Energy and Buildings 66 (2013) 22–32

Contents lists available at ScienceDirect

Energy and Buildings

journal homepage: www.elsevier.com/locate/enbuild

Multi-objective building energy consumption prediction and optimization for eco-community planning

Xu Han, Jingjing Pei*, Junjie Liu, Luyi Xu

School of Environmental Science and Engineering, Tianjin University, Tianjin 300072, China

ARTICLE INFO

Article history:
Received 8 November 2012
Received in revised form 4 July 2013
Accepted 7 July 2013

Keywords:
Eco-community planning
Carbon emission
Energy consumption prediction
Optimization tool
Sensitivity analysis

ABSTRACT

The planning of an eco-city/community involves multiple factors, including building energy consumption, carbon emission, initial cost, as well as local natural, geographical and socio-economic conditions. To assist policymakers and planners to make the optimum decisions, especially in the early planning stage of an eco-city/community, this paper developed a quick and convenient multi-objective prediction and optimization tool. Building energy consumption, carbon emission and initial cost were considered as three sub-objectives. The optimization parameters include those for building envelope (i.e. heat transfer coefficient, window shading coefficient, unit cost) and those for air-conditioning system (i.e. coefficient of performance) for each type of buildings. The building energy consumption was calculated based on the BIN method. The carbon emission was determined with the energy consumption and carbon emission factor of each energy type. The initial incremental cost was calculated with the material and product price. Priority consideration of the three sub-objectives was achieved by weight factor method during the optimization process. The weight factors could be determined empirically by policymakers, investors, or planners. The optimization results can be referred by decision makers. Finally, an eco-community in Chongqing, China was taken for a case study, and parameter sensitive analysis was conducted.

1. Introduction

Building sector in China accounts for 23% of the country's total energy consumption [1], which significantly contributes to the environmental pollution and total carbon emission. As energy and environment problem becomes a public concern all over the world, China is accelerating the exploration and construction of eco-cities and eco-communities. With Tianjin Sino-Singapore eco-city, Tangshan Caofeidian eco-city, and Shenzhen Bright eco-city under construction, there are more and more cities participating in the practice of the low carbon eco-city or eco-community in China. It is estimated that there are more than a dozen cities carrying out the implementation of the eco-city planning and more than one hundred Chinese municipal governments proposing to build eco-cities or eco-towns [2]. Multiple factors need to be considered during the planning and design stage of a new eco-community while choosing from numerous available low carbon technologies, green materials, renewable energy sources, and so on. Those factors include capital investment, energy-saving potential, carbon emission level, as well as local natural, geographical and socio-economic conditions.

To predict the building energy consumption, statistical methods and engineering methods can be used [7]. The statistical methods estimate energy consumption by correlating the energy consumption with the influencing factors based on vast statistical data. The relationship between the energy consumption and the influencing factors was usually obtained through regression models or artificial intelligence models [3–6]. For example, the heating and cooling load can be regressed as a function of single variable (e.g. outdoor dry-bulb temperature) and such a single variable model is feasible for a certain type of weather condition [3]. The artificial intelligence models, including Artificial Neural Networks (ANNs) [4,5] and Support Vector Machines (SVMs) [6], can give highly accurate prediction of the building energy consumption, but require sufficient historical data and complex calculation [7]. The statistical method may be used for energy consumption estimation of traditional building types, but its application for green buildings or eco-cities/communities is restricted due to the lack of enough historical reference cases.

Engineering methods utilize the physical principles to simulate the building energy behavior, and can be further classified into elaborate methods and simplified methods, including DOE-2, EnergyPlus, BLAST, degree day method and the BIN method [8,9].

* Corresponding author at: Room 240C, Building 14, Tianjin University, Tianjin 300072, China. Tel.: +86 022 27403416; fax: +86 022 87401561.
E-mail address: jpei@tju.edu.cn (J. Pei).

0378-7788/$ – see front matter
http://dx.doi.org/10.1016/j.enbuild.2013.07.016

With the development of computer technology, the elaborate engineering methods are more and more popular. Researchers have developed optimization tools based on DOE-2 to select the optimal combinations of several building features considering both energy consumption and life cycle cost [10–12]. Although the simulation tools are accurate, the utilization of these tools needs professional knowledge and detailed input parameters, which may be not available especially during the planning stage. Furthermore, even with advanced computers, the simulation still takes significant computational efforts, especially for community or regional energy consumption prediction. As a result, although there are many available building energy consumption simulation (e.g. DOE-2, ANNs) [7] and optimization tools [13,14], an easy and convenient tool is still needed to predict the energy and environmental performance of an eco-community, especially during the design and planning stage.

Compared with a single building, the building energy consumption prediction for an eco-community has the following characteristics:

(1) An eco-community consists of more than one type of buildings, and each type of buildings has its own properties. Engineering methods need to simulate the building energy consumption for each building, which will cost vast computational effort and time. In addition, the elaborate simulation tools based on physical principles require detailed input parameters of the building and environment [7,9]. However, the lack of the detailed information of buildings in the early stage of planning may lead to a low accurate simulation.
(2) Plenty of new energy saving or eco-concept technologies are normally applied in one eco-community. For example, advanced envelop materials, heat pump technologies, solar power, wind power, etc., were used in the Sino-Singapore Tianjin eco-city [15]. It is difficult to gain enough historical data for such project, which makes the statistical methods not suitable for the building energy consumption prediction for an eco-community.
(3) In the early stage of planning, there are usually more than one choice of energy saving or eco-concept measures. For example, one can choose from wall insulation, roof type, window type, etc. to improve the energy performance of the building envelope. Each measure has more than one implementation option. For example, one can improve wall insulation through changing materials or thickness of insulation. The performance of one option to different types of buildings may be different. As a result, there are numerous options available during the optimization of an eco-community, which makes the optimization complex.

To assist policymakers and planners to make the optimum decision in the early planning stage, the current research aimed to develop a fast and easy model to predict and optimize the building energy consumption, energy-saving potential, carbon emission, and initial investment for an eco-city/community. The building energy saving and carbon emission reduction potential are estimated by comparison between benchmark models and eco-concept models. The initial cost of those models can be compared considering the investment payback period. An optimization program was developed to reach the best design considering weight factors for different sub-objective functions. The weight factors vary for specific cases and may be determined empirically or by policymakers, experts and designers. Finally, an eco-community in Chongqing, China was taken for a case study, and the optimum design considering different weight factors was obtained with the optimization tool developed.

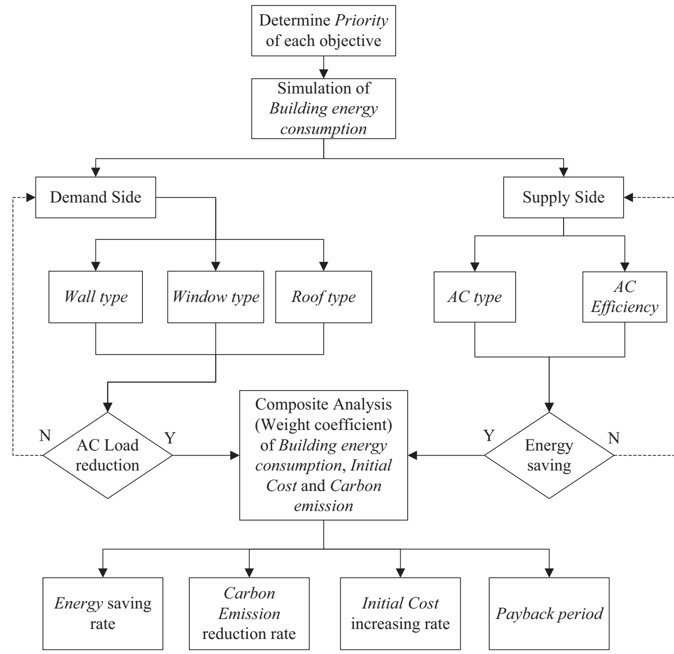

Fig. 1. Composite of the optimization design model.

2. Methodology

2.1. Model structure

Both building energy (cooling/heating) demand side and supply side are considered in the current model as shown in Fig. 1. The optimization of each variable, including the wall type, window type, roof type and AC (air conditioning) heating/cooling source type, would lead to reduction of the building energy consumption or carbon emission with usually incremental initial cost. As a result, the objective of this model is to obtain the optimum combination of variables for each type of buildings, to achieve the minimum of building energy consumption, carbon emission and initial cost. To solve this multi-objective problem, three sub-objectives are considered through the weight factor method as described by Eqs. (1) and (2).

$$\min W(X) = \sum_{i=1}^{N} (\varepsilon_i \times F_i) \qquad (1)$$

$$X = [x_1, x_2, \ldots, x_n]^T \in R^D \qquad (2)$$

where $W(X)$ is the objective function. N, F_i, ε_i represent the number, function and weight factor of the sub-objectives respectively. In the current model, the sub-objectives include the building energy consumption (F_Q), carbon emission (F_{CE}) and initial cost (F_{IC}). The weight factor is defined in such a way that in the array of $[x\,y\,z]$, the element x, y and z represent the weight factor of F_Q, F_{CE} and F_{IC} respectively. For example, [1 0 0] means the most priority consideration of building energy consumption (F_Q) while no carbon emission (F_{CE}) and initial cost (F_{IC}) consideration.

The discrete integers were used to describe the variables. For example [1–3] for the variable "window type" represented three options: single glass, hollow glass and low-e hollow glass. Each variable has more than one property. For example, the variable "window type" has three properties including the coefficient of heat transfer, shading coefficient and incremental cost. In Eq. (2), $X = [x_1, x_2, \ldots, x_n]^T$ are discrete variables, where n stands for the number of the variables. In this paper, n equals 4 and the four variables include