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Original Article/Research

Efficient Genetic Algorithm sets for optimizing constrained building design problem

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Abstract

The main aim of this paper is to find the appropriate set of Genetic Algorithm (GA), control parameters that attain the optimum, or near optimum solutions, in a reasonable computational time for constrained building optimization problem. Eight different combinations of control parameters of binary coded GA were tested in a hypothetical building problem by changing 80 variables.

The results showed that GA performance was insensitive to some GA control parameter values such as crossover probability and mutation rate. However, population size was the most influential control parameter on the GA performance. In particular, the population sizes (15 individuals) require less computational time to reach the optimum solution. In particular, a binary encoded GA with relatively small population sizes can be used to solve constrained building optimization problems within 750 building simulation calls.

Keywords: Constrained building optimization problem; Genetic Algorithm (GA); GA control parameters; Simulation calls; Thermal comfort

1. Introduction

Energy used in buildings has the highest potential and lowest cost for carbon reductions. There are many regulations and policies were established to encourage construction of sustainable buildings. In addition, there are many building simulation tools made available freely to assist designers and practitioners to attain a sustainable design. However, the design of sustainable buildings is not straight forward. There are many physical processes that lead to conflicting objectives such as making the buildings energy efficient by well tightening and insulation of the envelope without compromising the occupants' comfort. This requires trying large possible solutions which need heuristic optimization algorithms.

A comparison between several heuristic optimization algorithms showed that Genetic Algorithm (GA) is robust on getting the optimum(s) simulation (Wetter and Wright, 2004; Brownlee et al., 2011; Bichiou and Krarti, 2011; Sahu et al., 2012) while the building simulation program "EnergyPlus" is very operative (Crawley et al., 2001). In addition, many researchers have developed platforms to utilize different simulation engines and optimization algorithms to optimize building design problems (Wetter, 2001; Mourshed et al., 2003; Wang et al., 2005; Bleiberg

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and Shaviv, 2007; Geyer, 2009). Other works have evaluated the building variables significance on the optimum solutions (Wang et al., 2005; Bleiberg and Shaviv, 2007; Geyer, 2009).

Wright and Loosemore (1993) developed a new method of constraint by combining many constraints into a single objective of a multi-objective optimization problem. Wright and Zhang (2005) developed an 'aging operator' that penalized highly dominant solutions to aid in solving highly constrained problems. Evins et al. (2012) optimized the solar gain to a building by evaluating the population size, number of generations, crossover and mutation probabilities, selection method and seeding method to investigate the configuration of a Genetic Algorithm, while, Hamdy et al. (2009) used a single-objective preparation step and a post-optimization refining step to improve the performance of a Genetic Algorithm.

The authors of the present paper have examined the robustness of Genetic Algorithms in solving unconstrained building optimization problem with limited number of variables (Alajmi and Wright, 2014). The authors also proved that small population sizes (5 and 15 variables) showed better performance than the largest population size (30) in respect of reaching the optimum solutions with less number of building simulation program calls.

The sensitivity of the optimization algorithm and its components such as population size, number of generations, crossover and mutation probabilities, selection method and seeding method is a real concern in solving a whole building optimization design problem.

Therefore, the main aim of this paper is to find the most appropriate GA set that can find the optimum (energy efficient building), or near optimum solutions, in a reasonable computational time (less numbers of simulation calls to the building simulation program "EnergyPlus" as it is required to calculate the building consumption and occupants' comfort index) for constrained building optimization problem. This will be conducted by manipulating two different population sizes 5 and 15 which are considered to be relatively small. Also, two different probabilities (70% and 100%) of the reproduction parameters (crossover and mutation rate) will be encountered. This approach will be tested for eight different control parameter sets for 750 number of generations to find the most efficient set that can achieve efficient energy building without compromising the occupants' comfort.

2. GA parameters sets

The Genetic Algorithms (GA's) iterate on a set of solutions "population". First, an initial solution for the population is assigned (each variable being randomly assigned a value within its bounds). Then, the process of generating a new better solution goes through five main subordinate operations in an iterative manner. Although the GAs showed effectiveness in handling building optimization problems, the GA's main operators such as population size, crossover probability, and mutation rate need to be tuned in order to find the best performance for the constrained building optimization problem. Selection of appropriate GA operators is a trade-off between fast convergence, and maintaining the exploratory power of the algorithm (to prevent false convergence).

A detailed configuration of the simulation-based building optimization problem and the most effective parameters of GA on solving unconstrained building optimization problem are explained by the authors in a previous study (Alajmi and Wright, 2014). Therefore, in this study, the control parameter sets are only composed of two population sizes 5 and 15 with two crossover probabilities 0.7 and 1.0 and mutation rates of 1 and 2 based on the outcomes of the previous study. In addition, the number of simulation calls is restricted to 750. Therefore parameter sets that will be implemented in this numerical experiment (constrained building optimization problem) are listed in Table 1.

The number of building simulation runs performed during this experiment can be found by multiplying the number of parameter sets (8) by the number of initial population runs (10 in this work) times the number of simulations (750 calls). This ends up with 60,000 building simulation runs.

3. The building design variables

The building is a typical mid-floor layout of an office building (located at Chicago, Illinois, 42° latitude, −88° longitude) that was chosen to test the GA performance. As shown in Fig. 1, the floor consists of five zones (North, South, East, West, and Interior) each of which has an exterior wall along its perimeter and a single window with overhang shading. The internal zone "I" is bounded by partition walls of perimeter zones. The total floor area is ($46\ m \times 24\ m = 1104\ m^2$) with a floor height of 2.7 m. The finding that comes out as a result of this floor can be later multiplied by the number of identical floors in the building.

The considered variables can be classified into the building envelop (indices 1–23) which are self-explanatory and the HVAC system control (indices 24–80) which includes pre-cooling or pre-heating starting time, AHU setpoint temperatures, and zone heating and deadband setpoints. The variables with their lower, upper limits, and their initial start, are listed in Table 2.

The design variables in Table 2 (indices 24–26) are representing the time that the HVAC system will start on. These are three options of starting the system on before the occupants arrived (pre-heating/cooling concept). The design variable in the table (indices 27–38) gives each month an option to select from the three defined system availability schedules (A, B, and C).

The indices 39–44 define the air supply setpoint temperature via the AHU equipment design variables. Three schedules of air supply set points are formulated for