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Selecting the most efficient genetic algorithm sets in solving unconstrained building optimization problem

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Abstract

Effective optimization of unconstrained building optimization problem involves coupling a building energy simulation program with an optimization evolutionary algorithm such as the genetic algorithm (GA). The aim of this paper is to find the most appropriate GA set that obtains the optimum, or near optimum, solutions in a reasonable computational time (less numbers of simulations). Twelve control parameter sets of binary encoded GA are tested to solve unconstrained building optimization problems that are coupled with EnergyPlus simulation program.

The results show that population size is the most significant control parameter and that the crossover probability and mutation rate have insignificant effects on the GA performance. In general, a binary encoded GA with small population sizes can be used to solve unconstrained building optimization problems by around 250 building simulation calls. In particular, the smaller population size of about 5 individuals helps reach the optimum solution faster than larger population sizes.

Keywords: Genetic algorithms; Building Simulation program; EnergyPlus; Simulation-based building optimization problem; GA control parameters

1. Introduction

Energy consumption in buildings accounts for a considerable proportion of energy consumption in urban areas, and this sector will increase in the coming decades (EU, 2002). For instance, in Europe the demand of electricity in residential buildings will increase from 1% to 2% annually over the next decade. Therefore, energy saving in buildings is an important aspect for reducing national energy consumption, and consequently reducing greenhouse effect. For example, the energy consumption in buildings has a potential to be reduced by 22% in EU countries (Caldas, 2001). Building simulation provides an excellent way to study such potential and opportunities to achieve optimum building consumption.

Traditionally, parametric studies were done on building optimization problems such as the study on the effect of window size on the building performance while holding = other effective design variables constant (Jo and Gero, 1998; Guillemin and Molteni, 2002; Guillemin and Morel, 2001; West and Sherif, 2001a,b). Later, new optimization techniques were created which could handle

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a limited number of design variables (Wright and Farmani, 2001; Caldas and Norford, 2002, 2003). Fortunately, new techniques were found (Evolutionary Algorithms, EAs) which can handle efficiently a larger number of parameters. Also, the EAs have the advantages of being less sensitive to the problem characteristics, such as the availability of the objective function in a closed form mathematical expression and the design of variable types (discrete or continuous).

In particular, genetic algorithms (GAs) have been found to be robust in finding the optimum solutions for various engineering optimization problems (Wetter and Wright, 2003).

Recent research has shown that more efficient buildings can be designed using simulation-based building optimization (Wetter and Wright, 2003; Caldas and Norford, 2001) that couples an optimization algorithm, such as GA (genetic algorithms), with a building energy simulation program such as the "state-of-the-art" EnergyPlus (Crawley, 2001). The building design control parameters are entered to the simulation program and simultaneous changing within these parameters will lead to different possible solutions that can be systematically searched by an optimization algorithm.

The form and operation of genetic and other evolution algorithms are extensively studied (Bäck, 1996; Bäck et al., 2000; Deb, 2001). In brief, genetic algorithms (GA's) iterate on a set of solutions "population" that are randomly initialized. Each solution consists of all variables that are assigned a value within its lower and upper bounds. Then the process of generating new solutions commences after assigning fitness values for each solution (chromosome) accomplished by main operators. These main operators are known as: selection, recombination (crossover), and mutation. In addition, to ensure the solution does not become totally random the best solution will remain in the new generation. This process is known as "replacement".

The problem variables are combined together in a term known as a "chromosome" and part of it is named as "gene". Practically, the chromosome(s) is encoded in a concatenated string of binary numbers (binary encoding), or a vector of real values (real encoding). In the case of the binary encoding, a gene is represented by a single bit in the binary string (the value of a problem variable being represented by several bits). In contrast, real encoded GAs operate directly on the real value of the problem variable.

Although the GAs showed effectiveness in handling building optimization problems, the GA's main operators, such as population size, crossover, and mutation rate, have not been fully examined in building optimization problems (Alajmi and Wright, 2006). In fact, selecting appropriate GA operators is a trade-off between fast convergence and maintaining the exploratory power of the algorithm (to prevent false convergence).

In this paper, a GA and its alternative operator forms will be selected for solving a whole building optimization problem with 23 design variables (building envelop variables) without limiting the search space (constraints). The convergence behavior of the GA in relation to the number of required calls of the building simulation program is mainly considered.

2. Selection of genetic algorithm structure

Genetic algorithm structure incorporates the five main operations in iteration to create the new chromosome. In contrast to a real vector chromosome, a binary encoding has potentially greater exploratory power than a real vector chromosome, and naturally lends itself operating with both discrete and continuous variables. This is harmonious with the nature of building optimization problems that have mixed-integer parameter problems. For example, alternative wall constructions might be identified by an integer index that points to a particular combination of construction materials, whereas a supply air temperature set point may be treated as being continuous.

Choosing the algorithm operators and parameters is a balance between the convergence reliability and the convergence velocity (or "exploration" versus "exploitation"; (Bäck, 1996). One of the principal operators governing this balance is the selection mechanism.

2.1. Binary encoding

Both continuous and discrete variables can be encoded in a binary chromosome through controlling the number of bits assigned to a given variable (a three bit encoding will result in 8 discrete values for the variable). The inherent encoding of mixed-integer problems and the associated control of variable precision, make a binary encoding very useful in the solution of building optimization problems.

2.2. Fitness assignment

In this study, we seek to minimize the building energy use and therefore, the lower the energy use, the higher the fitness of an individual selection. Then, solutions (obtained from EnergyPlus simulation program runs) will be ranked-ordered (stochastic ranking) based on the energy use obtained from objective function. Hence the stochastic ranking will simply rank all solutions based on their objective function values alone. It sorts the solutions in order of the "best" to the "worst".

2.3. Selection

The selection operator is used to select solutions from the current population that will be used to form the next population of solutions (this being the basis for the next iteration of the algorithm). In this research, we seek robust convergence with as few building simulations as possible (that is, reliable convergence with a high convergence velocity). The tournament operator randomly selects