Energy and Buildings 121 (2016) 57–71

Contents lists available at ScienceDirect

Energy and Buildings

journal homepage: www.elsevier.com/locate/enbuild

# A performance comparison of multi-objective optimization algorithms for solving nearly-zero-energy-building design problems

Mohamed Hamdy[a,b,c,*], Anh-Tuan Nguyen[d], Jan L.M. Hensen[a]

[a] Department of the Built Environment, Building Physics and Services, Eindhoven University of Technology, P.O. Box 513, 5600 MB Eindhoven, The Netherlands

[b] Department of Mechanical Power Engineering, Helwan University, P.O. Box 11718, Cairo, Egypt

[c] Department of Energy Technology, Aalto University School of Engineering, P.O. Box 14400, FI-00076 Aalto, Finland

[d] Faculty of Architecture, The University of Danang—University of Science and Technology, 54 Nguyen Luong Bang, Danang, Viet Nam

ARTICLE INFO

*Article history:*
Received 16 November 2015
Received in revised form 13 January 2016
Accepted 13 March 2016
Available online 15 March 2016

*Keywords:*
Multi-objective optimization
Algorithms
Experimentation
Building simulation
Comparison

ABSTRACT

Integrated building design is inherently a multi-objective optimization problem where two or more conflicting objectives must be minimized and/or maximized concurrently. Many multi-objective optimization algorithms have been developed; however few of them are tested in solving building design problems.

This paper compares performance of seven commonly-used multi-objective evolutionary optimization algorithms in solving the design problem of a nearly zero energy building (nZEB) where more than $1.6^{10}$ solutions would be possible. The compared algorithms include a controlled non-dominated sorting genetic algorithm with a passive archive (pNSGA-II), a multi-objective particle swarm optimization (MOPSO), a two-phase optimization using the genetic algorithm (PR_GA), an elitist non-dominated sorting evolution strategy (ENSES), a multi-objective evolutionary algorithm based on the concept of epsilon dominance (evMOGA), a multi-objective differential evolution algorithm (spMODE-II), and a multi-objective dragonfly algorithm (MODA). Several criteria was used to compare performance of these algorithms.

In most cases, the quality of the obtained solutions was improved when the number of generations was increased. The optimization results of running each algorithm 20 times with gradually increasing number of evaluations indicated that the PR_GA algorithm had a high repeatability to explore a large area of the solution-space and achieved close-to-optimal solutions with a good diversity, followed by the pNSGA-II, evMOGA and spMODE-II. Uncompetitive results were achieved by the ENSES, MOPSO and MODA in most running cases. The study also found that 1400–1800 were minimum required number of evaluations to stabilize optimization results of the building energy model.



*Abbreviations:* BOP, building optimization problem; DHW, domestic hot water; DMn, diversity metric; *e*, escalation rate of energy price [%]; ENSES, elitist non-dominated sorting evolution strategy; EPBD, energy performance of buildings directive; evMOGA, multi-objective evolutionary algorithm based on the concept of epsilon dominance; FIT, feed-in tariff [€/kWh]; GA, genetic algorithm; GDn, generational distance; HVAC, heating, ventilation and air-conditioning; IGDn, normalized inversed generational distance; LCC, life cycle cost; MODA, multi-objective dragonfly algorithm; MOEA, multi-objective evolutionary algorithm; MOOA, multi-objective optimization algorithm; MOPSO, multi-objective particle swarm optimization; NoPsolution, number of solutions on the pareto-optimal set; NSGA, non-dominated sorting genetic algorithm; nZEB, nearly zero energy building; PEC, primary energy consumption; pNSGA-II, non-dominated sorting genetic algorithm-II with a passive archive; PR_GA, two-phase optimization using the genetic algorithm; PSO, particle swarm optimization; spMODE-II, multi-objective differential evolution algorithm.

* Corresponding author at: Eindhoven University of Technology Department of the Built Environment, Building Physics and Services P.O. Box 513, Eindhoven 5600, The Netherlands.

*E-mail addresses:* m.h.hassan.mohamed@tue.nl, DSc.M.Hamdy@gmail.com (M. Hamdy).

http://dx.doi.org/10.1016/j.enbuild.2016.03.035

## 1. Background and objectives of the study

Today, simulation-based optimization has become an efficient design approach to satisfy several stringent requirements indesigning high performance buildings (e.g. low- energy buildings, passive houses, green buildings, net zero-energy buildings, zero-carbon buildings...) [1]. In real-world building design problems designers often have to deal with conflict design criteria simultaneously such as minimum energy consumption versus maximum thermal comfort, minimum energy consumption versus minimum construction cost... Multi-objective optimization is therefore, in many cases, more relevant than the single-objective approach. This has led to the application of multi-objective optimization algorithms (MOOAs) that identify the Pareto optimum trade-off between conflicting design objectives (e.g. [2–6]).

It is found that efficient MOOAs are essential to find the optimal solutions without a need for numerous time consuming simulations. However, performance of MOOAs on building optimization problems has not been well understood due to the lack of research-based evidences. This study is among the first efforts that comprehensively investigate performance of seven evolutionary optimization algorithms in solving multi-objective optimization problems by using the simulation-based optimization approach. The test problem is a building energy model, which has a discrete solution space of energy saving measures and energy supply systems options, including renewable energy sources (RES). The major aims of this study are:

- To compare performance of different evolutionary algorithms in optimizing building energy models.
- To understand behavior of these evolutionary algorithms in solving a multi-objective optimization problem.

In this study, we provide an overview on performance comparison of optimization algorithms in building energy analysis. The investigated MOOAs and their performance criteria are described in the next section, which is followed by a description of the nZEB optimization problem (that is in accordance with the implementation of the new EPBD-2010). The results of this study were reported to support the performance criteria.

## 2. An overview on the performance of optimization algorithms in building energy analysis

Due to the large amount of design variables of building energy models as well as their discrete, non-linear, and highly constrained characteristics, simulation results are generally multi-modal and discontinuous, generating discontinuities or noise in the objective functions in building optimization problems (BOPs). As a result, optimization algorithms that require smoothness were found not efficient [7,8]. In many cases, stochastic population-based MOOAs (evolutionary optimization, swarm intelligence...) that do not require smoothness are able to handle the discontinuity of the search space. It is clear that performances of different algorithms are not equal. An algorithm may perform well by one criterion but fails by other criteria. Thus, performance of the optimization algorithms in solving BOPs is really an attractive research question that needs to be investigated.

### 2.1. *Performance comparison of single objective optimization algorithms*

The performance is often considered the major criterion for selecting an optimization algorithm. There have been several studies on the performance of different optimization algorithms on single-objective BOPs. Wetter and Wright [9] compared the performance of a Hooke-Jeeves algorithm and a GA in optimizing building energy consumption. Their result indicated that the GA outperformed the Hooke-Jeeves algorithm and the latter was attracted by a local minimum. Wetter and Wright [7] compared the performance of eight algorithms (Coordinate search algorithm, Hooke-Jeeves algorithm, particle swarm optimization (PSO), PSO that searches on a mesh, hybrid PSO-Hooke-Jeeves algorithm, simple GA, simplex algorithm of Nelder and Mead, discrete Armijo gradient algorithm) in solving simple and complex building models using a low number of cost function evaluations. Performance criteria include number of iterations, and optimal objective values. They found that the GA consistently got close to the best minimum and the Hybrid algorithm achieved the overall best cost reductions (although with a higher number of simulations than the simple GA). When the discontinuities in the cost function were small, the Hooke–Jeeves algorithm achieved good performance with a small number of iterations. Performances of other algorithms were not stable and the use of simplex algorithm and discrete Armijo gradient algorithm were not recommended. In GenOpt [10], Wetter introduced an improved hybrid algorithm PSO-Hooke-Jeeves in which the PSO performs the search on a mesh, significantly reducing the number of function evaluations called by the algorithm. Kampf et al. [11] examined the performance of two hybrid algorithms (PSO-Hooke-Jeeves and CMA-ES/HDE) in optimizing five standard benchmark functions (Ackley, Rastrigin, Rosenbrock, sphere functions and a highly-constrained function) and real-world problems using EnergyPlus simulation program. The results indicated that the CMA-ES/HDE performed better than the PSO-Hooke-Jeeves in solving the benchmark functions with 10 dimensions or less. However, if the number of dimensions is larger than 10, the hybrid PSO-Hooke-Jeeves gave better solutions. Both these algorithms performed well with the real-world BOPs using EnergyPlus models. Lee et al. [12] compared the performance of the differential evolution algorithm with that of a PSO, a GA and the Lagrangian method by solving the optimal chiller loading problem for reducing energy consumption. They found that the proposed differential evolution algorithm could give similar results as the PSO did, but obtained better average solutions. The differential evolution algorithm outperformed the GA in finding optimal solutions and also overcame the divergence problem caused by the Lagrangian method occurring at low demands.

Tuhus-Dubrow and Krarti [13] examined the performance of a GA against the PSO and the sequential search method in building envelope design to minimize lifecycle cost. The result reveals that the GA was more efficient than the two remaining methods in the complex cases (more than 10 optimization parameters were included in the building model). Moreover, the GA optimization method could define the optimal solution with an accuracy of 0.5%, and required only a half of the number of iterations needed by the PSO and the sequential search method.

Bichiou and Krarti [14] compared a GA with the PSO and the sequential search in optimizing building envelops and HVAC system design, in terms of computational time and cost reduction. They found that the GA and the PSO required typically less computational time to obtain optimal solutions than the sequential search. The optimal results given by the three algorithms were almost similar.

From these studies, it can be seen that the stochastic population-based optimization algorithms (e.g. evolutionary algorithms, swarm intelligence...) generally outperform the others and are likely suitable for BOPs. However, it is worthy of note that the cost reduction by an algorithm not only depends on the natures of the algorithm, but also depends on the settings of algorithm parameters [7,11]. According to the so-called 'no free lunch theorem' [15], there