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A strategic optimization model for energy systems planning

Emilio L. Cano [a,*], Markus Groissböck [b,c], Javier M. Moguerza [a], Michael Stadler [b,c]

[a] Department of Statistics and Operations Research, Rey Juan Carlos University, Calle Tulipán s/n. 28933 Móstoles, Madrid, Spain
[b] Center for Energy and innovative Technologies (CET), Austria
[c] Lawrence Berkeley National Laboratory (LBNL), CA, United States

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ABSTRACT

Strategic decisions regarding energy systems deployment at the building level are becoming a great challenge in the global market. On the one hand, competition policies are allowing the arriving of new actors to the market, resulting in sophisticated pricing options. On the other hand, efficiency and sustainability policies and regulations aim at encouraging building managers and operators to adopt an active role in the energy market. In this paper, an optimization model which deals with such strategic decisions is presented. The model integrates features such as scaled operational performance in the short term, different technologies and market options, and different energy types, as well as technologies' aging and renovation. This integration results on a holistic model, which constitutes the main contribution of the paper, suitable to be implemented in decision support systems (DSS).

1. Introduction

1.1. Overview

In this paper, an optimization model for strategic decisions concerning energy planning in buildings is presented and assessed. The model is being developed within the EnRiMa research project [1]. The result of the project will be a decision support system (DSS) for building managers and operators, which will help making decisions for energy efficient buildings. This DSS will deal with both strategic and operational decisions. Thus, in addition to the strategic model presented in this paper, an operational model has been also developed [2]. The strategic model has been designed in order to make strategic decisions concerning which technologies to install and/or decommission in the long term, that is, the energy technologies portfolio planning. Besides technologies, this planning includes market options selection. In an attempt to tackle short- and long-term decisions simultaneously, the strategic model includes a simplified version of operational energy-balance constraints. At that stage, we can find in the literature strategic optimization models whose energy-balance constraints (which assures covering the building energy demand) are aggregated in the long term [3]. This approach does not allow the decision maker to take into account the performance of the installed technologies in the short term, leading to optimal solutions that may result in unrealistic implementations. In order to avoid this drawback, the strategic module includes upper-level operational variables and constraints that manage the energy flows from inputs to outputs through technologies. It is important to remark the difficulty of this integration since several parameters interfere and could easily lead to questionable outcomes. Nevertheless, through the scaling of the operational parameters to the overall strategic scope using representative profiles this effect is diluted.

The optimization model presented in this work gathers the interrelations between the building's energy subsystems outlined above, and the time-scaling between different time spans. In particular, the integration of different energy types, technologies aging modeling, and accounting for operational performance, are novel contributions to the state of the art. Thus, ignoring the aging and therefore the decay of equipment can have consequences for buildings mid-term and long-term management. Likewise, this model allows the inclusion of operational parameters in addition to the strategic modeling, which is something new regarding existing proposals. Moreover, the model has been designed so that it may be straightforwardly used within a stochastic programming approach as discussed in Section 5. Finally, a numerical example using data from an EnRiMa project test site illustrates the model.

* Corresponding author. Tel. +34 665676225.
E-mail addresses: emilio.lopez@urjc.es, emilopezcano@gmail.com (E.L. Cano), mgroissboeck@cet.or.at (M. Groissböck), javier.moguerza@urjc.es (J.M. Moguerza), mstadler@cet.or.at (M. Stadler).

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1.2. Background

In the last decades, several regulatory and market changes have altered the way energy is being used. The energy market liberalization process, initially mainly focused on the electricity market [4], has widened leeway to building managers and operators. They can adopt an active role by making decisions about how to fulfill the energy needs of buildings. Thus, they can choose between different energy providers at different levels and periods under the customer-retailer-producer market structure [5]. Several initiatives fostering "energy-balanced" buildings have arisen worldwide. Using different nomenclatures (e.g., zero-net energy, net-balance), the aim is to locally produce as much energy as it is consumed [6]. Other challenges are likely to appear regarding building energy management such as demand response or load shifting. Furthermore, new technologies for energy generation, renewable energy, or self-consumption are emerging. In this regard, a DSS is desirable to help decision makers choosing the optimal equipment to deploy in the building.

We can find in the literature research about energy systems planning from different approaches. Some of them deal with specific technologies, for example [7,8], focus on distributed energy resources (DER) technologies; [9] focus on wind technologies. Other optimization models are designed from the production point of view [10,11], or from a regional perspective [12]. Only recent papers tackle systems planning at the building level [13].

2. Modeling

In this section, the optimization model is explained step by step. Variables, represented by small Latin letters, and parameters, represented by capital Latin letters, are defined as they appear in the equations. Superscripts are for time-related sets and subscripts are for the rest of the sets. For the sake of clarity, equations and sums domains are expressed in terms of sets, even though in the implementation more precise boundaries through the definition of subsets and multidimensional sets is needed to avoid spurious variables creation. A complete nomenclature can be found in Appendix A.

2.1. Time modeling

As mentioned above, operational decisions and constraints are embedded in order to take into account the energy systems performance and decisions in the short-term, e.g., hours. To achieve this goal, instead of including all the possible hours for each year, i.e., 8760, which will likely result in unacceptable computational time, a given number of representative "in-between" mid-term periods are considered [14]. In this way, we can consider concurrently different parameter values for different performance scenarios, e.g., day/night hours, hot/cold seasons, and so on. The proposed model tackles this multiple time resolution including three time sets: $\mathcal{P}$ for long-term periods, $\mathcal{M}$ for mid-term representative periods, and $\mathcal{T}$ for short-term periods. Decision variables and parameters including the counterpart indices p, m, and t gather this logic. Note that operational decisions include indices m and t in addition to the p index, whilst strategic decisions only refer to yearly decisions, hence they do not include m neither t indices. In order to scale between different time resolution terms, the parameters DT and DM^m contain the time duration for the short-term period (e.g., one hour) and mid-term representative periods (e.g., days). Mid-term representative periods can be seen as *profiles* of days with a similar building behavior, e.g., 'winter weekdays', 'summer weekend days', and so on. The set $\mathcal{A} = \{0, \ldots, |\mathcal{P}| - 1\}$ is used to model technologies' aging.

It is important to remark that the decisions to be actually made after solving the model are only the strategic decisions for the first long-term period ($p = 1$). Nonetheless, a long-term decision horizon is needed in the model in order to consider the systems performance throughout the time, and to allow a long-term objective optimization, e.g., minimize global cost for the next 25 years. Even though the model allows different time duration for each index, for the sake of clarity in the following we will refer to long-term periods as years, short-term periods as hours, and mid-term periods as profiles.

2.2. Technologies modeling

Both installation and decommissioning of energy systems are considered in the model. Technologies are modeled through the $\mathcal{I}$ set and they can be energy-generation technologies such as combined heat and power (CHP) or photovoltaic (PV), storage technologies such as batteries, or passive technologies such as insulation. Thus, actual decisions on how many units of a technology to install or to decommission at the beginning of each year are represented by the variables xi_i^p and $xd_i^{p,a}$ respectively. Note that decommissioning decisions are also related to the age of the technologies, as for a given year we may have technologies installed at different previous years. The variable $x_i^{p,a}$ is used to dynamically calculate the available units of each technology $i \in \mathcal{I}$ and their age throughout the decision horizon $p \in \mathcal{P}$:

$$x_i^{p,0} = xi_i^p \quad \forall\, i, p, \tag{1}$$

$$x_i^{p,a} = x_i^{p-1,a-1} - xd_i^{p,a} \quad \forall\, i;\, a > 0, p > 1, \tag{2}$$

$$x_i^{1,a} = XZ_i^a - xd_i^{1,a} \quad \forall\, i;\, a > 0. \tag{3}$$

Eq. (1) states that the available units of technologies whose age is zero ('new technologies') are equal to the ones that are installed at the beginning of such period. Eq. (2) computes the available units of 'old technologies', subtracting the decommissioned ones to the one year younger existing the previous year. Technologies with a given age a already installed in the building are accounted for by the XZ_i^a parameter, and Eq. (3) computes the 'old technologies' available at the beginning of the first year. Once we have the units available per age during each year, we can compute the available real capacity (xc_i^p) taking into account the aging of technologies and their capacity:

$$xc_i^p = G_i \cdot \sum_a AG_i^a \cdot x_i^{p,a} \quad \forall\, i, p. \tag{4}$$

The AG_i^a parameter is an aging factor reflecting the decay of the technology capacity over time. In general, it should be 1 for $a = 0$ and lower down to its residual capacity, or zero at the end of its lifetime. The G_i parameter is the nominal capacity of the technology, i.e., kW per unit installed. Note that for continuously sized technologies, which we can decide directly the capacity to be installed instead of the number of units, $G_i = 1$. For simplicity of exposition, we consider xi_i^p, $xd_i^{p,a}$, and $x_i^{p,a}$ integer variables. Nevertheless, it is straightforward to define subsets for discretely- and continuously-sized technologies in order to reduce the number of integer variables so as to improve the computational solution time.

Usually we must consider a physical limit for the number of devices we can install as a function of the building characteristics, e.g., the total surface suitable to allocate PV panels. The parameter LP_i^p states this limit which is controlled by the following equation:

$$\sum_a x_i^{p,a} \le LP_i^p \quad \forall\, i, p. \tag{5}$$