THE IMPORTANCE OF DERIVATIVES FOR SIMULTANEOUS OPTIMIZATION OF SIZING AND OPERATION STRATEGIES: APPLICATION TO BUILDINGS AND HVAC SYSTEMS

Van-Binh Dinh, Benoit Delinchant, and Frederic Wurtz
Univ. Grenoble Alps, CNRS, G2Elab, F-38000 Grenoble, France

ABSTRACT

This paper presents optimization approaches for a complex nonlinear constrained optimization problem: sizing integrating operation strategies of energy systems (heating, ventilation) for positive energy buildings. This is a multi-criteria optimization problem of big size with differentiable objective functions (thermal comfort and life-cycle cost) and a lot of continuous decision variables. To solve it, 2 optimization methods will be studied: (i) derivative-free method (NSGA2) et (ii) derivative-based method (Sequential Quadratic Programing). The study case is a positive energy house in South-East of France in which we will show that derivative-based optimization approach will be more efficient with much less computation time and a better quality of Pareto front solutions.

INTRODUCTION

Optimization studies in the field of building science have increased within the last two decades (Nguyen et al., 2014). The applied optimization algorithms can be divided into two main approaches: stochastic and deterministic methods. (Wystrcil et al., 2015) has presented avantages and drawbacks of stochatic ones such as genetic algorithms GAs (Goldberg 1989), generalized pattern search GPS (Audet et al., 2003), particle swarm optimization PSO (Kennedy et al., 1995). Their advantages are derivative-free and easy applicable with existing simulation software like e.g EnergyPlus, TRNSYS and Dymola. Nevertheless, these algorithms are time-consuming due to a large number of iterative simulation so that the number of optimization parameters is limited. Most of deterministic algorithm for continuous problems are gradient-based methods (Newton's methods) like e.g Sequential Quadratic Programming SQP (Boggs 1996) or interior points method (Potra et al., 2000). These methods offer a faster convergence by determination of a search direction, but have higher requirements to the system model. Nowadays, there does not exist a generic rule for algorithms selection because of the complexity and diversity of building optimization problem. Howerver, for a specific optimization problem, the choice of optimization algorithms is usually based on many considerations: (1) nature of decision variables (continuous, discrete or mixed-interger); (2) presence of constraints; (3) nature of functions (linear or nonlinear, continuous or discontinuous, mono or multi objective); (4) availability of derivatives; (5) characteristics of problem (dynamic or static)... Detailed reviews on optimization algorithms can be seen in (Evins et al., 2013) and (Nguyen et al., 2014).

In recent years, research on HVAC system optimization has become very popular. One of the first examples of the sizing of heating, ventilating and air-conditioning systems is presented in (Wright et al., 1987) or (Wright 1996). A more complex problem of the simultaneous optimization of HVAC system size and operation strategies has been studied in (Wright et al., 2001). In this problem, the control variables of system are considered as optimization variables, which significantly increases the problem dimension (e.g. 203 decision variables and 15 constraints). A genetic algorithm has been used in order to take discrete variables into account. The simultaneous optimization of HVAC system has also been studied in (Patteeuw et al., 2014) and (Ashouri et al., 2014) in which models are linear and a mixed integer linear programming (MILP) approach has been used. However, to the author's best knowledge, very few publications can be found in the literature that discuss optimization approaches for the simultaneous optimization of HVAC system size and operation strategies with highly constrained nonlinear functions and continuous decision variables. Our paper tries to describle such a complex optimization problem.

For high efficiency energy buildings, the summer comfort is usually guaranteed by building envelope so that cooling system is not recommended to be installed. Therefore, current research is focused on heating and ventilation systems optimization for assuring the indoor air quality (the winter thermal and aeraulic comfort).

In our study, for a positive energy house in south-east of France, the simultaneous optimization of the sizing and the operation strategy is studied. The heating and ventilation systems will be considered such that it maximizes the winter thermal comfort and minimizes the life-cycle cost in maintainting the aeraulic comfort. The objective functions and constraints are nonlinear functions of decision variables, while the number of continuous variables and constraints are relatively high (337 variables and 504 constraints). To solve such a complex multi-objective optimization problem, we would like to compare the performances of derivative-free and derivative-based optimization approaches knowing that the automatic code differentiation is available in order to produce gradients automatically. To do that, the multi-objective genetic algorithm NSGAII is a good candidate among the derivative-free algorithms while SQP is chosen as one of the most efficient derivative-based algorithms.

The remainder of the paper is organized as follows: Section 2 describes the modelling for optimization problem. Section 3 introduces the multi-objective optimization problem formulation. In section 4, the basic idea and applications of NSGAII and SQP algorithms are presented. Section 5 analyses the optimization results and the performances of the algorithms. Conclusions are reported in the final section.

BUILDING MODELLING

Case study

The studied building is part of the ADEME[1] research project "COMEPOS[2]" aiming at constructing twenty five positive energy buildings in France by 2018. This house has one heated zone, one garage and two basements with a floor area of more than 200 m^2. It is designed with high performance materials to reduce heat losses and to ensure a summer thermal comfort without cooling system. An energy operation system based on optimal predictive control will be installed by Vesta-System[3]. Then, we would like to apply our methodology to size the energetic system based on the fact that it would be managed optimally.

Thermal envelope model

An accurate model (Figure 1), produced with the EnergyPlus[4] software that enables the dynamic thermal simulation, was previously built by our partner LOCIE[5] laboratory.

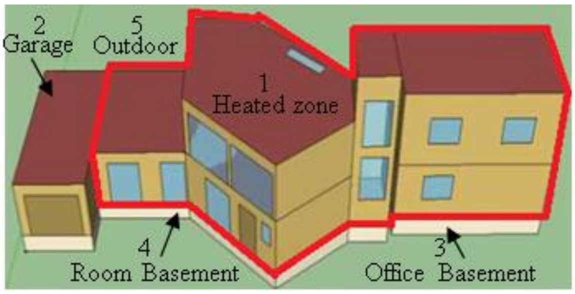

Figure 1 EnergyPlus model

This model is considered as a reference from which a reduced order model for optimization purpose is built in the form of an electrical equivalent circuit (Figure 2). This circuit uses a thermal-electrical analogy: thermal resistances, capacities, heat gains and external temperatures correspond to electrical resistances, capacities, current sources and voltage sources respectively. In Figure 2, T_{int} and T_{ext} represent the interior temperature of heated zone and the exterior temperature respectively. T_{gar} defines the temperature of garage while $T_{BSoffice}$ and T_{BSroom} express the temperatures of office and room basements. T_{we}, T_{wg}, T_{wbso} and T_{wbsr} are inside temperatures of wall or floor linked to the exterior, garage, office basement and room basement respectively. The heat gains come from the power transmitted to the zone by the sun (P_{solar}), electrical equipments (P_{elec}), occupants ($P_{occupant}$) and heating system (P_{heat}).

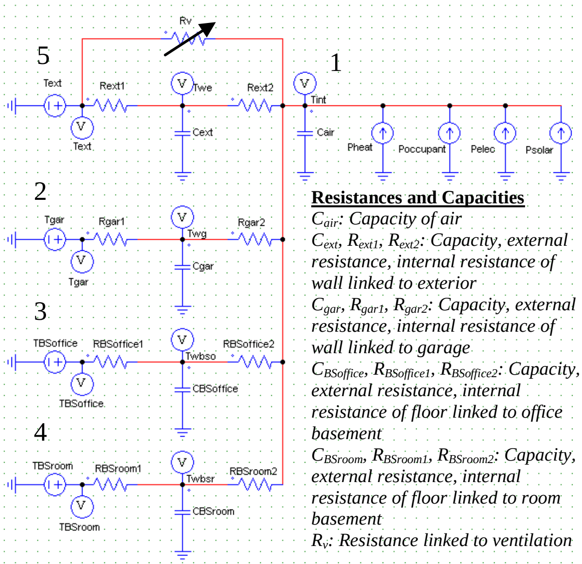

Figure 2 Electrical equivalent circuit

Thanks to the Ohm's law and Kirchhoff's laws, the circuit equations can be described:

$$C_{ext} \cdot \frac{dT_{we}}{dt} = \frac{T_{ext} - T_{we}}{R_{ext1}} + \frac{T_{int} - T_{we}}{R_{ext2}} \tag{1}$$

$$C_{gar} \cdot \frac{dT_{wg}}{dt} = \frac{T_{gar} - T_{wg}}{R_{gar1}} + \frac{T_{int} - T_{wg}}{R_{gar2}} \tag{2}$$

$$C_{BSoffice} \cdot \frac{dT_{wbso}}{dt} = \frac{T_{BSoffice} - T_{wbso}}{R_{BSoffice1}} + \frac{T_{int} - T_{wbso}}{R_{BSoffice2}} \tag{3}$$

$$C_{BSroom} \cdot \frac{dT_{wbsr}}{dt} = \frac{T_{BSroom} - T_{wbsr}}{R_{BSroom1}} + \frac{T_{int} - T_{wbsr}}{R_{BSroom2}} \tag{4}$$

$$\begin{aligned} C_{air} \cdot \frac{dT_{int}}{dt} &= \frac{T_{we} - T_{int}}{R_{ext2}} + \frac{T_{ext} - T_{int}}{R_v} + \frac{T_{wg} - T_{int}}{R_{gar2}} + \\ &\frac{T_{wbso} - T_{int}}{R_{BSoffice2}} + \frac{T_{wbsr} - T_{int}}{R_{BSroom2}} + P_{heat} + P_{occupant} + \\ &+ P_{elec} + P_{solar} \end{aligned} \tag{5}$$

The equations from (1) to (5) can be rewritten in the form of an equation system:

$$x'(t) = A(t).x(t) + B(t).u(t) = f(x(t), u(t), t) \tag{6}$$

Where x represents temperature variables; u presents heat gains and external temperatures; $A(t)_{5x5}$, $B(t)_{5x8}$ are state matrices depending on the resistances and capacities. For example:

[1] www.ademe.fr
[2] www.comepos.fr
[3] www.vesta-system.fr
[4] http://apps1.eere.energy.gov/buildings/energyplus
[5] www.polytech.univ-savoie.fr/locie

$$A(t)_{(5,5)} = -\frac{1}{C_{air}}\left(\frac{1}{R_v(t)} + \frac{1}{R_{ext2}} + \frac{1}{R_{BSoffice2}} + \right.$$

$$\left. + \frac{1}{R_{BSroom2}} + \frac{1}{R_{gar2}}\right)$$

$$B(t)_{(5,1)} = \frac{1}{C_{air}} \cdot \frac{1}{R_v(t)}$$

It can be noted that $R_v(t)$ is a variable resistance according to airflow $Q_v(t)$ (m^3/h) which is not constant over time:

$$R_v(t) = \frac{3600}{\rho_{air}.C_{pair}.Q_v(t)} \quad (7)$$

ρ_{air} and C_{pair} are the mass density (kg/m^3) and the specific heat (J/(kg.K)) of air respectively.

Numerical integration method

The time domain simulation by equation (6) with a given initial value $x(t_0) = x_0$, can be solved using Heun's scheme (modified Euler's method) (Süli et al., 2003):

$$x(t_{k+1}) = x(t_k) + \frac{dt}{2}.[f(x(t_k), u(t_k), t_k) + \\ + f(x(t_k) + dt.f(x(t_k), u(t_k), t_k), u(t_{k+1}), t_{k+1})] \quad (8)$$

Where $dt = t_{k+1} - t_k$ is the step size (in second). Equation (8) allows to determine the heated zone air temperature T_{int} at time step.

Identification of parameters of RC model

To have the same behavior between the macroscopic model and EnergyPlus model, an optimization procedure was proceeded which identifies the parameters of the RC model.

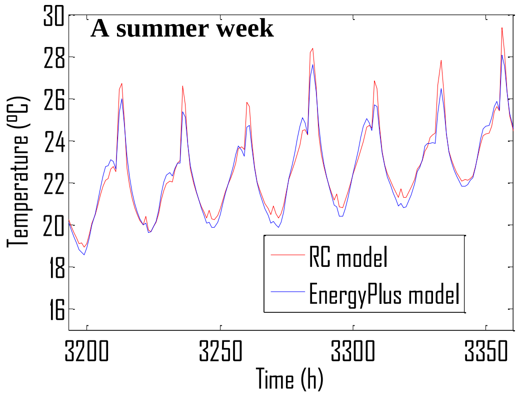

Figure 3 Heated zone air temperature by EnergyPlus and RC model using the validation data set

This identification uses the SQP algorithm aiming to minimize the difference between the heated zone air temperature T_{int} computed by RC model and by EnergyPlus for a constant 120 m^3/h ventilation. The data profile of one year has been used for the identification then another year data has been taken for the validation of parameters obtained. This optimization is not the aim of this paper even if many interesting issues may occur.

Table 1

Identified parameters R, C

PARAMETERS	IDENTIFIED VALUES
C_{air} (J/K)	3747281
C_{ext} (J/K)	38832547
C_{gar} (J/K)	233332
$C_{BSoffice}$ (J/K)	3038849
C_{BSroom} (J/K)	8110949
R_{ext1} (K/W)	0.00789
R_{ext2} (K/W)	0.00417
R_{gar1} (K/W)	0.17195
R_{gar2} (K/W)	0.16600
$R_{BSoffice1}$ (K/W)	0.06713
$R_{BSoffice2}$ (K/W)	0.01350
$R_{BSroom1}$ (K/W)	0.12775
$R_{BSroom2}$ (K/W)	0.00220

Figure 3 shows that the output temperature of reduced order model has a good agrement with the one of EnergyPlus model. The mean error value over 1 year between the two models is about 0.48°C.

CO_2 model

The CO_2 concentration at t_{k+1} can be calculated by equation (Dang 2013):

$$CO_2(t_{k+1}) = CO_2(t_k) + \left(N_p(t_k).Q_p.CO_{2p} - \\ - Q_v(t_k).(CO_2(t_k) - CO_{2air})\right).\frac{\Delta t}{V} \quad (9)$$

Where $CO_2(t_{k+1})$ and $CO_2(t_k)$ are the CO_2 concentration (ppm) at t_{k+1} and t_k respectively; $N_p(t_k)$ is number of person in the room at t_k; Q_p and CO_{2p} are the airflow (m^3/h) and CO_2 concentration (ppm) breathed out by a person respectively; $Q_v(t_k)$ is the airflow (m^3/h) supplied to the room; CO_{2air} is the CO_2 concentration (ppm) of the outside air; $\Delta t = t_{k+1} - t_k$ is the step size (h); V is the volume (m^3) of the room.

Economic model

In our study, the life cycle cost (LCC) (€) will be taken into account as an optimization criteria, which contains the initial capital cost, the replacement cost, the maintenance cost of energy system and the energy cost bought from the grid. The life span of building L_p is considered as 30 years. The expression of cost equations can be seen in (Kaabeche et al., 2010).

PROBLEM FORMULATION

Objective function

The problem in this study is a multi-objective optimization problem whose two optimization criteria to minimize are: thermal discomfort and life cycle cost. The thermal discomfort is calculated from a winter scenario (a typical day or a typical week) and described in degree-hour of discomfort:

$$discomfort = \sum_{k=1}^{N} e_T(t_k).\Delta t \ \text{ for } e_T(t_k) > 0 \qquad (10)$$

$e_T(t_k)$ is the difference between the heated zone air temperature and the set point temperature at t_k:

$$e_T(t_k) = \left(T_{set}(t_k) - T_{\text{int}}(t_k)\right) \qquad (11)$$

N is the period length (N=24 for a day and N=168 for a week of operation for instant). It can be noticed that the thermal discomfort is increasing when the building temperature is smaller than the set point value in winter.

Design scenario, variables and constraints

To see the performance of derivative-free and derivative-based approaches for optimization problem, we have done 2 tests. The first test is based on the scenario of a typical winter day and the second test is done during a typical winter week. The aim of the second test is to check the behavior of optimization algorithms when the number of decision variables and constraints is increasing. For all tests, a time step of 10 minutes is used for simulation and a time step of 1 hour is for decision variables.

Table 2
Continuous decision variables

VARIABLE TYPE	RANGE OF VALUES	NUMBER OF VARIABLES	
		TEST 1 t_k=0:23h	TEST 2 t_k=0:167h
$P_{heatmax}$	[0;20000] (W)	1	1
$P_{heat}(t_k)$	[0;20000] (W)	24	168
$Q_v(t_k)$	[120;3000] (m^3/h)	24	168
	TOTAL	**49**	**337**

Table 3
Constraints functions

FUNCTION	FORM	LIMIT	NUMBER OF CONSTRAINTS	
			TEST 1 t_k=0:23h	TEST 2 t_k=0:167h
$P_{heat}(t_k)$- -$P_{heatmax}$	≤	0 (W)	24	168
$CO_2(t_k)$	≤	1000 (ppm)	24	168
$T_{int}(t_k)$	≤	21 (°C)	0	168
		TOTAL	**48**	**504**

Table 2 presents the continuous decision variables including the design variable (heating size $P_{heatmax}$) and operation variables (heating power P_{heat} and airflow Q_v at each step t_k) for 2 test cases. Table 3 is for the constraints on the CO_2 concentration ($CO_2(t_k)$), heated zone air temperature ($T_{int}(t_k)$) and heating system operation power ($P_{heat}(t_k)$-$P_{heatmax}$). For test 1, the optimization problem has 49 decision variables and 48 constraints. For test 2, there are 337 decision variables and 504 constraints. It can be noticed again that the objective functions and constraints functions are nonlinear with respect to decision variables (e.g. nonlinear dependence of *discomfort* and CO_2 in Q_v).

To solve such a complex problem, we are using the CADES software[6] (developed in collaboration with our laboratory) in which models (envelope, CO_2, cost) are defined as modules, and are connected together for the global simulation. The optimization algorithms (SQP and NSGAII) are available in the framework for our optimization tests.

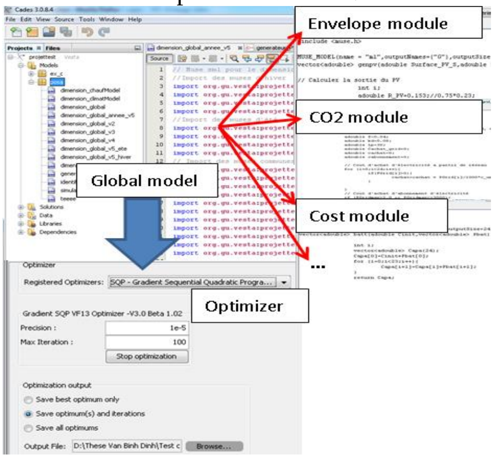

Figure 4 Optimization Implementation in CADES

OPTIMIZATION ALGORITHMS

NSGAII and SQP are two algorithms with advantages and drawbacks, so it is important to understand their limits and performances for our application domain (nonlinear constrained optimization problem):

$$\begin{aligned} &\min_x \ f(x) \\ &h_i(x) = 0, i = 1,2,..., p \\ &g_j(x) \le 0,\ j = 1,2,..., m \end{aligned} \qquad (12)$$

With $x \in \Re^n$; $h_i(x)$ and $g_j(x)$ are assumed continuously differentiable on $\Re^n$.

NSGAII algorithm

NSGAII is well-known fast elitist Non-dominated Sorting Genetic Algorithm proposed by (Deb et al., 2002). It uses non-dominated sorting and a crowed-comparison approach to find a set of evenly distributed solutions to multi-objective optimization problems. NSGAII is a modified version of NSGA (Srinivas et al., 1994) with the improvements of computational complexity, diversity of solutions and the incorporation of elitism.

For multi-objective optimization problems in building performance simulation, NSGAII is one of the most widely used algorithms. (Daum et al., 2010) used NSGAII to identify important state variables for a blind controller by optimizing the energy

[6] www.vesta-system.fr

consumption and thermal comfort. In order to design optimally compact heat exchangers, (Sanaye et al., 2010) applied NSGAII to obtain the maximum effectiveness and the minimum total annual cost. (Chantrelle et al., 2011) coupled NSGAII with TRNSYS to develop a multi-criteria tool for optimization of renovation operations, with an emphasis on building envelopes, heating and cooling loads and control strategies. (Evins et al., 2011) presented a new analysis and optimization procedure to aid decision-making exploiting the Non-dominated Sorting Genetic Algorithm for the environmental and financial objectives. NSGAII was also investigated in (Wright et al., 2013) for optimizing the cellular fenestration design. Recently, (Brownlee et al., 2015) has presented the constrained, mixed-integer and multi-objective optimization of building design by NSGAII with fitness approximation.

Through the applications of NSGAII algorithm, it is notable that the quality of results heavily depends on the population size N and the maximum number of generation M. A small size of N and M may result in the convergence with a poor confidence. On the contrary, a large size of N and M generally allows to obtain better results but requires high computation time due to a large number of simulations (Wetter et al., 2004). The choice of the most effective size is still a big challenge and is dependent on the complexity of optimization problems.

SQP algorithm

(Schittkowski et al., 2010) indicates that Sequential Quadratic Programming (SQP) belongs to the most powerful nonlinear programming algorithms for solving nonlinear optimization problems (12).

The basic idea to solve this problem is to seek to a search-direction $d_k \in \Re^n$ from a given iterate x_k (an approximation of the solution) using a quadratic programming sub-problem:

$$\begin{aligned} &\min_{d_k} \frac{1}{2}.d_k^{\,T}.H_k.d_k + \nabla f(x_k)^T.d_k \\ &\nabla h_i(x_k)^T.d_k + h_i(x_k) = 0, i = 1,2,..., p \\ &\nabla g_j(x_k)^T.d_k + g_j(x_k) \le 0, j = 1,2,..., m \end{aligned} \tag{13}$$

Where $\nabla f(x_k), \nabla h_i(x_k), \nabla g_j(x_k)$ are the gradients of functions $f(x_k), h_i(x_k), g_j(x_k)$ respectively.

$H_k = \nabla_x^{\,2} L(x_k, \lambda_k, \mu_k)$ is the Hessian of the Lagrangian function:

$$L(x, \lambda, \mu) = f(x) + \lambda^T.h(x) + \mu^T.g(x) \tag{14}$$

$\lambda \in \Re^p, \mu \in \Re^m$ are the multiplier vectors.

Once equation (13) solved, the search-direction $d_k \in \Re^n$ found allows determining a new iterate:

$$x_{k+1} = x_k + \alpha_k.d_k \tag{15}$$

In which $\alpha_k \in [0,1]$ is a suitable step-length parameter.

In SQP, the Hessian is not really required because it is generally approximated iterativelly using gradients.

A more detailed description about this algorithm is in (Boggs 1996). Generally speaking, SQP method is rapid and accurate but requires gradients of the model which is not always available in modelling tools. However, automatic code differentiation is a mature technique that allows engineers to focus on modelling and not in mathematics. We have implemented such an automatic differentiation technic in CADES software based on AdolC (Walther et al., 2012). Then, all previous models that we have defined in CADES framework have their gradient available for SQP.

RESULTS AND ANALYSIS

We now analyze in detail the performance of solutions obtained by the gradient-based approach (SQP) and the gradient-free approach (NSGAII) in the two tests mentioned above. All computations were run on a 2.7 GHz computer under window 7.

Table 4
Iteration number and computation time of test 1

	ITERATION NUMBER	COMPUTATION TIME (s)
SQP	180	10
NSGAII N50M100	10101	19
NSGAII N100M200	20201	38
NSGAII N100M1000	100201	174 (2min54s)
NSGAII N300M1000	300601	537 (8min57s)
NSGAII N300M2000	600601	1072 (17min52s)
NSGAII N500M3000	1501001	2795 (46min35s)

Table 5
Iteration number and computation time of test 2

	ITERATION NUMBER	COMPUTATION TIME (s)
SQP	69	176 (2min56s)
NSGAII N500M3000	1501001	21438 (5h57min18s)
NSGAII N1000M5000	5002001	72215 (20h3min35s)

Analysis of test 1:

Test 1 in our study is the nonlinear optimization problem with 49 continuous decision variables and 48 constraints. We started with the population size N=50 and the maximum number of generation M=100 for NSGAII. Figure 5 shows that the non-dominated front obtained by NSGAII with N=50 and M=100 is worse than the Pareto front obtained by

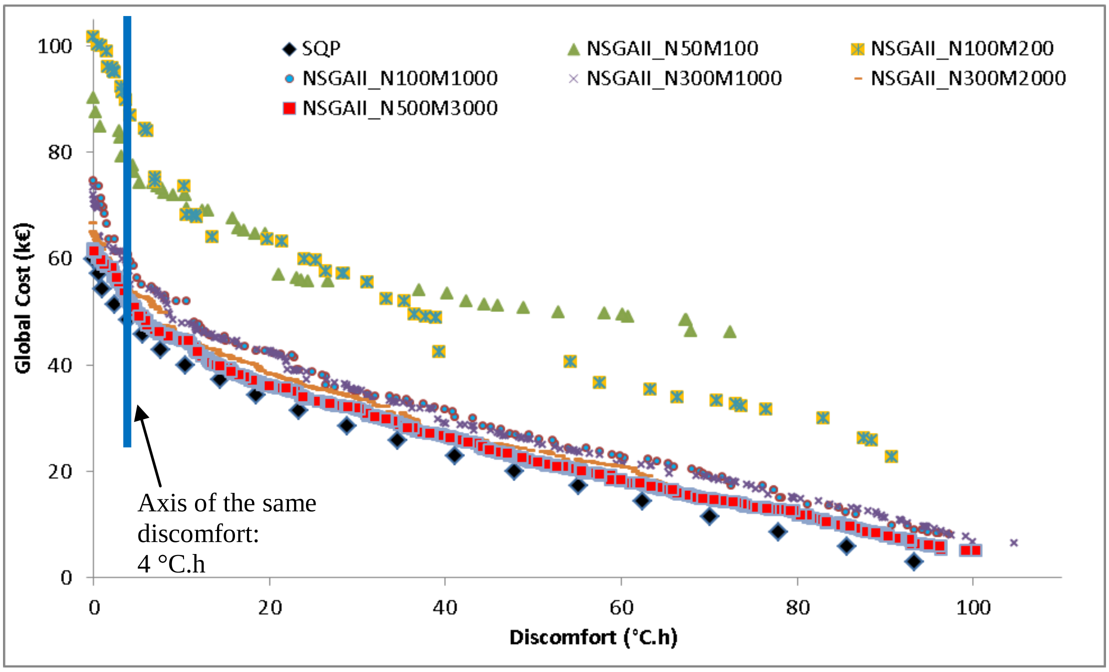

Figure 5 Non-dominated solutions obtained with NSGAII and SQP for test 1

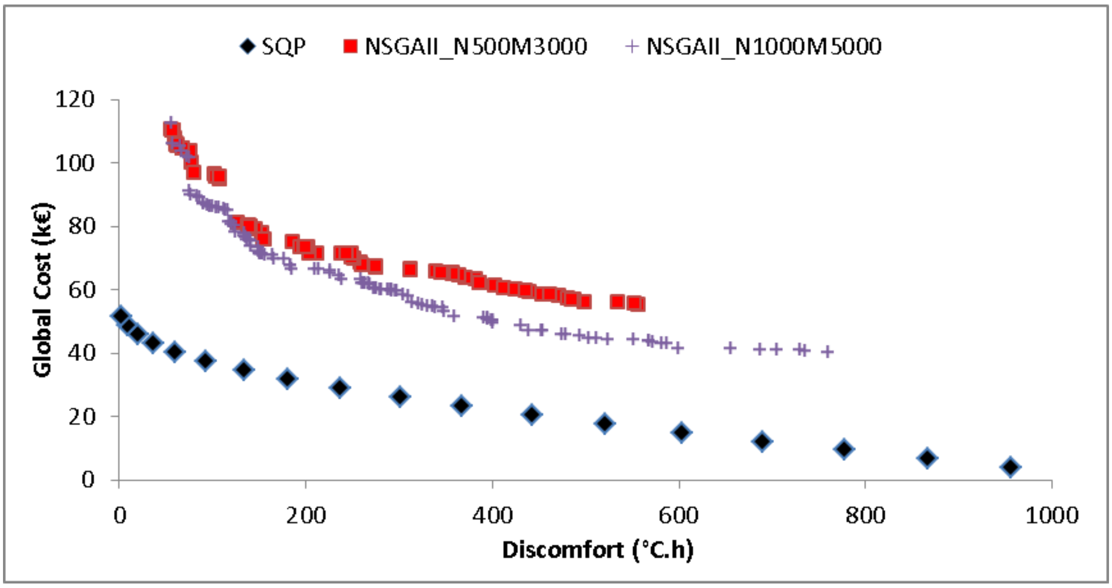

Figure 6 Non-dominated solutions obtained with NSGAII and SQP for test 2

SQP. Therefore, we increased step by step the size of N and M to hope improving the result with NSGAII. As a result, we obtained a Pareto front with N=500 and M=3000 converging near the Pareto front of SQP (Figure 5). To get this result, it takes approximately 45min with NSGAII and 10s with SQP, i.e. the optimization using the gradient-based approach is 280 times faster. A more detailed comparison about function evaluations number and computation time between both algorithms is summarized in Table 4. Regarding the optimum solutions, Figures from 7 to 11 analyze solutions obtained by SQP and NSGAII (N=500 and M=3000). The blue axis of Figure 5 indicates solutions with the same discomfort of 4 (°C.h). For this discomfort, it is observed that the solutions found by SQP and NSGAII in Figure 9 and Figure 11 lead to the relatively same trajectories of room temperation (Figure 8) and CO2 concentration (Figure 10). As it can be seen in Figure 9, regardless of the optimization method used, the heating system is turned on in advance from 2 a.m to 5 a.m so that the temperature tries to reach the set point at 6 a.m (Figure 8). Such a pre-heating when electricity cost is cheap allows to increase smoothly the interior temperature and so avoid a peak power of heating when the set point changes rapidly.

Figure 10 depicts that the constraint on the CO_2 concentration is well satisfied by the two optimization methods. However, there is a small difference between the solutions: SQP sizes a smaller heating system (Figure 9) and reduces airflow at some moments (Figure 11) compared to NSGAII. Due to these facts, the life-cycle cost of solutions using gradient-based method is a litte bit lower than ones using gradient-free method (Figure 5).

Analysis of test 2:

Test 2 is much more complex than test 1 with 337 decision variables and 504 constraints. In this case, SQP converges after 176s with a uniform spread of solutions (Figure 6). Regarding the gradient-free algorithm, we began with N=500 and M=3000 which was the NSGAII configuration used to obtain the best result in test 1. It is observed in Figure 6 that SQP has a better spread of solutions and converges much better to the true Pareto-optimal front. We tried a bigger population size N=1000 and number of generation M=5000. As it can be seen in Figure 6 the non-dominated set of solutions obtainted by NSGAII is improved but still much worse than ones obtained by SQP. In addition, Table 5 indicates that the computation time of NSGAII with this configuration

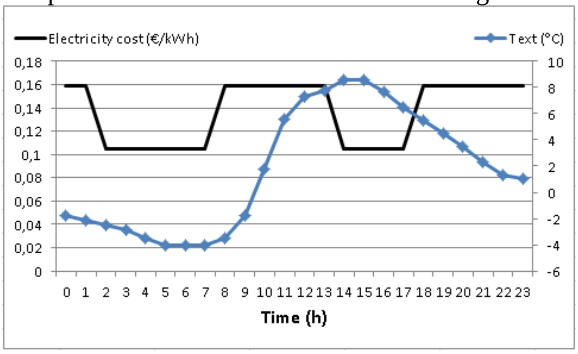

Figure 7 Scenario of electricity cost and exterior temperature for a typical winter day

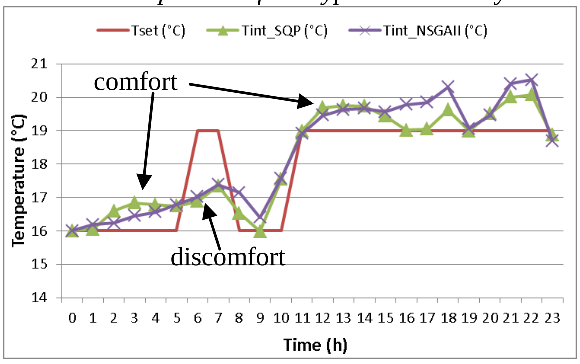

Figure 8 Winter interior temperature and set point

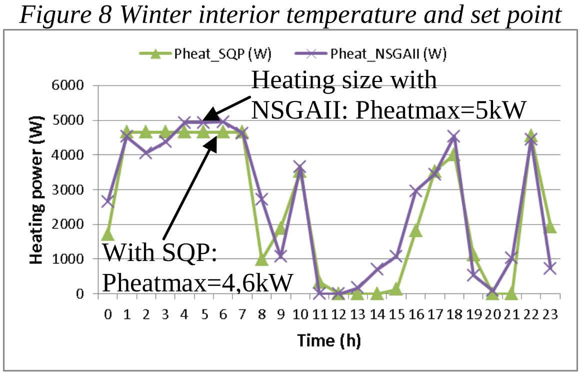

Figure 9 Heating system operation

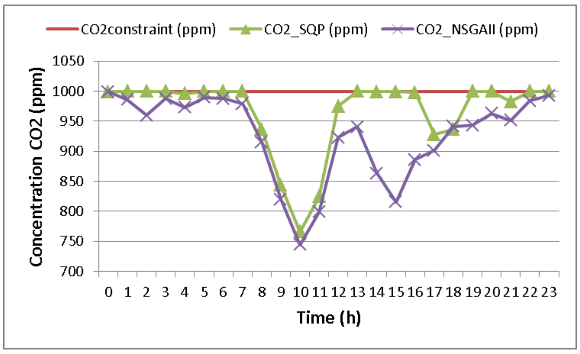

Figure 10 CO_2 Concentration and constraint

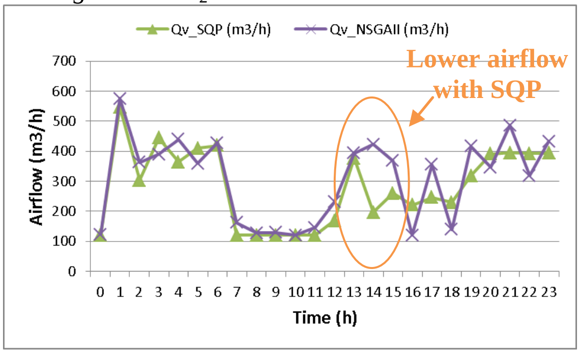

Figure 11 Ventilation system operation

is about 20 hours which is prohibitive regarding the number of optimization that are required during a design process. Meanwhile the computation time of SQP is much less (only 3 minutes). Thus, the solution using NSGAII in this test is clearly ineffective and impractical while the SQP method always ensures the high confidence for the computation time and the quality of Pareto front. With the obtained results, SQP method can completely be applied for complex optimization problems.

CONCLUSION

In this paper we study gradient-free and gradient-based optimization approaches for solving the complex nonlinear multi-objective optimization problem. This problem is optimizing simultaneously the heating nominal power and the operation strategy (heating and ventilation) for the criteria of winter comfort and energy cost. The originality of this study lies in the fact that we investigate the capacity of the optimization algorithms for solving the big size optimization problems with continuous decision variables and nonlinear constraints. Based on the results, it can be concluded that the approach using gradients (SQP) outperforms a gradient-free approach (NSGAII) in term of computation time and Pareto front quality. This research also indicates the limit of the genetic algorithm and shows perspectives of derivative-based methods for treating more and more complex problems in the real world of building performance.

REFERENCES

Ashouri, A., Benz, M.J. 2014. Simultaneous optimal design and control of future building energy systems under various pricing systems and governmental directives, Zurich, Switzerland.

Audet, C., Dennis, J.E. 2003. Analysis of Generalized Parttern Searches, SIAM Journal on Optimization 13(3): 889-903.

Boggs, P.T. 1996. Sequential Quadratic, National Institute of Standards and Technology, Gaithersburg, Maryland 20899, USA.

Brownlee, A., Wright, J.A. 2015. Constrained, mixed-integer and multi-objective optimisation of building designs by NSGA-II with fitness approximation, Applied Soft Computing, Vol. 33:. 114-126.

Chantrelle, F.P., Lahmidi, H., Keilholz, W., Mankibi, M.E., Michel, P. 2011. Development of a multicriteria tool for optimizing the renovation of buildings, Applied Energy 88(4): 1386-1394.

Dang, H.A. 2013. Modélisation en vue de la simulation énergétique des bâtiments: Application au prototypage virtuel et à la gestion optimale de PREDIS MHI, EEATS, Grenoble, France.

Daum, D., Morel, N. 2010. Identifying important state variables for a blind controller, Building and Environment 45(4): 887-900.

Deb, K., Pratap, A., Agarwal, S., Meyarivan, T. 2002. A Fast Elitist Multi-Optimal objective Genetic Algorithm:NSGA-II, IEEE Transactions on Evolutionary Computation 6(2): 182-197.

Evins, R., Pointer, P. and Vaidyanathan, R. 2011. Multi-objective optimisation of the configuration and control of a double-skin facade, Proceedings of the Building Simulation 2011 Conference, Sydney, Australia, pp. 1343-1350.

Evins, R. 2013. A review of computational optimisation methods applied to sustainable building design, Renewable and Sustainable Energy Reviews 22:230-245.

Goldberg, D.E. 1989. Genetic Algorithms in Search, Optimization and Machine Learning, Adisson-Wesley, USA.

Kaabeche A., Belhamel M., Ibtiouen R., 2010. Optimal sizing method for stand-alone hybrid PV/wind power generation system, Ecole Nationale Polytechnique d'Algiers, Algeria.

Kennedy J., Eberhart R. 1995. Particle Swarm Optimization, Proceedings of IEEE International Conference on Neural Networks, pp. 1942-1948.

Nguyen, A.T., Reiter, S., Rigo, P. 2014. A review on simulation-based optimization methods applied to building performance analysis, Applied Energy 113: 1043–1058.

Patteeuw, D., Helsen, L. 2014. Optimal design of HVAC systems as part of the future energy system, KU Leuven, Belgium.

Potra, F.A., Wright, S.J. 2000. Interior-point methods, Journal of Computational and Applied Mathematics 124 (1–2): 281–302.

Sanaye, S., Hajabdollahi, H. 2010. Thermal-economic multi-objective optimization of plate fin heat exchanger using genetic algorithm, Applied Energy 87(6): 1893-1902.

Schittkowski, K. 2010. A Robust Implementation of a Sequential Quadratic Programming Algorithm with Successive Error Restoration, Department of Computer Science, University of Bayreuth.

Srinivas, N., Deb, K. 1994. Multiobjective Optimization Using Nondminated Sorting in Genetic Algorithms, Journal of Evolutionary Computation 2(3): 221-248.

Süli, E., Mayers, D.F. 2003. An Introduction to Numerical Analysis, Cambridge University Press, ISBN 0-521-00794-1.

Walther, A., Griewank A. 2012. Getting started with ADOL-C. In U. Naumann und O. Schenk, Combinatorial Scientific Computing, Chapman-Hall CRC Computational Science, pp. 181-202.

Wetter, M., Wright, J.A. 2004. A comparison of deterministic and probabilistic optimization algorithms for non smooth simulation-based optimization, Building and Environment 39(8): 989–999.

Wright, J.A., Hanby, V.I. 1987. The formulation, characteristics, and solution of HVAC system optimized design problems, ASHRAE Transactions 93(2): 2133–145.

Wright, J.A. 1996. HVAC optimisation studies: sizing by genetic algorithm, Building Services Engineering Research and Technology 17(1): 7-14, ISSN: 0143-6244.

Wright, J.A., Farmani, R. 2001. The simultaneous optimization of building fabric construction, HVAC system size, and the plant control strategy, Loughborough University of Technology, Leicestershire, LE113TU, UK.

Wright, J.A., Zhang, Y., Angelov, P., Hanby, V.I., Buswell, R.A. 2008. Evolutionary Synthesis of HVAC System Configurations: Algorithm Development, International Journal of HVAC&R Research 14(1): 33-55, ISSN 1078-9669.

Wright, J., Brownlee, A., Mourshed, M. (in press). 2013. Multi-objective optimization of cellular fenestration by an evolutionary algorithm, Journal of Building Performance Simulation, DOI: 10.1080/19401493.2012.762808.

Wystrcil, D., Kalz, D. 2015. Comparison of control optimization approaches for low-exergy heating and cooling systems, Fraunhofer Institute for Solar Energy Systems ISE, Freiburg, Germany.