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Evolutionary Multi-objective Optimization in Building Retrofit Planning Problem

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Abstract

Energy efficiency has been a primary subject of concern in the building sector, which consumes the largest portion of the world's total energy. Especially for existing buildings, retrofitting has been regarded as the most feasible and cost-effective method to improve energy efficiency. When planning retrofit in public buildings, the most obvious objectives are to: (1) minimize energy consumption; (2) minimize CO_2 emissions; (3) minimize retrofit costs; and (4) maximize thermal comfort; and one must consider these concerns together. The aim of this study is to apply evolutionary multi-objective optimization algorithm (NSGA-III) that can handle four objectives at a time to the application of building retrofit planning. A brief description of the algorithm is given, and the algorithm is examined using a building retrofit project, as a case study. The performance of the algorithm is evaluated using three measures: average distance to true *Pareto*-optimal front, hypervolume, and spacing. The results show that this study could be used to find a comprehensive set of trade-off scenarios for all possible retrofits, thereby providing references for building retrofit planners. These decision makers can then select the optimal retrofit strategy to satisfy stakeholders' preferences.

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Keywords: Building retrofit; CO_2 emissions; Energy consumption; Evolutionary multi-objective optimization; Retrofit costs; Thermal comfort

1. Introduction

The primary energy consumed in the building sector worldwide is 40% of total annual energy consumption, and increasing every year [1]. Also, 30% of greenhouse gases come from the sector, making it the main cause of global warming [2]. Therefore, countries around the world have developed and implemented various policies to reduce the energy consumed in the buildings. For the effective accomplishment of the energy saving policies in the building sector, increasing the energy efficiency of each building is essential [3]. Due to recent reinforcement of legal energy

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efficiency requirements, old buildings built under less regulation have lower energy efficiency than newly constructed ones [4]. For such existing buildings, retrofitting has been regarded as the most feasible and cost-effective method to improve energy efficiency [2].

Recently, government organizations in each country have supported such retrofit [5]. Despite these support policies, decision makers who perform the retrofit have difficulty planning [6]. The reason is because there are multiple objectives to accomplish through the retrofit, and it is difficult to verify how much the different retrofit alternatives satisfy them [7]. Also, there are numerous alternatives; hence, it is difficult to select the appropriate retrofit scenario by comparing all possible alternatives [8]. When planning retrofit in public buildings, the decision maker plans to minimize energy consumption and CO_2 emissions at minimal expense and in maximum comfort [9]. However, these objectives contradict each other and have trade-off relations; it is difficult to find an optimum alternative satisfying all of them [10]. For this reason, generally, the decision maker first sets a limited number of subjective alternatives, then, compares them. Or, the decision maker excludes some and then selects the scenario intuitively [11]. In these processes, the decision maker can only consider a few alternatives, making it difficult to find the best of all [12].

To solve this problem, previous studies have employed multi-objective optimization [13]. Multi-objective optimization is a process to find the optimal solutions that satisfies multiple objectives simultaneously [14]. It can obtain a *Pareto* solution comprising of a set of complementary alternatives [15]. In earlier studies, before selecting the alternative, the decision maker had first defined preference on the objectives to select one scenario among the set complementary alternatives satisfying all objectives [16]. However, the preference may vary with the decision maker, and not all objectives can be compared equally, therefore, it is difficult to provide an accurate preference in real-world problems [17]. Therefore, it has been regarded that it is efficient to derive the set of complementary alternatives via methods with a posteriori articulation of preferences.

The most popular of these is the evolutionary algorithm [18]. The evolutionary algorithm is designed to evaluate multiple alternatives simultaneously through the global search, therefore, it has a high possibility of converging the actual optimal solutions [19,20]. In a few previous studies (e.g. [10,11,21,8,22]) in solving multi-objective optimization in building retrofit planning problem, non-dominated sorting genetic algorithm (hereafter, NSGA-II) was mainly used among the evolutionary algorithms to derive the set complementary alternatives. In addition, these studies considered only three or less objectives. When solving the optimization problem using four or more objectives, the convergence performance of NSGA-II is diminished [23]. In addition, it is more difficult to derive a set of complementary alternatives with four or more objectives because of the difficulty in intuitive selection. For this reason, the reference-point based non-dominated sorting genetic algorithm (hereafter, NSGA-III) was developed based on the reference-point to be more efficient optimization, thereby enhancing the performance of NSGA-II [24,25]. Recently, NSGA-III has shown better performance on the problem of multi-objective optimization with four or more objectives (so-called as many-objective optimization problems) than the previously investigated NSGA-II [26,27].

The aim of this study is to solve the optimization problem in building retrofit planning via an evolutionary multi-objective optimization algorithm, which considers four objectives at a time: (1) minimizing energy consumption; (2) minimizing CO_2 emissions; (3) minimizing retrofit costs; and (4) maximizing thermal comfort. This study applies and evaluates evolutionary multi-objective optimization algorithm, the NSGA-III, which can handle four objectives at a time, to retrofit planning. Section 2 presents some materials on the proposed methodology. Section 3, the data analysis and a discussion of experimental results is provided. Section 4 contains conclusions and suggestions for future research.

2. Building Retrofit Planning via Multi-objective Optimization

Multi-objective optimization is a process of considering a series of constraints to enable the given objective functions to be maximum or minimum, and the alternative process of enabling the objective function to become maximum is called the decision variable. Generally, in the multi-objective optimization, several objective functions show the contradicting relationship on the decision variable; therefore, it is almost impossible to enable perfect optimization on all objective functions at the same time [28,29]. For this reason, to solve the multi-objective problem, the rational "set of solutions" satisfying the acceptable level of objectives is derived [30].

2.1. Building retrofit elements

The elements considered in previous studies (e.g., [10,11,21,8,22]) have differences depending on the characteristics of the building, but, generally, the addition of insulation, such as the wall, floor, roof and ceiling, change in the window type, and change in heating, ventilating, and air-conditioning system were considered. In this study, exterior wall insulation materials, internal wall insulation materials, insulation materials in the ground floor, floor insulation materials excluding the ground floor, roof insulation materials, ceiling insulation materials, window types (glazing and gas), and HVAC system types were considered as selectable elements.

2.2. Objective functions

The amount of energy consumption, amount of CO_2 emissions, retrofit costs, and thermal comfort were set as the objective functions. The calculation of amount of energy consumption and thermal comfort are done by the energy simulation program, EnergyPlus 8.1. The multi-objective optimization algorithm is used together with the energy simulation program, EnergyPlus 8.1, to select a set of optimized retrofit alternatives. The process is illustrated in Fig. 1. The amount of energy consumption is the total energy used in the building, including the cooling, heating, lighting, and appliance use. The thermal comfort was calculated in the sum of time feeling discomfort by the most occupants according to the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) 55-2004 standard. In order to calculate the amount of CO_2 emissions, the Inventory of Carbon & Energy (ICE) database [31] was referred on the materials and pieces of equipment used. In order to enable proper multi-objective optimization, the CO_2 emission amount generated in the life-cycle of the materials and pieces of equipment, comprising of raw materials collection, production, delivery, and disposal stages excluding the operation stage, was considered as the objective function. The retrofit costs include the costs of the materials and pieces of equipment considered as well as the installation and construction costs. The costs of the materials and pieces of equipment were referred through the price information disclosure of facility construction in the Public Procurement Service [32], and for the installation and construction costs, the market wage in the construction sector by the Construction Association of Korea [33] was referred.

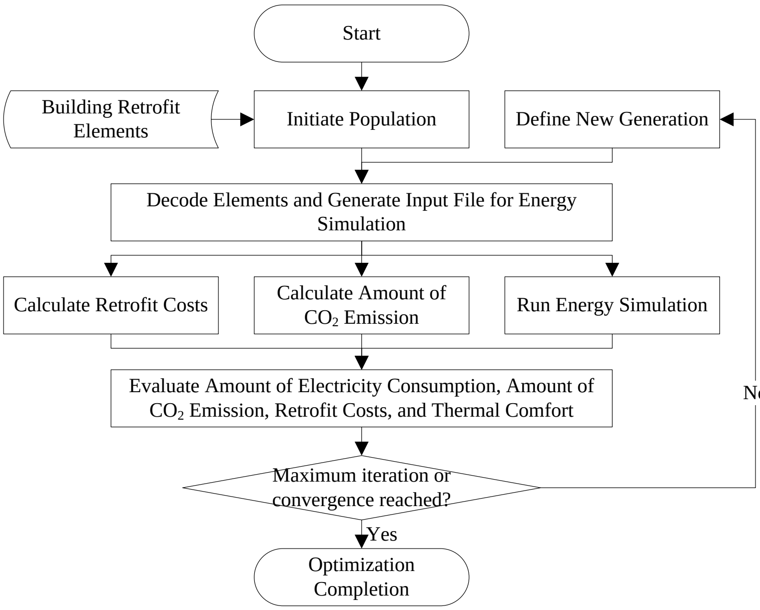

Fig. 1. Outline of process of the multi-objective optimization in building retrofit planning problem.

2.3. NSGA-III

The basic framework of the NSGA-III [34] is similar to the original NSGA-II [35]. NSGA-III is operated with a set of reference points for selecting a well-distributed set of points, unlike NSGA-II [36]. The idea is to use reference points that could be a set of predefined points or ones that are generated systematically. The pseudo-code of NSGA-III is shown in Deb and Jain [24]. The algorithm starts with the initial (parent) population, and the individuals (solutions) of the population are randomly initialized. Then, the offspring is created by the binary tournament selection and an arithmetic crossover operator proposed by Michalewicz [37]. The next step is to apply mutation operators to the new offspring. In this study, the mutation operator is assumed to be Gaussian, which results in more mutation at the beginning of the algorithm compared with the end of the algorithm. In this process, each individual (solution) should satisfy the constraints of problems described in Section 3.2. Thereafter, the parent population and the offspring are combined and sorted based on *Pareto* dominance. After finding different levels of non-dominance levels, the next step in the NSGA-III is to select the best alternatives from the combined population to be the parent population for defining the next new generation. This process is repeated until the population size reaches a predefined population value. Details of NSGA-III can be found in Deb and Jain [24] and Tavana et al. [25].

3. Experiments and Results

A set of complementary alternatives to a retrofit plan for the main building of Chung-Ang University was derived. The building is a public school building. The performance of the NSGA-III algorithms was evaluated in optimizing four objectives. In implementing the NSGA-III algorithm, the parameters of generation and population were set at 20 and 100, respectively. Three performance measures that have been widely used in previous studies evaluating the performances of multi-objective optimization algorithms were used to evaluate the properties (e.g., convergence and diversity) of the derived alternatives: distance to true *Pareto*-optimal front, hypervolume, and spacing [38]. Convergence indicates how close the alternatives derived through the optimization process are to the true *Pareto* solution, while diversity indicates the solution's level of equal distribution [23].

The average distance to the true *Pareto*-optimal solutions was evaluated in the objective space, by calculating the sum of each Euclidean distance between the solutions to its nearest *Pareto*-optimal solution [38]. Since the true *Pareto*-optimal solution is unknown in this problem, the true *Pareto*-optimal solution was therefore generated artificially by merging the non-dominated individuals from all runs of the algorithms. When using a true *Pareto*-optimal solution that is generated artificially, it is difficult to calculate exact distances, but it can be used for relative comparisons of the closeness between derived alternatives to the assumed *Pareto*-optimal solution. The lower the calculated distance to the true *Pareto*-optimal front value, the higher the optimization performance is. The hypervolume was originally proposed by Zitzler and Thiele [23]. It is especially useful when the true *Pareto*-optimal solution is unknown. Also, it can be used to evaluate the closeness of derived alternatives to the assumed *Pareto*-optimal solution as well as the diversity of the derived alternatives, by calculating the hypervolume between a given reference point and a non-dominated front in the objective space. As the derived *Pareto* solution is closer to the true *Pareto* solution and shows equal distribution, the hypervolume value is higher, and the performance of the relevant algorithm is considered to be showing relatively better performance. The spacing, as proposed by Schott [39], is an index showing the diversity and distribution level of the *Pareto* solution. When the spacing value is equal to 0, it specifies that all *Pareto* solutions are distributed ideally, in equal intervals. The *Pareto* solution being distributed equally shows that the solution derived by the algorithm is not biased to the alternative with the extreme value of the objective function; therefore, when the decision maker selects the alternative, the alternative with various objective function values can be considered. A small spacing value specifies that the *Pareto* solution interval is equal; therefore, the algorithm with the smaller spacing value is the superior algorithm.

The results of applying the NSGA-III algorithm to select the optimized retrofit alternatives are shown in Table 1. A small distance to the true *Pareto*-optimal front value specifies that when optimizing into the generation number, the algorithm approaches the true *Pareto* solution quicker than the other algorithms to have better convergence performance [40]. This specifies that the decision maker can utilize NSGA-III to derive the retrofit alternatives that reduce energy consumption, CO_2 emissions, and retrofit costs, as well as improve thermal comfort.

Table 1. Performance measures summary for NSGA-III.

Performance measure	NSGA-III
Average distance to true *Pareto*-optimal front	**1.96E+09**
Hypervolume	**1.77E-02**
Spacing	**1.00E+08**

4. Conclusion

This study applied and evaluated the performance of evolutionary multi-objective optimization algorithm (NSGA-III) with four objectives: (1) minimizing energy consumption; (2) minimizing CO_2 emissions; (3) minimizing retrofit costs; and (4) maximizing thermal comfort—one must consider these concerns together. Based on these four objectives (making this a many-objective optimization problem), it is expected that multi-objective optimization using the NSGA-III algorithm can contribute to finding a comprehensive set of trade-off scenarios for all possible retrofits, thereby providing references for building retrofit planners. These decision makers can then select the optimal retrofit strategy to satisfy their stakeholders' preferences.

Our future work will involve comparing the relative performance between NSGA-III algorithm and other evolutionary multi-objective optimization algorithms on this problem (e.g., NSGA-II, multi-objective evolutionary algorithm based on decomposition (MOEA/D), and multi-objective particle swarm optimization algorithms (MOPSO)) to suggest the superior algorithm for the optimization problem in building retrofit planning, with four objectives. In addition, since the current experiment targeted a single building retrofit project, future work will therefore be devoted to conducting more experiments in order to reach definitive conclusions. Moreover, especially for practical applications with many-objective optimization problems, only a small, manageable number of alternatives are required for efficient decision making when using a posteriori articulation of preferences. The present study will be extended to focus on this purpose.

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