Purdue University
Purdue e-Pubs

International High Performance Buildings Conference

School of Mechanical Engineering

July 2018

An Efficient Global Optimization Scheme for Building Energy Simulation Based on Linear Radial Basis Function

Alessandro Prada
University of Trento, Italy, alessandro.prada@unitn.it

Andrea Gasparella
Free University of Bozen/Bolzano, andrea.gasparella@unibz.it

Paolo Baggio
University of Trento, Italy, paolo.baggio@unitn.it

An Efficient Global Optimization Scheme for Building Energy Simulation Based on Linear Radial Basis Function

Alessandro PRADA[1*], Andrea GASPARELLA[2],Paolo BAGGIO[3]

[1]University of Trento, Dep. of Civil, Environmental and Mechanical Engineering, Trento, Italy
Tel: +39 0461 282515, email: alessandro.prada@unitn.it

[2]Free University of Bozen-Bolzano, Faculty of Science and Technology, Bolzano, Italy
Tel: +39 0471 017632, Fax: +39 0471 017009, email: andrea.gasparella@unibz.it

[3]University of Trento, Dep. of Civil Environmental and Mechanical Engineering, Trento, Italy
Tel: +39 0461 282630, email: paolo.baggio@unitn.it

* Corresponding Author

ABSTRACT

Multi-objective optimization is considerably increasing its importance in building design since the design goals are moving from the solely energy saving target to the whole building performance, comprehensive of energy, cost and comfort targets. Optimization algorithms coupled with building simulation codes are frequently used in academic researches. However, they are limitedly adopted in real building design due to the high number of expensive simulation runs required by optimization algorithms such as direct search methods, evolutionary algorithm, particle swarm optimization and hybrid algorithms. For this reason, an efficient optimization scheme is essential for the diffusion of the optimization tools in building performance design outside the academic world. The research focuses on the development of an Efficient Global Optimization (*EGO*) scheme based on a radial basis function network (*RBFN*) model to emulate the expensive evaluations of the building performance simulation (*BPS*). The test bed of the method is the optimal building refurbishment of three simplified module representative of existing buildings, for which the optimal solutions have been also calculated by using the brute force approach, i.e. evaluating the performance of all the possible combinations of the retrofit measures. Finally, the *EGO* performances were also compared with those offered by the popular Non Sorting Genetic Algorithm (*NSGA-II*).
The results show the extent to which the *EGO* algorithm is able to find optimal solutions with a reduced number of expensive simulation runs. This capability makes the *EGO* algorithm suitable for the optimization of expensive simulation codes such as lighting models, *CFD* codes or dynamic simulation of building and *HVAC* systems.

1. INTRODUCTION

The European Directive 2010/31/EU guides the building designer to pursue the reduction of the energy demand, and consequently of the carbon emissions, by considering the economic effectiveness (Brinks *et al.,* 2016). Besides, when approaching the low energy target while maintaining economical convenience, buildings might be easily subject to overheating and poor comfort conditions (Penna *et al.*, 2015). Hence, the building design is always a multi-objective optimization problem with two or more conflicting goals and the achievable benefits in the design quality and cost reductions are high. Therefore, architects and engineers become increasingly aware of the potential advantages in applying building performance optimization in the early stages of the design process.
The gradient-based optimization and the linear programming methods are not suitable to building performance optimization (Wetter and Wright, 2004), consequently the evolutionary algorithms (*EA*) are frequently adopted. The *EA* popularity arises from the flexibility with which they can deal with high dimensional problems, integer or real parameters as well as continuous or discrete variables, non-differentiable cost functions and so on (Deb, 2001). However, the large number of cost function evaluations before a satisfying result can be obtained (Jeong and Obayashi, 2005) is the main challenge in the use of *EA* coupled with building performance simulation (*BPS*). This drawback reduces the effectiveness of the multi-objective optimization and especially its diffusion in the professional practice (Attia *et al.*, 2013). Additionally, the time required for the multi-objective optimization is not short enough to implement actions in the period of reliable weather forecasts for simulation predictive control.

For this reason, the efficient use of *EA* requires an approximation of the optimization problem. In this regard, an explicit expression in lieu of the *BPS*, i.e. a surrogate model, is constructed starting from the building simulation results and used together with *EA* to speed up the optimization process. The use of surrogate model in the optimization process is a possible strategy, as done in Eisenhower *et al.* (2012), Hopfe *et al.* (2012) and Chen and Yang (2017). However, the drawback of this approach is the low accuracy of surrogate models on the whole space of possible energy saving measures of the building refurbishment. For instance, Hopfe *et al.* (2012) points out the disadvantage of Kriging due to the limited number of design variables at which the meta-model still does accurate estimations. The second strategy is the "generation-based control" in which the surrogate model is firstly used in the *EA* code to find the optimal solutions. Following on from this point, the *BPS* is performed for the optimal points and the surrogate model is then updated. Xu *et al.* (2016) recently follow this approach.

In this paper, we propose an efficient global optimization algorithm based on the Radial-basis function networks (*RBFN*) surrogate model following the "generation-based control" approach.

The refurbishment of three simplified reference buildings are optimized following the cost-optimal approach by considering six types of energy saving measures (*ESM*). The integer optimization problem is solved by using the customized algorithm developed in Matlab. The same optimization problems are also solved by the popular non-sorting genetic algorithm (*NSGA-II*) proposed by Deb *et al.* (2002). According to Hamdy (2016), the *NSGA-II* is to a considerable extent the most implemented algorithms in the literature dealing with building optimization. Finally, the optimal solutions are evaluated through a brute-force method that provides the exact solutions of the optimization problem due to the discrete nature of all the energy saving measures. Finally, the performance of the *EGO* and *NSGA-II* algorithms are compared through some metrics.

2. METHODS

2.1 Genetic Algorithm (*GA*)

A large number of evolutionary algorithms for solving multi-objective optimization problems have been developed over the last decades in several research fields. The *NSGA-II* uses elitism by maintaining the current and the previous population. Then, after the population mating, the populations are sorted according to the non-domination concept and the best ranking solutions are selected as the next parent population.

In this work, some customizations of the original algorithm are used on sampling, archive and convergence criterion. Firstly, the possible *ESM* combinations in the variable domain are selected by a Sobol sequence sampling in order to overcome the clustering that can occur with other sampling techniques. The Sobol sampling method is based on a low-discrepancy sequence and it aims to give a uniform distribution of values in higher dimensions. Secondly, an external dataset of the results of the simulation runs is saved with the purpose of avoiding, during the optimization process, repeated expensive simulation runs.

Finally, the hypervolume measure (a.k.a. *S*-metric), proposed by Zitzler and Thiele (1999), is adopted as a stopping criterion. The maximization of this index is the necessary and sufficient condition for the Pareto optimal solutions of a discrete Multi-Objective Optimization problem, albeit with the drawback of the higher computational cost. The hypervolume is evaluated on the optimization objectives normalized with respect to the targets of the existing building. In this way, the different magnitude of the objectives does not affect the hypervolume index. A threshold of 10^{-4} in the variation of the normalized hypervolume between two consecutive generations has been adopted for the convergence criterion in the code.

2.2 Efficient Global Optimization Algorithm (*EGO*)

A customized algorithm was developed in Matlab, following the "generation-based control" approach (Figure 1). The algorithm firstly selects the initial population of the possible retrofit solutions through the Sobol sampling technique, as with the *NSGA-II* implementation in the previous section. The algorithm proceeds with the meta-model fitting, after the cost functions have been evaluated for the initial population through the *BPS*.

Among all the possible surrogate models, the code has been complemented with the radial basis function network (*RBFN*) proposed by Micchelli (1986). A linear combination of unknown coefficients w_j multiplied by a radial-basis function φ approximates each cost function (f) as shown in Equation (1).

$$f(x) = \sum w_j \cdot \varphi \cdot \left\| x - \mu^{(j)} \right\| \tag{1}$$

where $\left\| x - \mu^{(j)} \right\|$ is the Euclidean norm between the points in the variable domain (x) and a specific point in the variable domain ($\mu^{(j)}$) that is one of the model unknowns. Several radial-basis functions have been proposed in the literature. In this work, a linear basis was used and especially φ is equal to the pairwise distances between the variable points, already used in *BPS*, and the new points to be evaluated. The Matlab Neural Network Toolbox was used to approximate the *BPS* by means of the *RBFN*.

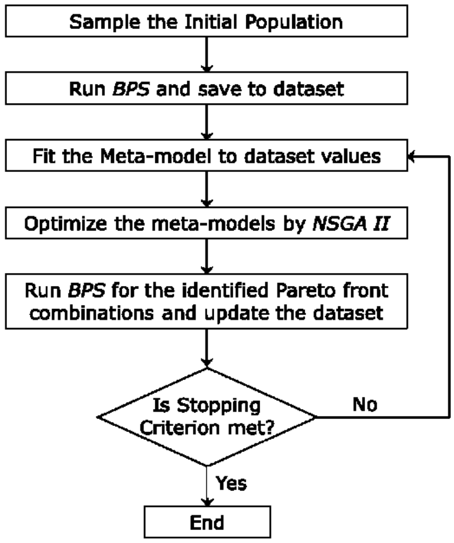


Figure 1: Flowchart of the EGO algorithm

Once the *RBFN* model is fitted, the optimization problem is solved by using the *NSGA-II* coupled with the *RBFN* functions, and the Pareto front is defined. The *EGO* evaluates then the actual cost functions of the Pareto solutions highlighted by the *NSGA-II* and it saves the *BPS* results to an external dataset.
If the Pareto front meets the stopping criterion, the algorithm finishes, otherwise it updates the meta-model, starting from all the solutions in the external dataset, and then it returns to the *NSGA-II* optimization. A threshold of 10^{-4} in the variation of the normalized hypervolume between two consecutive generations was adopted for the convergence criterion.

2.3 Optimization Problem

The refurbishment optimization of three simplified buildings, fully described in Penna *et al* (2015b), is the test bed for the two algorithms comparison. The investigated buildings are representative of a semi-detached house, a penthouse and an intermediate flat in an apartment building (Figure 2) in a typical configuration of Italian houses built prior to the first energy law and not renovated yet. Hence, a hydronic system with a standard gas boiler coupled with radiators and on-off control system is the initial configuration for all the test cases.

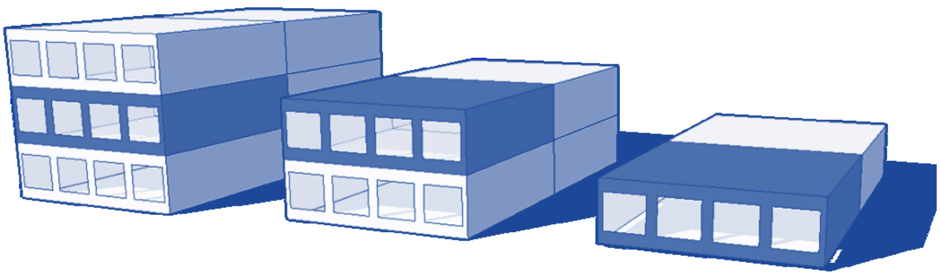


Figure 2: Test building for the optimization problems

Six conventional categories of energy saving measures (ESM) are considered:

- **external insulation** of the non-adiabatic envelope with an expanded polystyrene layer. The insulation thickness was changed independently for vertical walls, roof and floor in the range 0 to 20 cm, in steps of 1 cm
- **windows replacement** with double or triple pane with either high or low solar heat gain coefficient;
- **boiler replacement** with either a modulating or condensing boiler with an outside temperature reset control;
- **mechanical ventilation system** installation with a cross flow heat recovery system.

The total *ESM* combinations are 277830 for semi-detached house while they decrease to 13230 and 630 respectively for penthouse and intermediate flat due to the adjacency to other conditioned flats.

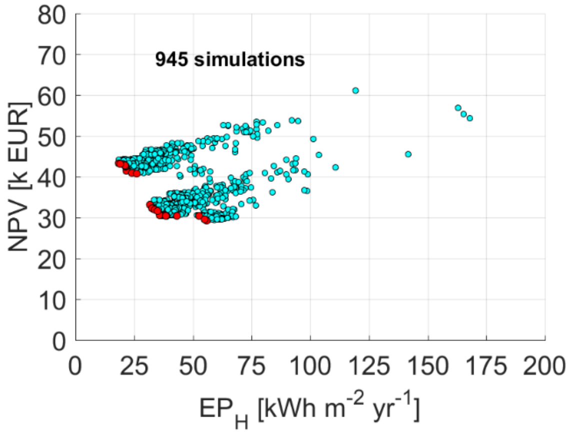
The optimal building refurbishment is evaluated by optimizing the energy and cost savings following the cost-optimal approach. The first optimization objective is the reduction of the primary energy for heating (EP_H). Moreover, the minimization of the total cost of the building is pursued. For this reason, the total cost of the building over a 30-year lifespan is quantified through the net present value (*NPV*) indicator. The initial cost derived from regional price lists (Penna *et al*. 2015b) is considered for all the *ESM* as well as the annual energy cost, the maintenance cost, the replacement cost and the residual value for the pieces of equipment with longer lifespan. The simulations are carried out in Trnsys simulation suite considering the weather data of Milan, a city having a *4A* climate according to Ashrae 90.1 classification.

3. RESULTS AND DISCUSSION

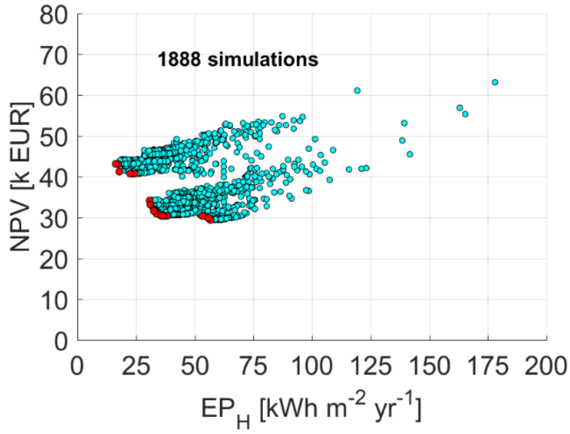
This study verifies the suitability of the *EGO* algorithm in speeding up the identification of the Pareto front in a multi-objective optimization problem adopted in the building refurbishment design. In the following sections, two aspects are investigated. Firstly, the research analyzes the *EGO* capability to filter out the variable domain regions with no eligible Pareto solutions (section 3.1). Secondly, we focuses on the *EGO* performance in identifying a good approximation of the true Pareto front (section 3.2).

3.1 Expensive simulation runs

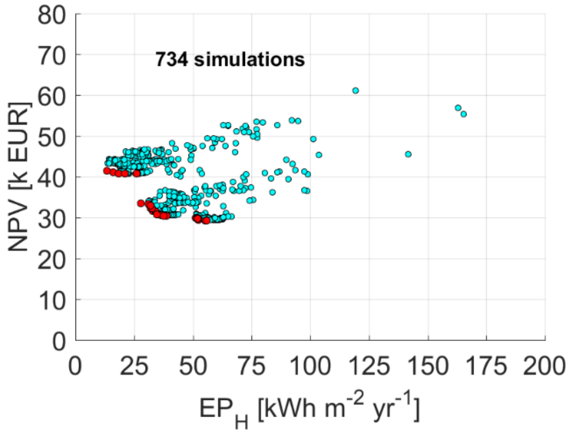
The first comparison between *EGO* and *GA* evaluates the number of expensive simulations necessary to achieve the convergence criterion when the two algorithms use the same number of individuals in the initial population. For this reason, the optimizations of the different test cases were repeated using an initial population of 128 and 256 individuals. The graphs in Figure 3 show the results for the semi-detached house. In particular, the analyzed solutions are represented simultaneously in the graph together with the non-dominated solutions (i.e. the red points).



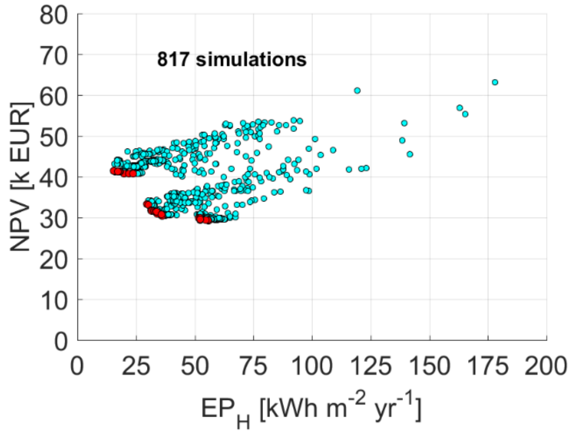
a) GA with an initial population of 128 individuals



b) GA with an initial population of 256 individuals



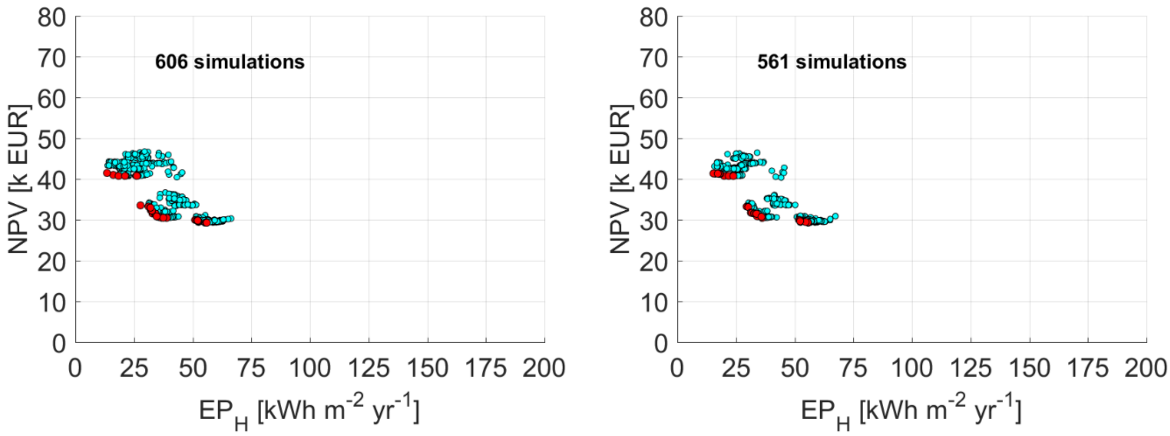
c) EGO with an initial population of 128 individuals



d) EGO with an initial population of 256 individuals

Figure 3: Results of expensive simulations runs for the semi-detached house

The number of expensive simulations required to achieve the convergence is the first result. There is a high number of *BPS* runs when *GA* is used for both the initial population sizes. The *BPS* run reduction with the EGO algorithm reaches about 22% and 57% respectively for the cases with a population size of 128 and 256 individuals. This shows the ability of the meta-model to guide the algorithm towards the more promising areas of the variable space from the point of view of the two-optimization goals. This is even more evident by looking at the simulated points in the graphs. Figures 3a and 3b show a greater concentration of points far from the Pareto front. These points therefore represent unnecessary *BPS* that slow down the optimization process. The *EGO* algorithm is however required to simulate a certain number of configurations throughout the variable domain in order to reduce the deviation between the surrogate model previsions and the *BPS* outcomes.
The expensive simulation runs carried out after the *BPS* performed for the initial population are plotted in Figure 4 for the semi-detached house. The graphs show the efficiency of the algorithm in filtering non-promising solutions, since after the initial populations, all the *BPS* provide solutions that are close to the Pareto Fronts. The *BPS* number is obviously reduced, but above all the simulated configurations are very close to the Pareto front. This therefore demonstrates the ability of the *RBFN* model to identify potentially optimal configurations.
Another interesting result in Figure 3 concerns the identified Pareto fronts. The *GA* identifies solutions that are dominated by the *EGO* optimal solutions, despite the greater number of expensive simulations performed to achieve convergence. This is especially evident for both the population sizes in the region with EP_H lower than $25\ kWh\ m^{-2}\ yr^{-1}$. This result seems to indicate therefore a better convergence of the solution obtained with *EGO*. However, some metrics were used in order to better quantify the performance of the two algorithms.

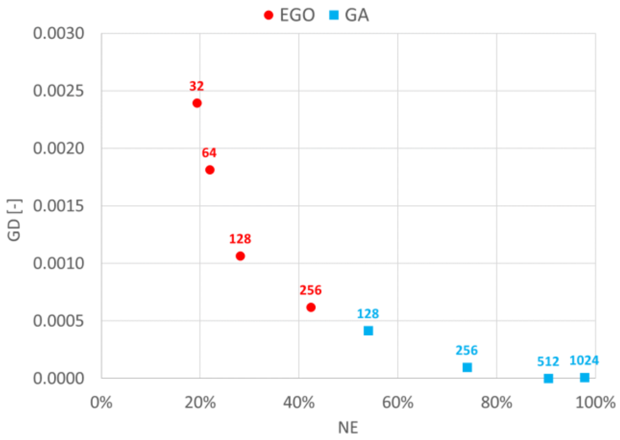


a) EGO with an initial population of 128 individuals b) EGO with an initial population of 256 individuals

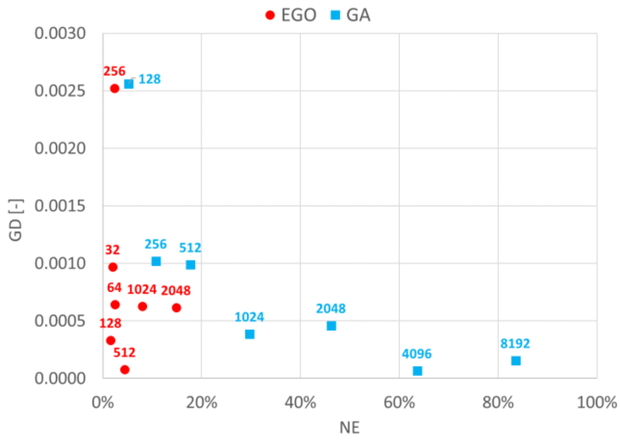
Figure 4: *BPS* runs for the semi-detached house after the simulations of the initial population

3.2 Performance comparison

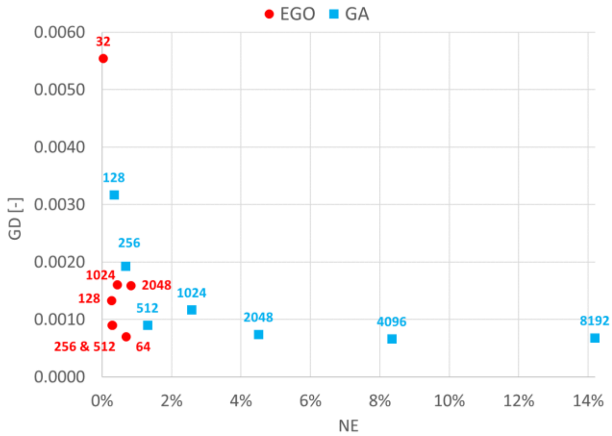
The algorithm performance are quantified by means of three metrics evaluating the efficiency, the efficacy and the solution quality. The efficiency index is meant to measure the resource level used by the algorithm whereas the efficacy is a measure of the distance between the predicted Pareto front and the true Pareto solution given by the brute force approach. Finally, a uniform Pareto front in the objective space is preferable since it provides decision maker with the maximum information about the possible alternative solutions, which is a measure of the quality. The efficiency is computed through the *NE* index, which is the ratio of expensive *BPS* runs over the brute force number of *ESM* combinations. This metric provides the same information of the *CPU* time but it is more objective since it is not affected by the quality of the Matlab codes, nor by the configuration of the hardware. The efficacy of the optimization algorithm is evaluated by means of the Generational Distance (*GD*) firstly proposed by Van Veldhuizen and Lamont (1998). This index quantifies the Euclidean distance between the algorithm front and the true Pareto, using the cost functions as space coordinates. Finally, the solution quality is quantified through the spacing index (*Sp*) introduced by Schott (1995). *Sp* assesses how evenly the members of the Pareto front are distributed and it approaches zero when the solutions are equidistant in the objective space.
The objectives normalized with respect to the initial case (i.e. the initial building configuration) allowed to avoid the different magnitude of the indices affects the metric calculations. The optimization runs were repeated with different population sizes in order to compare the performances and to broaden the results validity. Seven population levels were used in the *GA*, starting from an initial population of 128 individuals doubled each time up to 8192 individuals, or stopping earlier at the *ESM* combination number. On the other hand, seven levels were investigated for the *EGO*, starting from 32 and reaching 2048 individuals, always doubling the population for each optimization runs. The results are therefore a series of three-dimensional metrics, for each of the two investigated algorithms, which have been represented in two-dimensional planes for simplicity (Figure 5 and 6).



a) intermediate flat in an apartment building



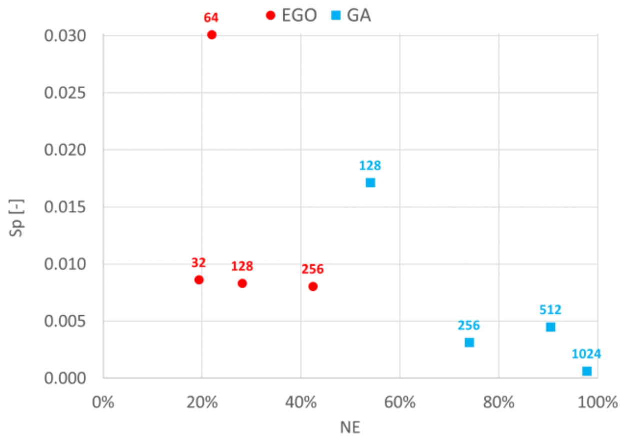
b) penthouse



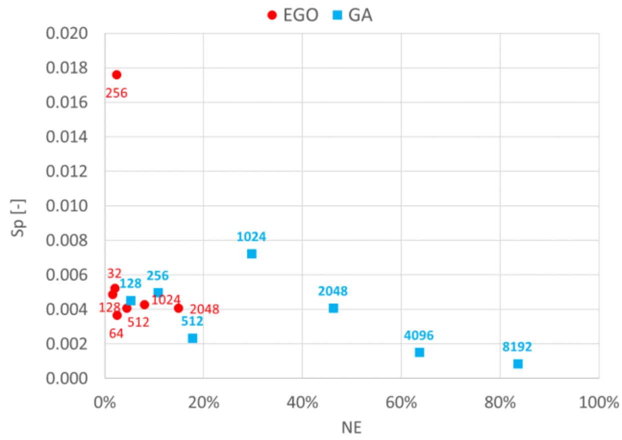
c) semi-detached house

Figure 5: Efficiency vs efficacy metrics for the *GA* and *EGO* algorithms

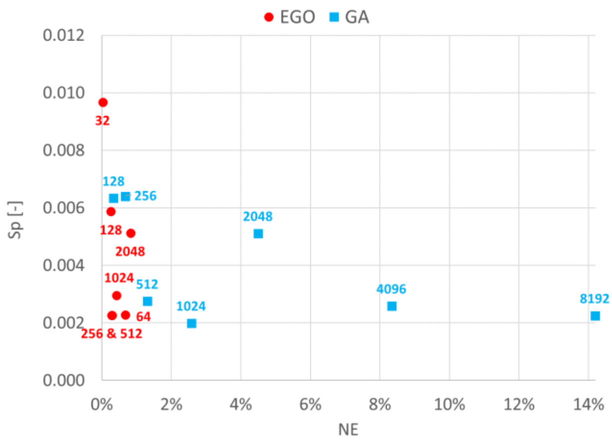
Figure 5 highlights the trend of the efficacy metric (*GD*) as a function of the efficiency (*NE*), for the three test cases. Note that in Figure 5a the metric pairs lie on the same curve both for the *EGO* and the *GA* algorithms. Hence, the *EGO* does not produce any benefit, but essentially leads to obtain the same performance of the *GA*. This result is strictly connected to the simplicity of the optimization problem (only 630 possible combinations). Indeed, the *EGO* points are always below the curve of th*e NSGA-II* in the other test cases (Figure 5b and 5c). This therefore indicates the *EGO* algorithm has a smaller distance from the real front when the two algorithms have the same efficiency metric. At the same time, consequently, identical efficacy *GD* can be reached with a smaller number of expensive simulation runs with respect to the *GA* algorithm.
Figure 6 shows, in a similar way, the trend of the metric inherent the diversity of the solutions (*Sp*) with respect to the number of expensive simulation runs. Again, there are no improvements in the use of the *EGO* algorithm for the case of the intermediate floor in an apartment building (Figure 6a). In this test case, the *EGO* procedure obtains solutions with a lower quality index if compared to the *GA* front, even if the *EGO* produces a considerable reduction in the number of simulations performed. For the other two buildings, we firstly note a less regular distribution of the points also for the *GA* algorithm. The *Sp* of the Pareto fronts have a dependence on the number of simulations performed even if it is not easily identifiable.
The *EGO* algorithm is characterized by lower *Sp* with respect to the *GA* configurations with similar *NE*, in penthouse and semi-detached houses. Therefore, the Pareto fronts obtained by the *EGO* have solutions that are more equidistant in the optimization targets. For this reason, this algorithm provides a better information about the possible optimal solutions to the decision maker.



a) intermediate flat in an apartment building



b) penthouse



c) semi-detached house

Figure 6: Efficiency vs quality metrics for the GA and EGO algorithms

4. CONCLUSIONS

In this work, a new efficient global optimization algorithm was developed for the optimization of the refurbishment of three existing buildings. The results confirm the capability of a *RBFN* surrogate model in guiding the optimization algorithm through variable space with eligible optimal solutions avoiding the simulation of non-optimal configurations.

The *EGO* algorithm is effective in guiding the optimization process to simulate the combinations of energy saving measures able to effectively produce optimal objectives. This clearly emerges when the optimization objectives, evaluated after the initial population, are investigated. The greater number of *BES* simulation in this region allows also to improve the convergence of the meta-model to the *BES* outcomes for solutions close to the Pareto front.

Nonetheless, the initial population plays a key role in the *EGO* algorithm since it has to cover as much as possible the space of the optimization variables in order to guarantee a greater proximity of the meta-model to the BES outcomes for all the possible variable combinations.

Additionally, the use of surrogate models can significantly speed up the optimization process leading to good results in terms of convergence to the true Pareto front with a limited number of evaluations of expensive cost functions. The analysis of the metrics shows how, for more complex optimization problems, the *EGO* algorithm is able to improve the effectiveness and the quality of the front obtained with respect to the *NSGA-II* optimization. This means that, having set the convergence and quality thresholds of the optimization solution that will depend on the application, they can be reached through fewer expensive simulations, and therefore with a reduced computational cost.

For simple optimization problems, however, the *EGO* algorithm does not produce any advantage but substantially offers the same performance as the *NSGA-II* algorithm. Nonetheless, it should be emphasized that in simple optimization problems the meta-model fitting procedure could lead to an increase in the computational cost of the whole process and, hence, it can produce an increase in computational time compared to the direct use of *BPS* in the *NSGA−II*.

REFERENCES

Attia, S., Hamdy, M., O'Brien, W., Carlucci, S. (2013) Assessing gaps and needs for integrating building performance optimization tools in net zero energy buildings design. *Energy and Buildings* 60, 110–124.

Brinks, P., Kornadt, O., Oly, R. (2016). Development of concepts for cost-optimal nearly zero-energy buildings for the industrial steel building sector. *Applied Energy* 173, 343–354.

Chen, X., Yang, H. (2017). A multi-stage optimization of passively designed high-rise residential buildings in multiple building operation scenarios. *Applied Energy* 206, 541 – 557.

Deb, K. (2001) *Multi-Objective Optimization Using Evolutionary Algorithms*. John Wiley & Sons, Inc., New York, NY, USA

Deb, K., Pratap, A., Agarwal, S., Meyarivan, T. (2002). A fast and elitist multi-objective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation* 6, 182–197.

Eisenhower, B., O'Neill, Z., Narayanan, S., Fonoberov, V. A., Mezić (2012). A methodology for meta-model based optimization in building energy models. *Energy and Buildings* 47, 292–301.

Hamdy, M., Nguyen, A.-T., Hensen, J. (2016). A performance comparison of multi-objective optimization algorithms for solving nearly-zero-energy-building design problems. *Energy and Buildings* 121, 57–71

Hopfe, C. J., Emmerich, M., Marijt, R., Hensen, J. L. M. (2012). Robust multi-criteria design optimisation in building design, in *BSO12 Proceedings of the 1st IBPSA-England Conference Building Simulation and Optimization*, Loughborough, United Kingdom, (118–125).

Jeong, S., Obayashi, S. (2005). Efficient Global Optimization (EGO) for Multi-Objective Problem and Data Mining. *IEEE Transactions on Evolutionary Computation*, 2138–2145.

Micchelli, C. A. (1986). Interpolation of scattered data: Distance matrices and conditionally positive definite functions, *Constructive Approximation* 2 , 11–22.

Penna, P., Prada, A., Cappelletti, F., Gasparella, A. (2015). Multi-objectives optimization of energy efficiency measures in existing buildings. *Energy and Buildings* 95, 57–69

Penna, P., Prada, A., Cappelletti, F., Gasparella, A. (2015b). Multi-objective optimization for existing buildings retrofitting under government subsidization, *Science and Technology for the Built Environment* 21,847–861.

Schott J. R. (1995). Fault Tolerant Design Using Single and Multicriteria Genetic Algorithm Optimization., *Master thesis, Massachusetts Institute of Technology*.

Van Veldhuizen, D. A., Lamont, G. B. (1998). Evolutionary Computation and Convergence to a Pareto Front, *Late Breaking Papers at the Genetic Programming 1998 Conference*. 221–228.

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

Xu, W., Chong, A., Karaguzel, O. T., Lam, K. P. (2016). Improving evolutionary algorithm performance for integer type multi-objective building system design optimization. *Energy and Buildings* 127, 714–729

Zitzler, E. Thiele, L. (1999). Multiobjective evolutionary algorithms: a comparative case study and the strength Pareto approach, *IEEE Transactions on Evolutionary Computation* 3, 257–271.