parameters describing the wall are (Clara 2012):

- $R_{co,1} = 0.01$ W/(m².K)
- $R_{co,2} = 0.0045$ W/(m².K)
- $R_{net} = 0.004$ W/(m².K)

We use the SVR and the kriging models to construct a polynomial function \hat{y}_p that predicts the behavior of:

$$\begin{aligned}
 F(R, C) = & \left\| \begin{pmatrix} C/2 \\ C/2 \end{pmatrix} \begin{pmatrix} \frac{\partial T_1}{\partial t} \\ \frac{\partial T_2}{\partial t} \end{pmatrix} - A(R, C) \cdot \begin{pmatrix} T_1 \\ T_2 \end{pmatrix} \right. \\
 & \left. - B(R, C) \cdot \begin{pmatrix} T_{z1} \\ T_{z2} \end{pmatrix} \right\| \quad (10)
 \end{aligned}$$

The search space is defined by the “typical” intervals of values $R \in [0.1; 50]$ K/W and $C \in [1; 1E8]$ (J/W).

Results and comparison

For the validation of the two substitution model studied in this paper, we used these models to estimate the function F . The estimation of this

function is performed according to an order 2 polynomial. The construction of the SVR models requires three experimental points by again the kriging model need six experimental points. To compare the two models, six samples points (set of evaluations function use to construct the models) are considered for the construction of the SVR and kriging model. The **Figure 5** shows the approximation of the function test F by the kriging and SVR models for distribution of the six samples points. The error average quadratic (MSE (6)) is illustrated in **Figure 6** for the two models (J. Sacks 1989).

$$MSE = \sigma^2 [1 - r^T R^{-1} r] + \frac{(1 - 1^T R^{-1} r)^2}{1^T R^{-1} 1} \quad (11)$$

With :

- R : the correlation matrix between the different samples points,
- r : the vector which represents the correction between the n samples points and unevaluated variable

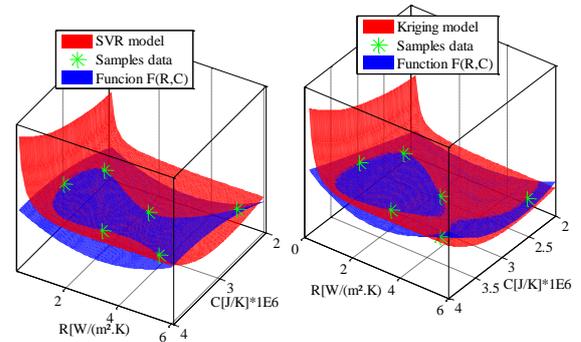


Figure 5 SVR and kriging polynomial model with 6 samples data

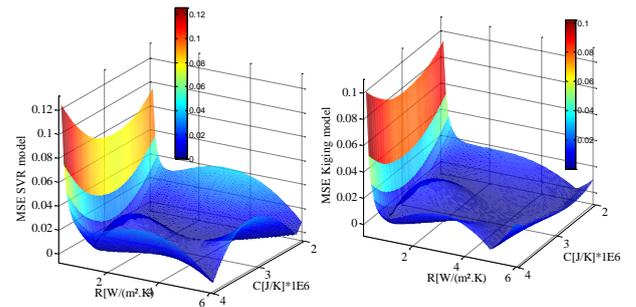


Figure 6 Mean squared error of the SVR and kriging polynomial model

We note that the average error between the model and the function is very low in the vicinity of the samples points. Furthermore, the error increases on the ends of the domain. In the cases treated, the SVR model could reproduce a faithful approximation of the function only on the vicinity of the samples points. In addition, an increase in the number of these sample points will significantly improve the modeling results. The same observation can be made with the kriging model but

the error is lower than the one obtained with the SVR model.

Algorithm based on SVR model

Since the two models seem to be able to fit the targeted function that implies thermal parameters the global procedure of parameters estimation could be described.

The algorithm starts by choosing n random samples (X_1, \dots, X_N) and then simulates these samples with our model (Y_1, \dots, Y_N) , so that the difference with the reference temperature $(\xi_1 = |Y_1 - Y_R|, \dots, \xi_N = |Y_N - Y_R|)$ is minimized. SVM is then used to determine a regression model denoted f such as $f(X_i) \approx \xi_i$. To validate this model, the following fitness function is used:

$$fitness = \frac{1}{N} \sum_{1 \leq i \leq N} |f(X_i) - \xi_i|.$$

Once the SVM regression model is validated, the PSO method is used to determine the minimum $(\xi_{SVR,min})$ of the SVR function f that matches to the set of parameters $X_{min,f}$ ($\xi_{SVR,min} = f(X_{min,f})$). The algorithm is stopped if the $\xi_{SVR,min}$ reaches the convergence criterion. Otherwise $X_{min,f}$ and other new particles are added to the set of samples. **Figure 7** summarizes the successive steps of the SVR-PSO algorithm.

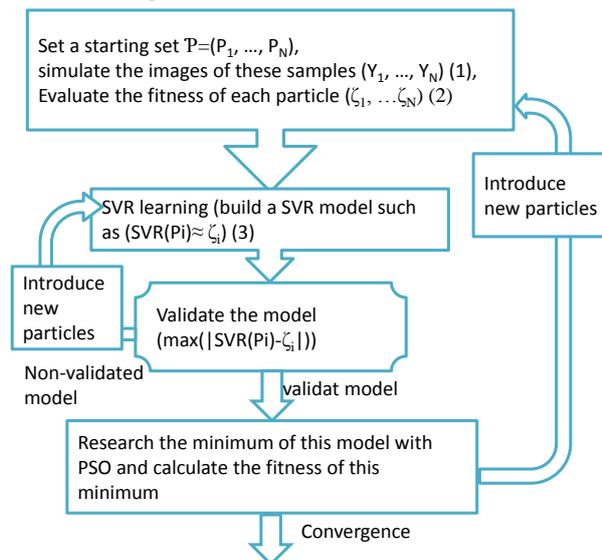


Figure 7 PSO-SVM algorithm

Algorithm based on kriging model

The algorithm starts with the selection of an initial set of samples and the simulation of all samples possible combinations (step 1 and 2); this leads to the construction of an observation data space (samples) $(X_1, Y_1), (X_2, Y_2), \dots, (X_r, Y_r)$ such as $X_i \in \mathbb{R}^n$ and $Y_i \in \mathbb{R} \forall i \in \{1, \dots, r\}$. The next step is to adjust r kriging metamodells for these simulation data (step 3) and validate these models (step 4). As the test proclaims one or more invalid meta-models, we update the design of models by simulating of additional input combination (step 5)

of global research area in order to further refine the r - metamodells.

When all r kriging models are valid, a solver is used to estimate the optimal location based on the kriging model (step 6). Then the algorithm checks whether the optimal sample has already been simulated and if the convergence criterion is reached (step 7). In the case where the convergence criteria have not yet been reached, another combination is added to the previous base (step 8). The algorithm is summarized in **Figure 8** (J.P.C. Kleijnen 2010), (J.P.C.Kleijnen 2014).

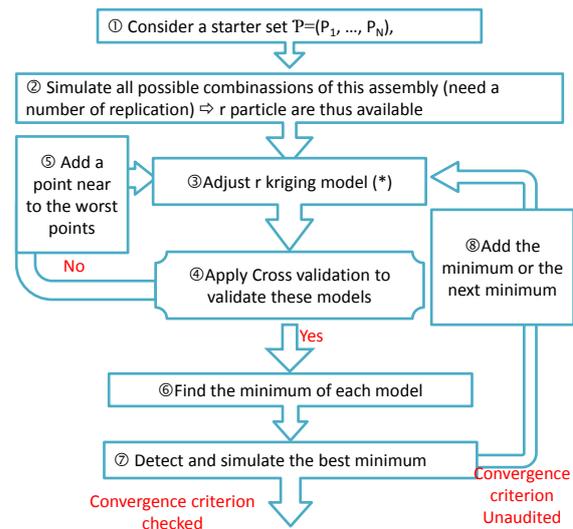


Figure 8 Kriging algorithm

RESULTS AND COMPARISON

The three methods previously described and validated on the theoretical case have been applied to the mono-zone building use case. The aim is to calculate the values of the seven thermal parameters listed in the previous section. The following figure shows the evolution of the error as a function of the number of iterations, for each the three methods until the convergence is obtained.

The results show the limitation of PSO method, where the convergence process is slow due to the attraction of local minima with 100 iterations whereas SVR or kriging obtain a similar error with only 30 iterations. Since each iteration requires a significant processing time, this approach does not seem to be well suited for our application scope. On the contrary, PSO-SVR and kriging give better results. They are able to significantly reduce the number of iterations and thus the calculation time. Kriging seems to bring an additional benefit from the robustness point of view: the algorithm is less sensitive to local minima and results in a smoother convergence pattern. The number of models evaluations required to reach the optimal solution is past from 500 with the PSO method to 250 with PSO-SVR method and 150 with kriging method.

This significant reduction is reflected in a significant reduction in calculation time (4h for PSO method, 2h for PSO-SVR method and 1.5h for kriging method). The number of models evaluation is different from the iteration number because the three algorithm start with a no-single set of samples. Moreover, the PSO algorithm reevaluates the start set sample at each iteration, which explains the considerable increase of the evaluation models total number.

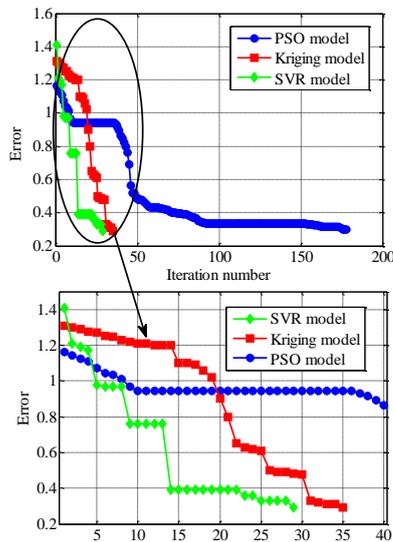


Figure 9 Application of the optimization methods to the use case. Evolution of the error as a function of the number of iteration.

The validation of our model is performed over a period of one year. However, for the clarification of the result visualization, only two weeks are represented. Indeed, **Figure 10** indicates the operative temperature over two weeks for the results obtain with the three proposed optimization algorithms compared with the EnergyPlus result. As we can see, the temperature estimated with the kriging model is much more representative of the reference temperature of EnergyPlus.

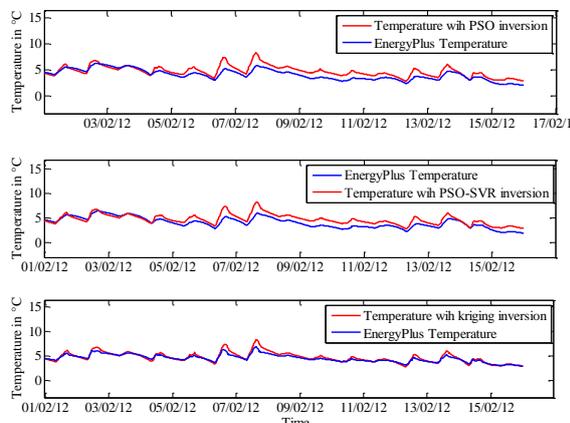


Figure 10 Operative temperature comparison of the optimization and EnergyPlus results for the quasi-passive monozone building

The evolution of the error between the operative temperature and the EnergyPlus simulation results displayed in **Figure 11** for the three algorithms. The error distribution around the average value is shown in the **Figure 12**.

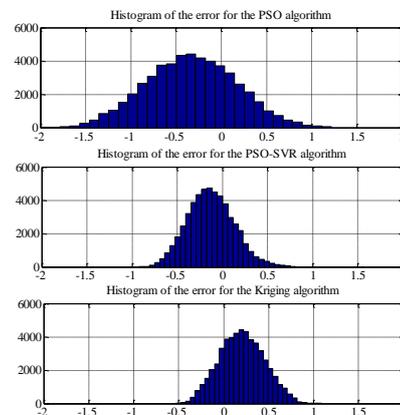


Figure 11 Histograms of the error between the operative temperature and EnergyPlus results for the quasi-passive monozone building

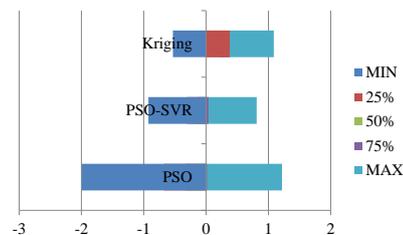


Figure 12 Distribution of the error for the 3 proposed optimisation algorithms

The three histograms show a Gaussian error distribution. The mean of the error distribution μ is equal to the value of convergence criterion of the algorithms. The standard deviation σ of the error distribution is significantly larger with the PSO algorithm compared to the two other algorithms where the standard derivation is almost identical (see **Figure 13**, where the values of the parameters identified obtained with the three algorithms is displayed).

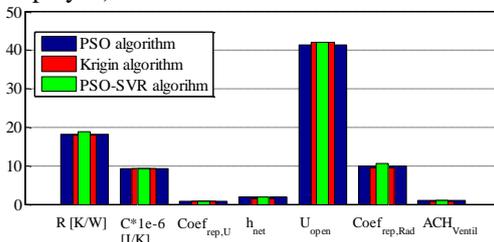


Figure 13 Numeric values of the parameters identified with the three algorithms optimization

The results presented above indicate a small error ($\leq 5\%$) between the parameters identified with the three algorithms. We can then use these algorithms not only for the calibration of our physical model but also the estimation of building intrinsic performances.

CONCLUSION

Energy efficiency is a prominent concern in the AEC sector. Modeling and simulation tools can help to reduce the energy consumption of the building and meet the requirements of existing energy labels, but fail to solve the “energy gap” problem – deviation of as-built energy performances from as-designed performances. It would therefore be beneficial to generalize as-built intrinsic performances assessment tools, able to reliably calculate the actual performances from limited (in time and scope) measurements. One promising path, to enable such tools, is to rely on so-called “grey-box” modeling approaches, which advocate the combination of simplified physical models and optimization algorithms. These approaches allow for the calibration of the models from measurements and, this way, for the deduction of the thermal parameters of the building, i.e. inverse modeling of the building.

This paper gave an account of as study lead as part of the development of such an inverse modeling tool. The first steps of this development focused on the definition of a simplified modeling approach (A. Fouquier 2013a) and (A.Fouquier 2013b). The study described in this paper focused on the assessment and selection of the optimization algorithm. Three optimization methods were implemented and compared (PSO, PSO-SVM, and kriging), based on a simple mono-zone building use case. The results show that convergence is faster in the case of PSO-SVM and kriging. PSO alone tends to get attracted by local minima and does not perform as well. The convergence patterns also suggest that kriging will be more robust and probably, the best candidate.

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