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Improving evolutionary algorithm performance for integer type multi-objective building system design optimization

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ABSTRACT

Building system design optimization is becoming popular for design decision making. State-of-the-art technique that couples evolutionary algorithms with a building simulation engine, which is time consuming and often cannot reach the "true" optimal solutions. Studies addressing these issues focus on implementing strategies such as fine tuning optimization algorithm's parameters, hybrid evolutionary algorithms with a local search algorithm or optimizing meta-models. Unlike the previous studies, this paper proposes two improvement strategies for building system design optimization. The two strategies, adaptive operators approach and adaptive meta-model approach, modify the behaviors of conventional evolutionary algorithms to improve the optimization convergency and speed performance. To demonstrate the effectiveness of these two strategies compared to conventional algorithms, a case study was conducted. The case study observed high convergency performance from both strategies with 30% and 60% time savings respectively. Furthermore, this study examines the performance comparison in respect to convergency, diversity preservation and speed between these two strategies.

1. Introduction

In building design process, decisions are usually constrained by multiple factors. Solutions that satisfy building owners' requirements are commonly infeasible to reach by performing parametric studies. Therefore, more efficient methods are needed in searching the solution space to find optimal solutions, which not only reduce the evaluation time, but also provide optimal designs to achieve building owners' investment goals. This raises the topic of building system design optimization (BSDO) that uses advanced optimization algorithms for searching for optimal design solutions. The topic has increasingly drawn attention from the academic community, as well as the architecture, engineering and construction (AEC) industry. Current studies well address the behavior of various optimization algorithms including pattern search methods and stochastic methods [1]. These studies have also extensively examined various objectives and levels of detail regarding single system performance optimization and integrated building design optimization [2]. In recent years, both academia and industry are developing tools that support the ease of implementing optimization in building design process. Tools such as MOBO [3], GenOpt [4] and jEPlus [5] provide user-friendly interface and capability of coupling building design evaluation toolset (TRNSYS, EnergyPlus, etc.) as well as allow stakeholders to explore their design options more effectively.

Although BSDO has been actively discussed among academic community for decades, it is still not a common technique used in today's typical building projects. One of the barriers is computation time. A typical BSDO process could take days to find optimal solutions. In order to reduce the computation time, many researchers are looking for computational efficient strategies which can fully utilize computational resources to boost the optimization speed [6]. Although these researches did not address the computationally expensive design evaluation process in BSDO, the strategies proposed can effectively alleviate the impact of evaluation speed.

Such strategies can be categorized into three types, namely: parallel computing, model simplification and meta-model approaches [1]. Parallel computing allows optimization algorithms distributing a number of simulation tasks into multiple process threads simultaneously, thus reducing the overall computation time. Implementation of this approach requires advance level of programming skills, nevertheless, the majority of current energy simulation software have included such features. Simplifying the complexity of problems is another popular approach that frequently appears in many studies. Such studies usually construct a simple geometry layout with small amount of design variables. However, simplification highly relies on expert knowledge and designers have to take risks for losing building system interaction

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information, which may result in sub-optimal solutions. Lastly, a meta-model approach that optimizes design parameters on a "model of model" instead of real simulations can effectively find optimal solutions in negligible time [7]. However, this method requires a pre-computed database that contains design variables and parameters for constructing the meta-model. Therefore, it demands hundreds of energy simulations upfront. Furthermore, a single meta-model is typically not general enough to adapt to different cases such as evaluating energy consumption for a building in different climates.

In addition, literature review indicates that current practice has no indication of optimization convergency, thus it is hard to examine whether the optimal solutions on pareto front curve are the "true" optimized solutions. Secondly, the expensive computational power of building energy simulation largely slows down the optimization process, thus performing optimization studies are not feasible at practice point of view. However, from these past studies, some unique characters of evolutionary optimizations in building designs are suggested:

- A number of design solutions may appear in multiple generations.
- Algorithm performance strongly depends on parameter settings of operators.
- A large amount of energy simulations are produced in every generation and they are discarded in the next iteration.
- Energy simulations in every generation are mainly used for providing search directions towards the optimal region.

Utilizing the findings, this study proposes two separate improvement strategies that change the behavior of the conventional evolutionary algorithm. These two strategies focus on reducing the number of building energy simulations at algorithm level and achieving better optimal solutions. The first strategy relates to optimize operator's parameters setting by employing adaptive strategy. This strategy transforms the algorithm's behavior by updating its operators' parameters adaptively based on the current generation performance so that the algorithm could dynamically optimize its search power. The second strategy proposes a dynamic meta-model based multi-objective optimization procedure. The idea of this procedure is to marry machine learning techniques with optimization procedure in order to enhance the algorithm's searching power. The above building optimization characteristics imply that optimization algorithms can potentially reuse all energy simulations evaluated in the previous generations for constructing a meta-model and employ this meta-model to adjust and advance its exploration direction and speed. In addition, the meta-model should be capable of self-update along with optimization process for refining its prediction power. Implementing these two strategies could reduce optimization time as well as improve the convergency of optimal solution set. The detail implementation and their performance in BSDO of these two strategies will be discussed in this paper.

2. Method

2.1. Multi-objective optimization

BSDO is a complex problem and it is typically solved by evolutionary algorithms with multiple conflicting objectives. Pareto optimality is a frequently used method for analyzing BSDO optimization results [2]. This method introduced a set of design solutions as optimal solution set. In this solution, a unique situation occurs where a single objectives adversely affects other objectives. Fig. 1 shows data plot results of a typical optimization study. It can be observed that there is no solution in this optimal solution set (purple dots), which has both lower first and operation costs than any other solutions in the same set.

A typical workflow for BSDO is summarized in Fig. 2. The study objectives are goals that clients would like their buildings to achieve through optimization. Fitness functions are the functions that perform energy simulations and post-process simulation outputs with respect to defined objectives. Design options are a limited set of building system designs that clients want to test on their properties. With defined objectives, fitness functions and design options, the optimization algorithm can be initialized. An initialization process usually involves setting the algorithm's parameters such as mutation probability and crossover probability in genetic algorithms. Results generated in the process indicate that the fundamental differences between single objective optimization and multi-objective optimization is lying in the cardinality of the optimal set. Although clients' need only one solution to their problem, this is natural behavior of multi-objective optimization with conflicting objectives because there is no single solution that performs better at every objective than any other solutions. Since a

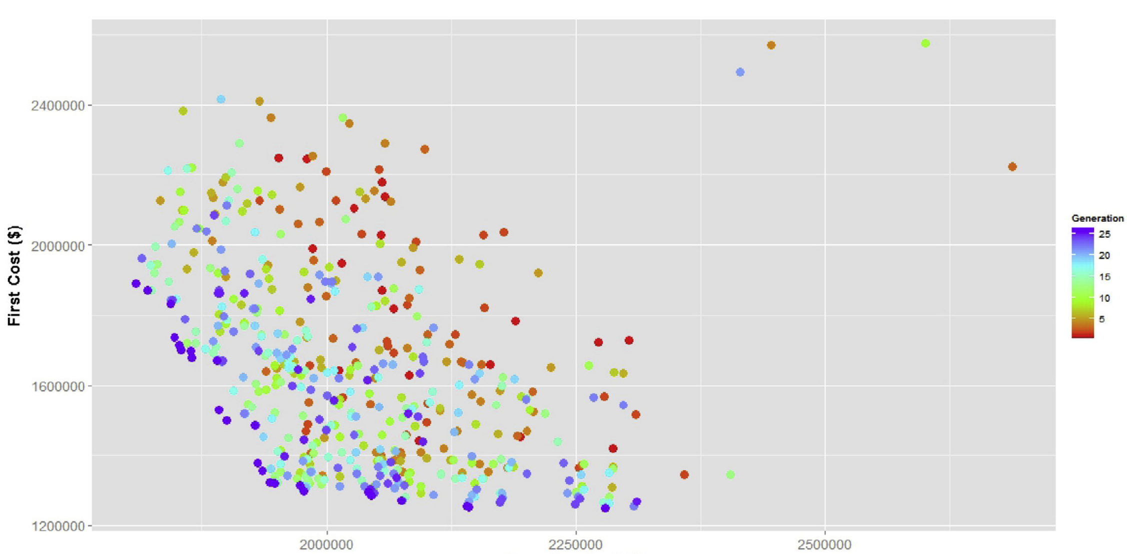

Fig. 1. A typical MOO solution plot with pareto front curve. (For interpretation of the references to color in text near the reference citation, the reader is referred to the web version of this article.)