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On the performance of meta-models in building design optimization

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HIGHLIGHTS

- The BPO performances are quantified by the efficiency, efficacy and quality metrics.
- Meta-models are suitable for speeding up the optimization of building simulation.
- MARS model outperforms all the other models in the efficiency and efficacy.
- The pursuit of the solution quality implies an efficiency reduction.
- Sampling methods of the initial population have a low impact on the performances.

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ABSTRACT

Although evolutionary algorithms coupled with building simulation codes are often applied in academic research, this approach has a limited use for actual applications of building design due to the high number of expensive simulation runs. The use of a surrogate model can overcome this issue.

In the literature there are several functional approximation models that can emulate the building simulation during the optimization, thus increasing the process efficiency. However, there are no evidence-based studies comparing the performances of these methods for the building design optimization.

This study compares the efficiency, the efficacy and the quality of the Pareto solutions obtained by Polynomial, Kriging (*GRFM*), Radial-basis function networks (*RBFN*), Multivariate Adaptive Regression Splines (*MARS*) and support vector machines (*SVM*) functional approximations. The test bed of the comparison is the evaluation of the optimal refurbishment of three reference buildings for which the actual Pareto front is also obtained through a brute-force approach.

The results show that the *MARS* method outperforms the other surrogate models both in terms of efficiency and effectiveness, and also by assessing the quality of the Pareto front.

1. Introduction

The coming into force of the European Directive 2010/31/EU [1] guides the member states to the reduction of energy demand, and consequently carbon emissions, of the European building stock. Moreover the directive considers the economic effectiveness by means of the "cost-optimal approach" [2]. Optimization of the building and *HVAC* design and control becomes an essential tool in the design of new buildings and building refurbishments approaching the *nZEB* target [3–6]. Besides, when approaching the *nZEB* target while maintaining economical convenience, buildings might be easily subject to poor comfort conditions [7,8]. Hence, the designers are always confronted with a multi-objective optimization problem with two or more conflicting goals. The overall gains in design quality as well as the cost reductions that can be achieved through a correct optimization process are high. For this reason, architects and engineers become increasingly aware of the potential benefits of applying building performance optimization (*BPO*) in the early stages of the design process, often coupling the optimization codes with dynamic building performance simulation (*BPS*) since it better describes the dynamic interactions between the building, energy systems, occupants and the outdoor environment.

The use of gradient-based optimization or linear programming methods are not easily adapted for *BPO* since the relationship between design variables and cost functions can be non-convex, non-linear and the optimization problem can be subjected to non-linear constraints or to numerical approximations [9]. Thus, evolutionary algorithms (*EA*) are frequently adopted since they have less requirements on the problem characteristics. The popularity that *EA* are enjoying arises from

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Nomenclature

β	unknown coefficients of surrogate models
γ	primal linear problem coefficient of the *SVM* model
Φ	radial basis functions of the *RBFN* model
$\mu^{(j)}$	center of the j-th radial basis function of the *RBFN* model
aCD	average crowding distance [–]
B_j	j-th basis function in MARS model
BPO	building performance optimization
BPS	building performance simulation
EA	evolutionary algorithms
EGO	efficient global optimization algorithm
EP_H	energy performance for heating [kWh m^{-2} y^{-1}]
ESM	energy saving measure
f_i	i-th cost function of the optimization problem
$\overline{f}$	vector of the cost functions
g_i	i-th regression function of the *GRFM*
GD	Generational Distance [–]
GRFM	Gaussian Random Field Model (a.k.a Kriging)
IF	intermediate flat in an apartment building
IGD	inverted generational distance [–]
HV	hypervolume [–]
LHS	Latin Hypercube Sampling
MARS	Multivariate Adaptive Regression Spline model
MVS	mechanical ventilation system
n_{BPS}	number of expensive *BPS* runs [–]
n_{Brute}	number of solutions in the true Pareto front obtained by the Brute Force [–]
NE	normalized number of expensive simulation runs [–]
n_{ESM}	number of *ESM* combinations [–]
nHV	hypervolume normalized with respect to the *HV* of the brute force Pareto front [–]
nP	population size of the optimization algorithm normalized with respect to n_{ESM} [–]
n_{Par}	number of solutions in the Pareto front [–]
nPD	pure diversity normalized with respect to the *PD* of the brute force Pareto front [–]
NPV	net present value [Eur]
PD	pure diversity [–]
PH	penthouse flat
PS	percentage of true Pareto solutions [–]
RBFN	Radial Basis Function Network
SD	semi-detached house
SHGC	solar heat gain coefficient [–]
Sp	spacing [–]
SRS	simple random sampling
SSS	Sobol sequence sampling
SVM	support vector machines model

the flexibility with which they can deal with various optimization problems including high dimensional problems, integer or real parameters as well as continuous or discrete variables, non-differentiable cost functions and so on [10]. The evolution of multi-objective optimization in building simulation is well documented in several works [7,11,12] and review papers illustrating the history and the current state of the art [13–15]. According to Hamdy et al. [12], genetic algorithms are to a considerable extent the most implemented algorithms in the literature dealing with building optimization and the NSGA-II [16] is probably the most popular.

The main challenge in the use of *EA* coupled with building simulation is that *EA* usually still needs a large number of cost function evaluations before a satisfying result can be obtained [17]. Moreover, when considering *BPS*, the evaluation of the cost functions is computationally very expensive and the time taken to perform a single *BPS* is of the order of minutes or hours, depending on the model complexity. This aspect reduces the effectiveness of the *BPO* and especially its diffusion in the professional practice [18]. For instance, if the simulation is used for a simulation predictive control in a complex building, the time required for the *BPO* is not short enough to implement actions in the time frame of reliability of weather forecasts. For this reason, an approximation of the optimization problem is required to use *EA* efficiently. According to Jin [19] the main approximation strategies are:

- *Problem Approximation*: when the *BPS* is replaced by a model that is computationally less expensive. For example, when quasi-steady state methods or hourly lumped capacitance models are used in lieu of *BPS* [20–24].
- *Evolutionary Approximation*: when the fitness function evaluation of the offspring is estimated from the fitness values of their parents by means of the fitness inheritance approach [25].
- *Fitness Imitation*: when the alternative design solutions are clustered and the fitness function is evaluated only for the centroid. The objective functions of the other individuals are then estimated from the centroid response [26].
- *Functional Approximation*: when an explicit expression of the *BPS* is constructed starting from the building simulation results and used together with *EA* (a.k.a. meta-model or surrogate model approximation) [27–34].

The functional approximation approach is the most used in *BPS* to speed up the optimization process and this is the approach followed in this research. The meta-model can be used in the *EA* in three main ways. The first strategy is the direct use of a surrogate model in the optimization process [35]. For instance, Eisenhower et al. [30] optimized the energy consumption and the thermal comfort of an existing building by using a gradient-based optimizer on the surrogate model fitted on the EnergyPlus outcomes. However, the drawback of surrogate models can be the accuracy, since the meta-model contains an uncertainty in it. For instance Hopfe et al. [32] highlights the disadvantage of Kriging due to the limited number of design variables at which the meta-model still does the quality estimations. For this reason, the second strategy is the “generation-based control” [36]. In this approach, the surrogate model is firstly used in the *EA* code to find the optimal solutions. Following on from this point, the cost functions are evaluated for the optimal points by means of *BPS* and the surrogate model is then updated. Xu et al. [34] used a support vector machine algorithm (*SVM*) to fit a meta model. The regression model is then used to investigate the variable space with the purpose of selecting the best candidates for the cost function evaluation through *BPS*. Similarly, Brownlee and Wright [33] used the surrogate model to generate a surrogate population, to rank it and to select the best individuals for the actual fitness function evaluation.

Finally, a local meta-model can be used alternatively to guide the selection of new offspring (i.e. “individual-based control”) since it is difficult to build a globally approximate model [37] especially in high dimensional problems. In one of the earliest works, Knowles [38] developed ParEGO (Pareto Efficient Global Optimization) which extended the local efficient global optimization algorithm *EGO* to the multi-objective optimization by converting the objective functions into a single objective through the augmented Chebyshev function. A similar study is proposed by Emmerich et al. [36], in which the authors extend the local Gaussian Random Field meta-model (a.k.a. Kriging) to the multi-objective problems.

An efficient optimization with functional approximation is essential to find the trade-off solutions in building design and refurbishment. Moreover it can broaden the diffusion of the cost-optimal approach in real world applications overcoming the issues that limit the diffusion among architects and engineers. The performance of meta-models in