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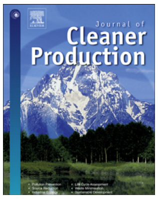

Evolutionary many-objective optimization for retrofit planning in public buildings: A comparative study

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ABSTRACT

There has been an increasing movement toward retrofitting existing (in-use) buildings to achieve a significant reduction in energy consumption and greenhouse gas emissions in the building sector. When planning retrofits for public buildings, decision-makers are required to make rational decisions that will achieve four critical objectives: minimize energy consumption, reduce CO_2 emissions, mitigate retrofit costs, and maximize thermal comfort. This study aims to solve this four-objective optimization problem (so-called the problem of many-objective optimization) for retrofit planning in public buildings via an evolutionary many-objective optimization (EO) algorithm that handles these objectives at the same time. This study involves the application of EO algorithms (NSGA-II, MOPSO, MOEA/D, and NSGA-III) and the evaluation of their performance. A description of these algorithms is presented, and each algorithm is implemented in a public-building retrofit project. The algorithms' performances were analyzed, and the results were compared based on two aspects: diversity and convergence. The results indicated that NSGA-III can be used to derive a comprehensive set of trade-off alternatives from possible retrofit scenarios, thereby serving as a useful reference for retrofit planners. These decision-makers can then utilize the provided references to select optimal retrofit strategies and satisfy stakeholders.

1. Introduction

The building sector accounts for two-fifths of the world's total annual energy consumption, and that proportion is increasing every year (EIA, 2017). The International Energy Agency pointed out that if there is no effort to improve energy efficiency, the energy demand will reach 50% by 2050 in the building sector (IEA, 2013a). In addition, 40% of all greenhouse gases are released by this sector—a main contributor to global warming (IEA, 2013b). Accordingly, several countries have implemented various policies to decrease the energy that buildings consume for the purpose of reducing greenhouse gas emissions. For example, the United States implemented the Energy Independence and Security Act (2007) to make all commercial buildings zero energy by 2050 (U.S. Congress, 2007). Europe implemented a policy that all new buildings must be nearly zero energy by 2020 (public buildings must meet this regulation after 2018) to reduce the energy consumption of buildings (Groezinger et al., 2014). Through these efforts, the European Union has aimed to reduce greenhouse gas emissions in the building sector by 88–91% by 2050 compared to 1990 (COM, 2011). South Korea created a policy that all new buildings must be nearly zero energy by 2025 (public buildings after 2020), aiming at reducing greenhouse gas emissions by 18.1% by 2030 in the building sector (MOLITT, 2016). To effectively accomplish the goals of these energy-saving building-sector policies, it is essential that each building is highly energy efficient (BPIE, 2011; World Green Building Council, 2017).

The energy-efficiency requirements have been strengthened in recent years, so older buildings built that were constructed under less-strict regulatory requirements now have poor energy efficiency compared to those that are newly constructed (IEA, 2008; Li and Shui, 2015). Generally, buildings constructed within the past 10 years are defined as newly constructed (European Commission, 2010); in 2012, 18% of U.S. buildings were newly constructed (EIA, 2015), and there were 5–10 times as many older buildings. In the building sector in the European Union, 75% of buildings were reported as energy inefficient (World Green Building Council, 2017). Overall, according to the report by the GABC (2016), the existing buildings (which were not recently constructed) would account for more than two-thirds of the entire building stock. For these existing

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buildings, there is a way to reduce the energy consumption and minimize the greenhouse gas emissions by improving the building envelope and upgrading the mechanical systems while maintaining the maximum level of thermal comfort; which is referred to as retrofitting (Xu et al., 2015). It has been considered the most cost-effective and feasible option for improving energy efficiency and reducing greenhouse gas emissions rather than demolishing and rebuilding those buildings (UNEP, 2009; Pombo et al., 2016). Acting from this perspective, government organizations around the world have supported such retrofitting (Ma et al., 2011). In the United States, when retrofits reduce energy consumption, the costs are exempt from relevant taxes (IRS, 2012). In Europe, the European Union has partially supported such retrofit expenses (Bertoldi et al., 2010). In China, government organizations have funded and made financial supports, such as subsidies and interest exoneration, to retrofitting projects of existing government and large public buildings for energy efficiency (Li and Shui, 2015; Yuan et al., 2016).

Despite these supportive policies, decision-makers who undertake retrofitting have difficulty planning such projects (Rahmat and Ali, 2010) because hundreds and thousands of retrofit alternatives exist, and various objectives need to be achieved. Therefore, it is difficult to determine to what extent the various retrofit alternatives satisfy the various objectives (Kaklauskas et al., 2005). As the number of alternatives increases, it becomes more difficult to compare them and select the optimal retrofit scenarios (Penna et al., 2015). In particular, when planning retrofits in public buildings, decision-makers need to consider critical objectives to make rational decisions. Each tries to establish a plan to minimize energy consumption, CO_2 emissions, and expenses while maintaining the maximum level of thermal comfort in the retrofitted buildings within a limited budget (Bojić et al., 2012; Xu et al., 2015). However, these objectives contradict each other and have a trade-off relationship; it is difficult to find an alternative that satisfies all of them (Chantrelle et al., 2011). For this reason, each decision-maker subjectively chooses a limited number of alternatives and compares them in general terms (Diakaki et al., 2008). Alternatively, the decision-maker can exclude some of the alternatives and then select a scenario intuitively (Shao et al., 2014). In such a process, the decision-maker intentionally considers only a few potential alternatives, making it difficult to choose the best option (Asadi et al., 2012a).

To solve this problem, researchers in previous studies employed the concept of multi-objective optimization (MOO) using evolutionary algorithms (Ma et al., 2012). Multi-objective optimization is a process for finding a solution that satisfies multiple objectives simultaneously (Abbass et al., 2001). It can obtain a Pareto-optimal solution (POS) that comprises a set of complementary alternatives (Marler and Arora, 2004). In earlier studies, before selecting an alternative, the decision-makers had to first define their preferences for the objectives so they could select one scenario from among the alternatives that would best satisfy all the objectives (Branke et al., 2001). However, as each decision-maker had different preferences and as the objectives could not be compared under equivalent conditions, it is difficult to determine accurate preferences in the context of real-world problems (Krettek et al., 2010). Thus, to overcome these limitations, researchers have proposed other methods to derive a set of complementary alternatives that satisfy multiple objectives and allow the decision-maker to find an optimal solution through a posteriori articulation of preferences. These methods have the advantage of not requiring predefined preferences from various decision-makers. The most well-known among these methods is the evolutionary algorithm (Jaimes and Coello, 2012), which is designed to evaluate numerous alternatives simultaneously through a global search and thus has a high possibility of obtaining an actual optimal solution (Goel and Deb, 2002; Saravanan et al., 2009). In a few previous studies (Chantrelle et al., 2011; Asadi et al., 2014; Shao et al., 2014; Penna et al., 2015; Fan and Xia, 2017) on the problem of MOO in building retrofit planning, a non-dominated sorting genetic algorithm (NSGA-II) was employed. In addition, none of these studies considered more than three objectives, which is referred to as the problem of many-objective optimization.

This study aims to solve the problem of many-objective optimization for retrofit planning in public buildings via EO algorithms that consider four objectives: minimizing energy consumption, CO_2 emissions, and retrofit costs, and maximizing thermal comfort. This study involves the application of EO algorithms and the evaluation of their performance. Because these algorithms can handle four objectives at a time, they are suitable for the context of retrofit planning in public buildings. Recently, the multi-objective evolutionary algorithm based on decomposition (MOEA/D), the multi-objective particle-swarm-optimization algorithm (MOPSO), and the reference-point-based NSGA (NSGA-III) have demonstrated superior performance in solving the problem of MOO with more than three objectives when compared to the previously investigated NSGA-II (Bechikh et al., 2014; Svensson, 2015). Hence, in this study, the NSGA-III is compared with NSGA-II in the optimization of building retrofit planning. The Related Works section presents a comprehensive review of the related studies. Building Retrofit Planning via Evolutionary Many-Objective Optimization focuses on the methodology. The Experiments section provides the experimental results and discussion, and the Conclusion contains conclusions and suggestions for future research.

2. Related works

Multi-objective optimization is a process for deriving several complementary sets of alternatives that satisfy two or more contradicting objectives simultaneously (Abbass et al., 2001; Marler and Arora, 2004). To select the scenario that best satisfies all the objectives, decision-makers need to define their preferences (Branke et al., 2001). Multi-objective optimization methods can articulate those preferences as either a priori or a posteriori (Fonseca and Fleming, 1998).

The a priori methods are as follows. Asadi et al. (2012a; 2012b) used Tchebycheff programming to derive sets of complementary alternatives comprising 11 and 66 alternatives, respectively. Diakaki et al. (2013) used compromise programming to derive a set of complementary alternatives with five alternatives. Antipova et al. (2014) used the ε-constraint method, a form of mixed-integer linear programming, to derive a set of complementary alternatives. Tchebycheff programming, compromise programming, and the ε-constraint method all use mathematical programming to derive sets of complementary alternatives according to the weighted values of the objective functions (in Tchebycheff programming and compromise programming) or the ε-value (in the ε-constraint method). The weighted values and the ε-value differ depending on the decision-maker's preferences; no definite condition for weighing them exists. This makes it difficult to get an accurate preference (Krettek et al., 2010). Therefore, to optimize retrofit planning, it is more efficient to first derive a set of complementary alternatives and then to apply the methods using a posteriori articulation of preferences.

The most widely used algorithms for this approach are the evolutionary algorithms (Veldhuizen and Lamont, 2000). These algorithms use search methods that originated from the survival of the fittest. They simultaneously evaluate many alternatives through a global search, which helps them find optimal solutions (Goel and Deb, 2002; Saravanan et al., 2009). The most popular of these algorithms are the multi-objective genetic algorithm (MOGA)