COMPARING THE PERFORMANCE OF OPTIMIZATION METHODS USED FOR BUILDING DESIGN AND OPTIMAL CONTROL OF BUILDING SYSTEMS

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ABSTRACT

This study compares the performance of three different optimization methods both used for the design of building enclosures and for optimal control of building systems with respect to energy use and air distribution. Tested methods include a recently developed algorithm called Equilibrium Optimizer (EO), Genetic Algorithm (GA), and LSHADE-SPACMA. EO and LSHADE-SPACMA showed similar behavior and performance in solving two case study building energy performance problems and both were superior to GA. In the optimal control problem, EO and LSHADE-SPACMA discovered near optimal schedules that were 8.3 % and 9.6 % more energy-efficient than GA, respectively. In the design problem, all methods reached a similar optimal design. Overall, EO and LSHADE-SPACMA showed higher performance and faster convergence toward the optimal solution than GA.

INTRODUCTION

Building performance optimization (BPO) is a process of selecting optimal solutions from sets of available solutions for a given design or control problem in meeting a set of performance criteria (Attia et al. 2013). In BPO research over the years, most studies have selected and applied simple but efficient optimization methods. Optimization methods are generally classified into gradient-based and non-gradient based methods. The first class includes derivative-based optimizers, which use the analytical gradient information and require the availability of derivatives of the problem for optimization, while the second class includes derivative-free methods, which do not need this information. One of the classes of non-gradient based methods includes metaheuristic algorithms with stochastic nature. These second class of methods are popular due to their simplicity, independency to the problem, flexibility, and the gradient-free nature (Faramarzi et al. 2019). The two most well-studied and well-known methods in this class are Genetic Algorithm (GA) (Holland 1975) and Particle Swarm Optimization (PSO) (Eberhart and Kennedy 1995). GA is an evolutionary algorithm while PSO is a swarm intelligence method. This classification is based on their source of inspiration.

A literature review on the application of optimization in building energy performance problems shows that research has tended to employ non-gradient metaheuristic search methods more often than other methods (Evins 2013). Evins (2013) also indicated that GA is the most popular computational optimization method applied to sustainable design and energy in the building domain. Further, Evins (2013) showed that 38 % of existing BPO were dedicated to optimization of the building envelope, 21% for form optimization and 17% for HVAC systems optimization, 16 % renewable energy, 7% control and 1% lighting. The system and envelope categories of optimization problems account for more than half of the research in the field of BPO. Consequently, this study conducted a detailed review of these two categories.

The design problems in the optimization of building envelope are construction and façade. For example, a study optimized the shape and envelope features of a residential building by GA (Tuhus-Dubrow and Krarti 2010). They considered wall and roof construction, orientation, foundation type, insulation level, air leakage level, window type and area as envelope features and buildings shape, including rectangle, L, T, cross, U, H, and trapezoid. A follow up study compared the performance of GA, Particle Swarm Optimization (PSO) and a sequential search method for optimal design of the building shape and construction materials to minimize the total heating and cooling energy cost (Tuhus-Dubrow and Krarti 2009). Their study revealed that GA is the best algorithm for a relatively large domain of optimization (i.e., different configuration of walls, ceilings, foundation, azimuth and other variables with full enumeration of 20,275,200 simulations), and it has advantages when evaluation of the cost function is more expensive and time consuming, such as when using EnergyPlus instead of DOE-2.

Many HVAC system optimization studies have explored control problems. For example, Rackes and Waring (2014) minimized energy consumption and improved indoor air quality by discovering an optimal ventilation strategy in a simulated office building located in Philadelphia, PA. They used Hooke-Jeeves, a generalized pattern search for the optimization of their discretized optimal control problem. They found that in the core zone of their model in January, it is possible to save 20 % to 30 % of mechanical system energy use with their strategy. May-Ostendorp et al. (2011) used PSO in a model predictive framework to optimize the control sequence of window operation in mixed-mode buildings. They discussed that since their objective function contained too many local minima, they chose to employ a metaheuristics method with the capability of global search instead of using pattern search techniques or gradient-based methods.

METHODS

This study explores three optimization algorithms applied to two case study problems in building energy performance. The optimization algorithms include: a recently developed optimization algorithm, called Equilibrium Optimizer (EO) (Faramarzi et al. 2019); GA as the most well-studied algorithm in building science; and a high-performance optimizer of LSHADE-SPACMA as one of the winners of IEEE CEC 2017 competition on numerical optimization (Mohamed 2017). The concept for the development of EO is the mass balance equation on a control volume, which is simple to understand and implement. In addition, EO is efficient compared to other heuristic search algorithms. LSHADE-SPACMA is one of the advanced variants of differential evolution approach hybridized with improved version of an evolution strategy method. The parameters for each algorithm are listed in Table 1.

Table 1. Parameter settings for the methods

Algorithm	Parameter	Value
EO	a_1, a_2	2,1
	Generation	0.5
GA	Type	Real coded
	Selection	Roulette wheel
	Crossover	Whole Arithmetic
		Probability=0.8
	Mutation	Gaussian
LSHADE-SPACMA	Learning rate (c),	0.8, max_nfes/2
	H, Pbest, Arc rate	5, 0.11, 1.4

REVIEW OF METHODS

- **Genetic Algorithm (GA)**

GA is inspired by a natural evolution process to generate improved solutions over the course of iterations. In the GA paradigm, solutions are called chromosomes and variables (dimension) are called genes. Each chromosome is associated with a fitness to be used in the selection process. Selection is a competitive process and determines which chromosomes will be used as parents to generate new chromosomes as offspring. Tournament, roulette wheel and random selection are among the popular selection operators. Crossover is another operator that combines two chromosomes already chosen by selection to produce a new offspring. In the crossover process, the best characteristics from each parent are combined to produce an offspring that might be better than both parents. Among the popular crossover methods are Single-point, Two-point, Arithmetic, and SBX. Another operator in GA is Mutation. This operation changes one or more genes from the selected chromosome to increase the structural variability of the population. Mutation is carried out by methods such as gaussian, non-uniform and random mutations. Elitism is an operator in GA that is adopted to guarantee the survival of the best performing chromosome from one generation to the next. More information is available in Holland (1975) and Herrera et al. (1998).

- **LSHADE-SPACMA**

LSHADE-SPACMA is a high-performance optimization method and is the state-of-the-art among metaheuristic algorithms. This method was nominated as one of the winners in the IEEE Congress on Evolutionary Computation (CEC) 2017. The method is structured by hybridization of two high-performance variants of Differential Evolution (DE) and Covariance Matrix Adaptation Evolution Strategy (CMA-ES). SHADE is the Success History Adaptive Differential Evolution. In this variant, the scaling factor (F) and the crossover rate (C_r) are archived in historical memory and used in the next iteration for a better evolution path. LSHADE is the SHADE algorithm with a linear population size reduction. LSHADE-SPA is the LSHADE with semi-parameter adaptation of the scaling factor and the crossover rate. This method involves two parts. In the first part, which considers the first half of the iterations, the scaling factor is generated using uniform distribution in a bounded region, while the crossover rate uses a formula based on the memory slot and normal distribution to be updated. In the second part, which considers the second half of iterations, the crossover rate remains as is while the scaling factor is updated based on memory slots and Cauchy distribution. CMA-ES uses

multivariate normal distribution to model the search space and generate the path for evolution. It learns from the correlation of parameters and uses it to accelerate convergence. It uses adaptation for two parameters, covariance matrix and step size, and then samples offspring from the normal distribution using the covariance matrix and step size. Interested readers can find more information from Mohamed (2017).

- **Equilibrium Optimizer (EO)**

EO is a recently developed optimization algorithm that is inspired by a mass balance on a control volume. In this method, each particle (solution) updates its concentration (position) based on some talented (best-so-far) solutions called equilibrium candidates. These candidates are nominated in each iteration and are saved in a pool called the equilibrium pool. The concentration updating process is referenced by a random selection from a pool. There is an exponential term in EO that controls the exploration and exploitation ability of the method. This term helps randomize the movement of particles with a large step size in initial iterations (exploration), while lowering the step size in the last iterations (exploitation). The term is composed of two control parameters: a_1 is defined to manage the exploration performance while a_2 oversees exploitation. One of the problems in optimization is that methods get stuck in local minima in some dimensions, and there is a need for a mechanism to escape from this stagnation. The generation rate (G) is a parameter defined in EO that helps alleviate this problem, along with improving the exploitation ability. This term does not always contribute to the optimization process. The possibility of the contribution is controlled by a sub-parameter called Generation rate Control Parameter (GCP), while its probability is controlled by Generation Probability (GP). The mathematical model of these interactive terms sometimes helps EO escape from local minima while sometimes aiding in exploitation (Faramarzi et al. 2019).

Case study applications

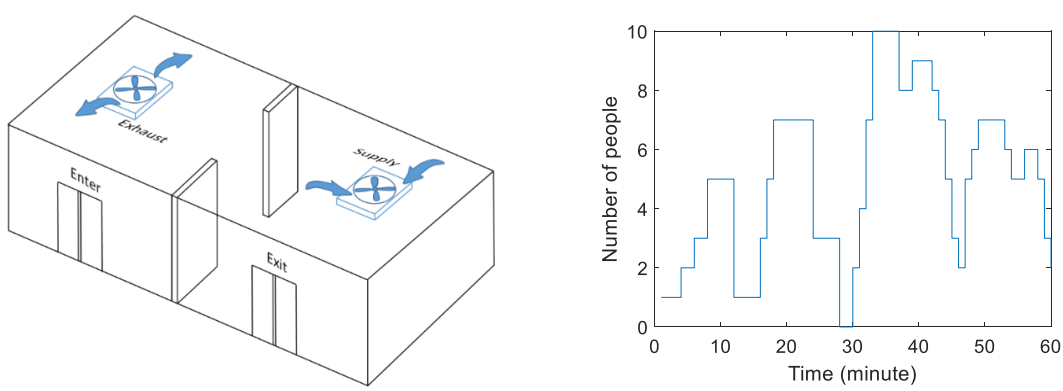
We considered two case studies of design and control problems. The first case study is the optimal ventilation control strategy in a retail store considering fan energy consumption as the objective function. The second case study is the optimal design of building enclosure characteristics considering the minimization of total source energy use for heating, cooling, and lighting as the objective function.

Case Study 1: Ventilation control strategy

This example considers a two-zone retail store building with one entrance and one exit, and one supply fan and one exhaust fan for ventilation. The objective is to minimize fan energy use while providing demand-controlled ventilation (DCV) subject to dynamic occupancy patterns under the constraints of airflow and zone CO_2 concentration. Based on the fan affinity laws, the power draw of each fan is proportional to the cube of its airflow rate. Both fans are equipped with variable frequency drives (VFD) to adjust the airflow rate based on the demand, driven by the number of people and resulting CO_2 concentrations. Figure 1 (a) illustrates a schematic of the retail store, and Figure 1 (b) shows the occupancy schedule for the zones containing the entrance and exit. The dimensions of both zones are 5 m long, 5 m wide, and 3 m high.

The objective function is to minimize the energy consumption of both fans for a time horizon of one hour (60 min). Q and W are the airflow rate (m^3/min) and power draw (W), respectively. Q_{ref} (6 m^3/min) and W_{ref} (46 W) are the airflow rate and power draw at full motor capacity.

We used 15,000 maximum function evaluations and 500 iterations for each method. Since all methods are stochastic optimizers, we ran 30 independent runs to get an acceptable result.



(a) (b)

Figure 1. (a) Schematic of retail store and (b) assumed occupancy schedule

$$Consider \qquad \vec{x} = [Q_1 Q_2 \dots Q_{60}]$$

$$Minimize\ f_{cost}(\vec{Q}) = \frac{1}{60} \sum_{supply}^{Exhaust} \sum_{i=1}^{60} W_{ref} \left(\frac{Q}{Q_{ref}}\right)^3 \quad (1)$$

$$Subject\ to \qquad 400 < C_{enter}, C_{exit} < 1000\ \ ppm$$

$$Variable\ range \qquad 0 \le Q_1, \dots, Q_{60} \le 6\ \ m^3/min$$

The CO_2 concentration limit of 1000 ppm is based on the discussion of demand control ventilation in the ANSI/ASHRAE Standard 62.1-2016 User's Manual (2016). The lower concentration of CO_2 is assigned given typical outdoor CO_2 concentrations of 400 ppm.

Case Study 2: Building energy performance

In this example, the annual energy use of a simple office building is minimized through enclosure optimization. Figure 2 shows the schematic of the office building.

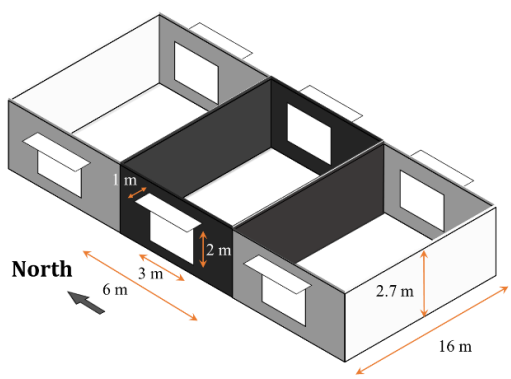


Figure 2. Schematic of the office building case study

The energy consumption of the middle thermal zone (dark color) is considered as representative of an elongated office building in Chicago, IL. The geometry, dimensions, and layout are shown in the figure. The external shading of the East and West windows is activated in the summer when total solar irradiation is more than 200 W/m^2. The illuminance for the zone is set at 500 lux with daylighting control. Heating and cooling setpoints are 20 °C and 25 °C, respectively. To simplify the HVAC system, the energy model uses an ideal load air system, meaning the loads are assumed to be met at each time step. Insulation for the exterior wall is 10 cm of foam with a U-value of $0.25\ \mathrm{W/m^2\,K}$. More information about this example can be found in (Wetter 2004).

The objective function is the sum of annual source energy consumption considering heating, cooling, and lighting as:

$$f_{cost}(\vec{x}) = \frac{Q_h(x)}{\eta_h} + \frac{Q_c(x)}{\eta_c} + \alpha E_l(x) \qquad (2)$$

Q_h, Q_c are the annual heating and cooling load, while E_l is the electricity consumption of the zone. Assumed on-site heating and cooling plant efficiencies are $\eta_h = 0.44$ and $\eta_c = 0.77$, and the conversion factor of site electricity to fuel energy consumption is $\alpha = 3$.

The enclosure-related design variables include orientation, solar transmittance of shading, the length of east- and west-facing windows, wall insulation thickness, wall insulation conductivity, and glazing solar transmittance. The termination criterion for the algorithms is set to a maximum of 2000 function evaluations with 100 iterations. Due to the high computational run time of this example, the results are achieved by 10 independent runs. The lower and upper bounds of the design variables are shown in Table 2.

Table 2. Variables, units and their bounds used in the second case study

Variables	Units	Lower bound	Upper bound
Orientation	Degrees	0	360
Shading solar transmittance	Dimensionless	0	0.9
West window	m	0.1	5.9
East window	m	0.1	5.9
Insulation	m	0.01	0.5
Insulation conductivity	W/(m-K)	0.01	1
Glazing solar transmittance	Dimensionless	0	0.28

EnergyPlus and jEPlus are used as simulation engine and interface (Zhang 2009). The data exchange architecture is shown in Figure 3. jEPlus acts as a middleware, which exchanges data between EnergyPlus and the optimizer. The optimizer creates the input files for jEPlus. Then jEPlus calls EnergyPlus with the prepared input files to run the simulation with the total number of tasks defined by the optimizer. The output file in comma-separated value (CSV) format is read by the optimizer to extract the heating, cooling, and lighting energy to estimate the objective function. The loop continues until the optimizer stops the process based on the defined criterion.

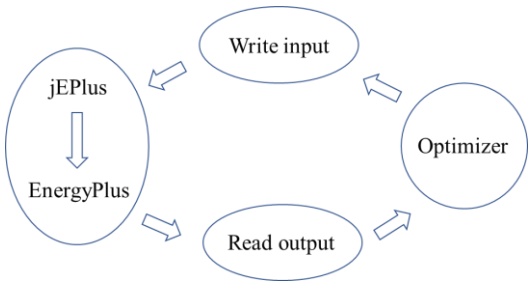


Figure 3. Simplified architecture for co-simulation

RESULTS

Case Study 1: Ventilation control strategy

Figure 4 shows the optimal operational fan schedule achieved by EO, GA and LSHADE-SPACMA. The near-exact solution, Figure 4 (d), is the schedule generated from running the model with LSHADE-SPACMA with 1,000,000 function evaluations. Since the problem is convex, a high-performance optimizer with a high number of iterations reaches the near global optimum. The EO, Figure 4 (a), and LSHADE-SPACMA, Figure 4 (c), optimal solutions both suggest an almost smooth schedule, more similar to the near-exact solution than GA. The optimal schedules provided by EO and LSHADE-SPACMA for this problem should yield a longer lifecycle of fans by not using sudden changes in motor speed.

The first column of Table 3 shows fan energy consumption estimates for the best solution among the 30 schedules; the remaining columns show the average, worst and standard deviation of the 30 runs. Based on this table, the performance of EO and LSHADE-SPACMA are similar and each finds an optimal schedule that is closer to the near-exact solution and better than GA. The best EO and LSHADE-SPACMA designs are 8.3% and 9.6% more energy-efficient than GA, respectively. It should also be noted that some of the solutions provided by GA at the end of iteration are infeasible, meaning that in some runs GA could not find a schedule in which CO_2 concentration was less than 1,000 ppm. In order to make a fair comparison, those results were removed from the study. Another point worth noting is that since the CO_2 concentration in this study is defined as a constraint to the problem, the optimization algorithm goal is to minimize the objective function, which in this case study it means minimizing energy use. Consequently, the minimization of energy consumption leads to maximation of the CO_2 concentration to the upper bound of 1000 ppm after around minute 40. As seen in Figure 4 (d), the near-exact solution schedules the fans to operate at their maximum speed at that time.

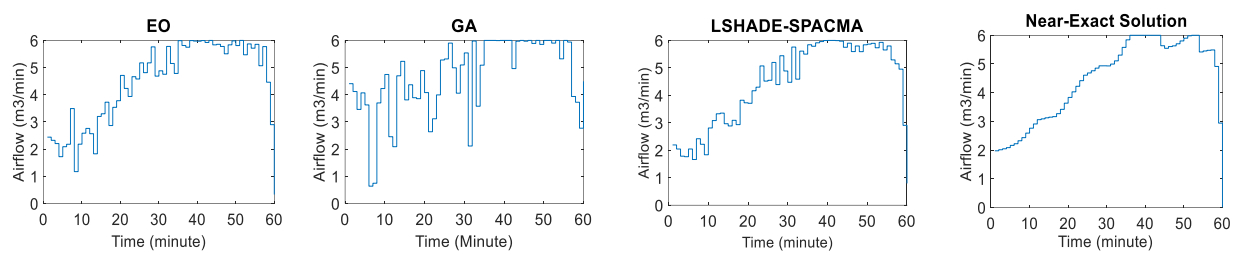


Figure 4. Optimal schedule estimated by different methods for ventilation

Table 3. Statistical results of fan energy use for different optimization methods in the ventilation case study (Wh)

Algorithm	Best	Mean	Worst	Std
EO	48.73	50.14	55.73	1.71
GA	53.16	55.58	60.70	2.87
LSHADE-SPACMA	48.03	48.24	48.74	0.16
Near-exact solution	47.76	-	-	-

Figure 5 shows the average cost history of different methods through independent runs of the optimization process. The value of each method at the end of iteration 500 is the mean value shown in the Table 3. The high cost value in initial iterations is due to infeasible solutions created in the initialization process. EO and LSHADE-SPACMA find feasible solutions shortly after the optimization process begins, but it takes more than half of the total iterations (250) for GA to reach a feasible solution.

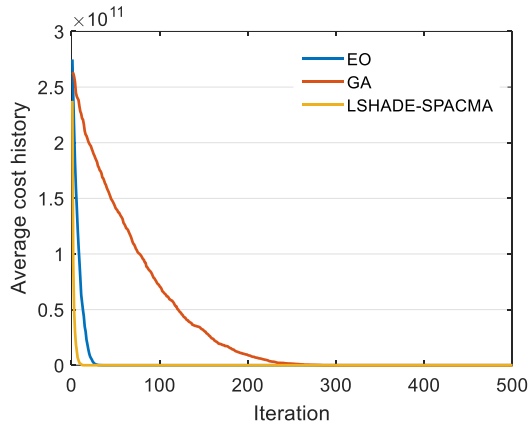


Figure 5. Convergence curve of optimization for different methods for the ventilation example

Overall, these results show that EO is able to solve optimal control problems with competitive efficiency compared to a high-performance optimizer.

Case Study 2: Building energy performance

Table 4 shows the estimated annual source energy consumption for the second case study (office building envelope optimization) achieved by EO, GA and LSHADE-SPACMA. The termination criterion for the algorithms is set to a maximum of 2000 function evaluations with 100 iterations. Table 4 includes statistical results of best, average, worst and standard deviation through 10 runs. All methods reached almost the same best solution, but with different mean, worst, and standard deviations. EO and LSHADE-SPACMA had almost the same results and performance in the mean, worst, and standard deviation, which were all better than GA. This means that EO and LSHADE-SPACMA show more reliable behavior in tackling the problem compared to GA. GA showed outstanding behavior in Wetter (2004) compared to other high performance deterministic and hybrid algorithms such as GPS and PSO-HJ. Thus, for this case, GA is a representative of a high-performance optimizer.

Table 4. Statistical results for different methods for the office building energy performance case study (J)

Algorithm	Best	Mean	Worst	Std
EO	4.4780E10	4.4787E10	4.4798E10	9.77E06
GA	4.4778E10	4.4806E10	4.4833E10	1.97E07
LSHADE-SPACMA	4.4779E10	4.4786E10	4.4798E10	7.22E06

Table 5 presents the best solutions obtained by the methods, which are all almost the same.

Table 5. Optimum parameters for building energy performance case study estimated by different methods (Units are provided in Table 2)

Variables	EO	GA	LSHADE-SPACMA
Orientation	265.96	265.96	265.96
Solar transmittance (shading)	3.12E-06	0	0
West window length	4.4976	4.4976	4.4989
East window length	5.9000	5.9000	5.9000
Insulation thickness	0.4935	0.5000	0.5000
Insulation conductivity	0.0101	0.0100	0.0100
Solar transmittance (glazing)	0.2800	0.2800	0.2800

Figure 6 shows the average fitness history for the three optimization methods. We can clearly see that before iteration 10, EO and GA showed similar performance, followed by LSHADE-SPACMA. But after iteration 10, the performance of EO is similar to LSHADE-SPACMA, and both show significantly better performance compared to GA. The performance becomes the same for all methods after iteration 80.

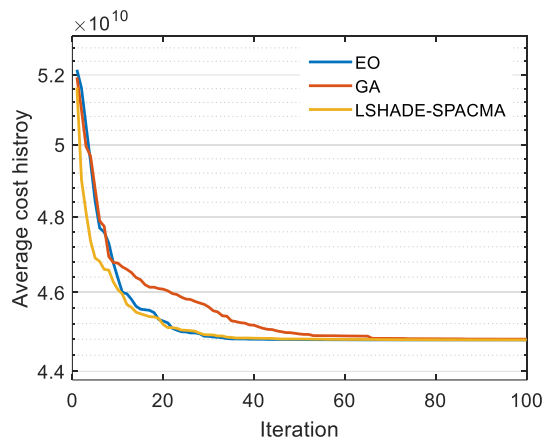


Figure 6. Convergence curve of optimization for different methods for energy performance example

CONCLUSION

Two building energy performance optimization problems were studied using three optimization algorithms, including a recently developed optimization algorithm called Equilibrium Optimizer (EO), GA as the most well-studied method, and LSHADE-SPACMA as a high-performance optimizer. In both problems, EO and LSHADE-SPACMA showed similar performance, achieving similar solutions. The optimal ventilation strategies obtained by EO and LSHADE-SPACMA in

the first case study were 8.3 % and 9.6 % more energy efficient than the GA strategy. In the second case study, all methods presented the same optimal design while the convergence rates of EO and LSHADE-SPACMA were faster than GA.

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