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Multi-objective optimization for building retrofit: A model using genetic algorithm and artificial neural network and an application

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ABSTRACT

Retrofitting of existing buildings offers significant opportunities for improving occupants' comfort and well-being, reducing global energy consumption and greenhouse gas emissions. This is being considered as one of the main approaches to achieve sustainability in the built environment at relatively low cost and high uptake rates. Although a wide range of retrofit technologies is readily available, methods to identify the most suitable set of retrofit actions for particular projects are still a major technical and methodological challenge.

This paper presents a multi-objective optimization model using genetic algorithm (GA) and artificial neural network (ANN) to quantitatively assess technology choices in a building retrofit project. This model combines the rapidity of evaluation of ANNs with the optimization power of GAs. A school building is used as a case study to demonstrate the practicability of the proposed approach and highlight potential problems that may arise. The study starts with the individual optimization of objective functions focusing on building's characteristics and performance: energy consumption, retrofit cost, and thermal discomfort hours. Then a multi-objective optimization model is developed to study the interaction between these conflicting objectives and assess their trade-offs.

1. Introduction

The energy sector faces significant challenges that everyday become more acute. The current energy trends raise great concerns about the "three Es": environment, energy security and economic prosperity, as defined by the International Energy Agency [1]. The building sector is among the greatest energy consumers, using large amounts of energy and releasing considerable amounts of green house gases (GHG). In the United States in 2010, buildings accounted for 41% of total primary energy consumption and 74% of electricity consumption [2]. About 40% of CO_2 emissions, 54% of SO_2, and 17% of NO_x produced in the U.S. are due to building-related energy consumption. A similar situation is also observed in the European Union (EU), where the building sector uses 40% of total final energy consumed and releases about 40% of total CO_2 emissions. In the last ten years (1999–2009), EU-27 dependency on imported energy has grown, reaching 53.9% in 2009. This represents an increase of 9 percentage points from 1999 [3]. As a consequence, the cornerstone of the European energy policy

Abbreviations: ANN, Artificial Neural Network; DM, Decision Maker; EC, Energy Consumption; EPBD, Energy Performance of Buildings Directive; EU, European Union; EWAL, External Wall insulation material; GA, Genetic Algorithm; HVAC, Heating, Ventilation, and Air-Conditioning; LHS, Latin Hypercube Sampling; MCA, Multi Criteria Analysis; MOGA, Multi-Objective Genetic Algorithm; MOO, Multi-Objective Optimization; PMV, Predicted Mean Vote; QHEAT, Energy consumption for space heating; QCOOL, Energy consumption for space cooling; QSC, Heating production by Solar Collector; QSHW, Energy consumption for sanitary hot water; ReCost, Retrofit Cost; ROF, Roof insulation material; SC, Solar Collector; SHW, Sanitary Hot Water; TPMVD, total percentage of discomfort hours; WIN, Window.

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has an explicit orientation toward the conservation and rational use of energy in buildings as the Energy Performance of Buildings Directive (EPBD) 2002/91/EC [4] and its recast [5] indicate.

Most European countries have succeeded in reducing energy consumption of new dwellings by more than 50% without increasing their building cost, and therefore energy efficiency has achieved great acceptance among building owners [6]. These buildings represent about 20% of the building stock but consume only 5% of the energy. However, even if all future buildings were to be built so that their electrical energy and heat energy demands were very low, it would still only mean that the increase in energy demand would be reduced. It would not reduce present demand. For many years to come, measures taken in existing buildings will have the most significant effect on the total energy demands in the building stock [7].

When designing new buildings, only relatively limited additional investments are often needed to make them very energy-efficient. On the other hand, it is more difficult and costly to bring about substantial energy savings in existing buildings, though it is nearly always possible to identify a number of measures that are both energy-saving and cost-effective [8]. However, both in designing new buildings and carrying out measures in existing buildings, it is extremely important that the solution applied and the measures taken are well founded and correctly chosen [9]. That is, when buildings are subject to retrofit, it is very important to select the optimal strategy in a timely manner, since if other solutions are chosen and implemented it will just be possible to change the building at a later occasion at a much higher cost.

The works involved in retrofit are usually of complex and heterogeneous nature that require various specialties to be integrated in highly variable conditions. Furthermore, a thorough building's retrofit evaluation is quite difficult to undertake, because a building and its environment are complex systems regarding technical, technological, ecological, social, comfort, esthetical, and other aspects, where every sub-system influences the total efficiency performance and the interdependence between sub-systems plays a critical role [10].

This paper has five sections, including the introduction. Section 2 presents a brief overview of models and methodologies developed to support decisions regarding building retrofit. The modules in the proposed approach are discussed in detail in Section 3. The application of the model to the retrofit of a school building is described in Section 4. Finally, Section 5 summarizes conclusions and discusses topics for future research.

2. Literature review

There are a number of models and methods developed to assess conditions and support decisions pertaining to building retrofit. These methodologies can be categorized into two main approaches: the models in which alternative retrofit solutions are explicitly known a priori (see e.g. [11–14]) and the models in which alternative retrofit solutions are implicitly defined in the setting of an optimization model (see e.g. [7,15–17]).

The most common a priori approach is one in which the decision maker (DM) assigns weights to each criterion, the weighted sum of the criteria then forming a single design criterion. It is then possible to find the single design solution that optimizes the weighted sum of the criteria. Gero et al. [11] were among the first to propose a multi-criteria analysis (MCA) model to be used at the process of building design in order to explore the trade-offs between the building thermal performance and other criteria such as capital cost and usable area. More recently, other researchers have also employed MCA techniques to similar problems. Jaggs and Palmer [12], Flourentzou and Roulet [13], and Rey [14] proposed approaches for the evaluation of retrofitting scenarios. Kaklauskas et al. [10] developed a multivariate design method and MCA for building retrofit, determining the significance, priorities and utility degree of building retrofit alternatives and selecting the most recommended variant.

These lines of research have allowed addressing many problems as far as buildings retrofit is concerned. However, most of them consider that a list of predefined and pre-evaluated alternative variants of the building retrofit options is given. In case a small number of such solutions have been defined, there is no guarantee that the solution finally reached is the best one (from the DM's perspective). On the opposite case, when a large number of solutions are defined the required evaluation and selection process may become extremely difficult to handle. Moreover, MCA-based methodologies do not provide the designer with information about how sensitive each criterion is to changes of the other criteria [18].

The second approach (based on multi-objective optimization, MOO) enables to consider a large set of building retrofit options implicitly defined by the constraints defining the search space and grasp the trade-offs between the objective functions helping to reach a satisfactory compromise solution. However, so far, relatively little attention has been paid to tackling building retrofit decision support with multiple objective optimization [19]. Diakaki et al. [15] investigated the feasibility of applying MOO techniques to the problem of improving energy efficiency in buildings, considering a simplified model for building thermal simulation. Asadi et al. [16] proposed an MOO model that supports the definition of retrofit actions aimed at minimizing energy use in a cost effective manner. Following this work, they developed an MOO model combined with TRNSYS (building performance simulation program) and GenOpt (an optimization program). The proposed model was used for the optimization of retrofit cost, energy savings, and thermal comfort of a residential building, in a framework of an MOO model [7].

Considering all the possibilities that the DM has available for building retrofit (e.g. HVAC systems and renewable energy sources), as well as all the objectives that he/she may wish to optimize (CO_2 emissions, social objectives, etc.) may lead to the combinatorial explosion of the decision problem, thus making the solving procedure extremely difficult and time-consuming. In such case, other optimization techniques, namely multi-objective genetic algorithms are necessary for tackling the problem. Wright et al. [20] used a multi-objective GA to find the trade-offs between the energy cost and occupant thermal comfort for the design of a single zone HVAC system. Hamdy et al. [21] proposed an MOO approach based on GA to tackle the problem of designing low-emission cost-effective dwellings, minimizing the carbon dioxide emissions and the investment cost for a two-story house and its HVAC system.

A main drawback of GA is the high burden whenever it is necessary to make a large number of calls to an evaluation function involving a high computational cost. In building applications, these evaluations are generally estimated by an external simulation program such as Computational Fluids Dynamics (CFD) or other simulation packages. If accurate results are required, each evaluation can be time consuming, and thus the complete computational process becomes extremely unattractive [22]. Accordingly, building optimization studies using GA generally tend to reduce the computational time by using two methods. The first method consists in using very simplified models instead of complex simulation software [23]. However, this method presents a risk of over-simplification and inaccurate modeling of building phenomena. The second method commonly used is to select very small GA populations and/or relatively small number of generations [24]. Again, the optimization can be significantly affected and may lead to narrow or non-optimal solution sets [25].

One very efficient, yet widely not exploited, solution to reduce the computational time associated with GA is to use a Response