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Decision-making based on network visualization applied to building life cycle optimization

Fraisse Gilles*, Souyri Bernard, Axaopoulos Ioannis, Rouchier Simon

LOCIE, UMR CNRS 5271, Université Savoie Mont-Blanc, 73376 Bourget du Lac, France

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A B S T R A C T

We present a building design optimization methodology that has been developed to address issues that researchers and engineers are currently facing when addressing the life cycle optimization of Nearly Zero Energy Buildings (NZEBs). In order to reduce the required computational time, a Kriging model is used to surrogate NZEB performance criteria during the optimization process. The error estimation of the Kriging model is used for an adaptive sequential design to improve the Kriging model accuracy. A genetic algorithm (NSGA-II) is considered efficient to find the global optimal solutions. We also propose a new algorithm to reduce the calculation time even further. The new individuals of the adaptive sequential design are filtered with satisfaction functions. It means that only the useful part of the Pareto front will be determined. Finally, we use network visualization for decision-making. We show that this approach is very powerful to help designers find one solution in the context of multi-objective optimization. Moreover, the partitions can give useful information about the characteristics of the optimal solutions.

1. Introduction

The residential sector consumes about 40% of the total annual final energy of developed countries (IEA, 2008). In 2015, the final energy consumption of the residential sector was 25.3% of the total final energy consumption in the European Union (EU). The energy ratio used by the EU households in 2015 for space heating was 64.7%, for domestic hot water (DHW) 13.9%, for lighting and other appliances 13.8%, and for air conditioning 0.5% of the total final energy of the residential sector. In an attempt to reduce the energy use in buildings, the EU applied a policy named "Energy Performance of Buildings Directive" (EPBD). The concept of "nearly Zero-Energy Buildings" (NZEB) has been defined in the EPBD: these buildings balance their small yearly energy consumption with electrical production using renewable energy. By the end of 2020, all new buildings will be required to be NZEBs.

The Energy Building Design (EBD) for NZEB is challenging in many ways. One challenge is to cover a large amount of their energy needs using renewable energy sources (RES) (Kalkan, Young, & Celiktas, 2012; Comodi et al., 2014; Marszal & Heiselberg, 2011). This is problematic because RES depend highly on the climate of the building location. This means that the energy supply from RES does not always match the energy needs (Cao, Hasan, & Sirén, 2013). The designer cannot therefore easily size, for example, the required installed power of the RES and the storage capacities (thermal and electrical) to meet the energy needs. Considering electricity, as feed in tariff variation is a downward trend, storage with batteries and self-consumption also become key issues.

Another challenge is to reduce the relatively high value of NZEBs embodied energy compared to their annual energy consumption (Giordano, Serra, Demaria, & Duzel, 2017; Giordano, Serra, Tortalla, Valentini, & Aghemo, 2015; Blengini & Di Carlo, 2010; Karimpour et al., 2014; Ramesh, Prakash, & Shukla, 2010). Once the operational energy needs of a building during its lifetime are balanced by the use of RES, then the embodied energy, i.e. the energy used during its construction, becomes significant (Chen & Ng, 2016; Chastas & Theodosiou, 2016; Ayaz & Yang, 2009; Fieldson, Rai, & Sodagar, 2009; Ibn-Mohammed, Greenough, Taylor, Ozawa-Meida, & Acquaye, 2013). This leads the designer of a NZEB to perform life cycle analysis (LCA) which is a more comprehensive approach that includes embodied energy assessment. Considering the building life time, the designer should also account for the climate change. Roux, Schalbart, Assoumou, and Peuportier (2016) performed a LCA and life cycle cost (LCC) assessment and Song and Ye (2017) an energy consumption analysis on residential buildings, both incorporating a weather data prediction on the climate on future years. To account for climate change, more dynamic simulations on possible climate scenarios are required. These extra simulations add to the overall increase of computational time.

In addition, another issue is the complexity of modeling a NZEB as a

* Corresponding author.
E-mail address: fraisse@univ-smb.fr (F. Gilles).

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whole (envelope, systems, etc.) that increases the computational time even further. Therefore, NZEB optimization needs to reduce the required computational time using specific methodologies (Wetter & Polak, 2004; Magnier et al., 2010). Moreover, the designer of a NZEB should consider many performance criteria, such as the cost, thermal comfort, embodied energy, CO_2 emissions, energy consumption, RES production, durability… All of the factors mentioned above lead to the need for a global approach of NZEB optimization (Evins, 2013). Thus, the designer should perform a multi-objective optimization that will result in many possible optimal solutions. These optimal solutions can be presented in a Pareto front.

Pareto fronts can be a good tool for the decision maker to choose a solution but it can be rather impractical for more than two performance criteria. There are many different Multi-Criteria Decision Making Analysis (MCDA) methods that can be used to post-process optimal solutions in EBD. Among these MCDA methods are TOPSIS e.g. used by Jin, Favoino, and Overend (2017), Wang et al. (2017); Analytical Hierarchy Process (AHP) e.g. used by Si, Marjanovic-Halburd, Nasiri, and Bel (2016), Roberti, Oberegger, Lucchi, and Troi (2017), Mulliner, Malys, and Maliene (2016); Elimination and Choice Expressing the Reality (ELECTRE) e.g. used by Catalina, Virgone, and Blanco (2011); Complex Proportion Assessment (COPRAS) e.g. used by Volvačiovas, Turskis, Aviža, and Mikštienė (2013), Mulliner et al. (2016); SMAA (Stochastic Multi-criteria Acceptability Analysis) e.g. used by Iwaro, Mwasha, Williams, and Zico (2014) and Stochastic Multicriteria Acceptability Analysis used by Kontu, Rinne, Olkkonen, Lahdelma, and Salminen (2015). Furthermore, it is not common in EBD literature, to use decision making tools before post-processing, i.e. integrated in the optimization algorithm (Cherif, Chabchoub, & Aouni, 2008). This could help reduce calculation time if the optimal solutions of little interest were not considered.

Building and energy systems optimization is currently a very active research area. Many authors are interested in optimizing a building's envelope and energy systems considering more than one performance criteria, i.e. multiobjective optimization (MOO) (Antipova, Boer, Guillén-Gosálbez, Cabeza, & Jiménez, 2014; Carreras et al., 2014), like Wu, Mavromatidis, Orehounig, and Carmeliet (2017) that apply a mixed integer linear program (MILP) optimization to minimize both the greenhouses gas (GHG) emissions and the life cycle cost of buildings' energy systems and envelope on a community level. Others, like Penna, Prada, Cappelletti, and Gasparella (2015) take three objectives into account (energy savings, costs and indoor thermal comfort) and apply the NSGA-II algorithm to define the optimal energy measures on a building as a whole, including both energy systems and envelope. Moreover, Evins (2013), Attia et al. (2013) and Machairas et al. (2014) have presented detailed literature reviews on optimization methods, used for EBD. In reviewed EBD literature it is less common to optimize more than three objective functions simultaneously (Penna et al., 2015).

The commonly used algorithms in building energy efficient design optimization can be grouped into three categories, namely evolutionary algorithms, gradient-based search algorithms, and hybrid algorithms (Terzidis, 2006). Several reviews that focus on performance-based building design optimization or similar methods are available. Evins (2013) conducted a review on computational optimization methods applied to sustainable building design. Nguyen, Reiter, and Rigo (2014) reviewed simulation-based optimization methods in building performance analysis. Machairas, Tsangrassoulis, and Axarli (2014) took a different angle and reviewed the algorithms used in performance-based building design optimization. Attia, Hamdy, O'Brien, and Carlucci (2013) reviewed the gaps and needs for integrating building performance optimization tools in NZEB design.

A current trend in EBD optimization is to reduce computational time using surrogate models (SM) to mimic time-costly transient simulation models. Carreras et al. (2016) apply an optimization of two objectives, to minimize cost and environmental impact of a building envelope using a SM (cubic spline interpolation) to reduce computational time.

These SM may be classified based on their employed techniques: Radial basis function, Kriging (KR), support vector regression (SVR), artificial neural network (ANN), multivariate adaptive regression splines (MARS), and others. Bornatico, Hüssy, Witzig, and Guzzella (2013) respectively apply Radial basis function surrogate modeling on a MOO to maximize solar yield and to minimize investments costs of a solar domestic hot water (SDHW) system. Kriging is a non-parametric technique, suitable for the identification of long term temporal and spatial trends (Zavala, Constantinescu, Krause, & Anitescu, 2009). Furthermore, one of its special features is the ability to predict not only numerical values, but also uncertainty boundaries. Many authors use Kriging to predict building energy performance, as Hopfe, Emmerich, Marijt, and Hensen (2012), Tresidder, Zhang, and Forrester (2016), Van Gelder, Das, Janssen, and Roels (2014) and Eguía, Granada, Alonso, Arce, and Saavedra (2016).

A different technique with similar applications is Support Vector Machines (SVM). The main advantage of SVM over ANN is related to the fact that the statistical learning process is cast as a convex optimization problem (Boyd & Vandenberghe, 2004). Eisenhower, O'Neill, Narayanan, Fonoberov, and Mezić (2012) uses SVM to perform a model-based MOO to minimize thermal discomfort (PMV) and annual energy consumption.

ANN is a parametric technique that has the ability to learn complex patterns (Beccali, Cellura, Lo Brano, & Marvuglia, 2004) and simulate non-linear systems (Kanarachos & Geramanis, 1998). Also, ANN is efficient in building studies (Magnier & Haghighat, 2010). It is the dominant technique for building energy performance (Ascione, Bianco, De Stasio, Mauro, & Vanoli, 2017).

However, in the case of a time-consuming transient simulation model, KR has a far lower training time compared to ANN because less samples would be needed. Usually, in EDB literature, Multivariate Adaptive Regression Splines (MARS) are preferred to KR because of their simplicity and clear relationship between inputs and outputs (Van Gelder et al., 2014).

MARS is an adaptive non-parametric regression method (Friedman, 1991). MARS has seen surprisingly little application in building-related studies to date (Cheng & Cao, 2014). Kusiak, Li, and Tang (2010) compares MARS to other SM in a model-based MOO problem, using a Particle swarm optimization (PSO) algorithm to minimize the energy consumption of a HVAC system.

Sequential design strategies for SM have been studied in the context of deterministic computer experiments, to perform either prediction or optimization (Kleijnen, 2017). Cheng and Cao (2014) used a hybrid technique, MARS and artificial bee colony in adaptive design of a SM to predict heating and cooling load of buildings. Ramallo-González and Coley (2014) apply a Covariate Matrix Adaption Evolutionary Strategy (CMA-ES-SA) optimization, to minimize cooling and heating demands of a building.

In the following sections, we present an EBD optimization methodology that has been developed to address issues that researchers and engineers are currently facing with the life cycle optimization of NZEBs. In order to reduce the required computational time, a Kriging model is trained to surrogate NZEB performance criteria during the optimization process. The error estimation of the Kriging model is used for an adaptive sequential design to improve the Kriging model accuracy. A genetic algorithm (NSGA-II) is implemented to find the global optimal solutions. We also propose a new algorithm to reduce the calculation time even more. The new individuals of the adaptive sequential design are filtered with satisfaction functions (Cherif et al., 2008). It means that only the useful part of the Pareto front will be determined. Finally, we use network visualization for MCDA. We show that this approach is very powerful to help designers find one solution in the case of multi-objective optimization. Moreover, the partitions can give useful information about the characteristics of the optimal solutions.