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A multi-stage stochastic optimization model for energy systems planning and risk management

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ABSTRACT

Strategic decision making at the building level is gaining importance in the context of a more and more deregulated energy market. The increase of the set of available options regarding distributed and renewable energy technologies leads to a complex decision process. Importantly, such decision making process is affected by uncertainties and therefore stochastic models are needed. In this paper, a comprehensive deterministic strategic optimization model for energy systems planning at the building level is extended to a stochastic optimization framework, thereby allowing the decision maker to manage risks in addition to considering the variability of the uncertain parameters. A numerical example shows the importance of taking into account uncertainty and risk in this kind of problems.

1. Introduction

1.1. Overview

Energy systems optimization is increasing its importance due to deregulations in energy markets and the setting of targets such as the European Union (EU) 20-20-20. In turn, those targets usually embody policies that motivate new regulations aimed at the achievement of such objectives. For example, emissions trading schemes, renewable-energy and/or efficient generators subsidies, or efficiency requirements such as buildings labeling, among others. Usually, those global changes must be tackled at a regional or local scale. Users' comfort, security, and energy availability are challenges for decision makers at the building level, who have to deal with limited budgets in addition to the regulations regardless their global, regional or local scope. Furthermore, new tariffs alternatives, as well as new technologies and refurbishment options are available and continuously evolving, widening the range of choices for decision makers.

In this paper, a Stochastic Optimization (STO) model for strategic decision making at the building level is presented. The STO framework allows, on the one hand, to cope with uncertainties in contrast with deterministic models based on point estimates of the parameters; on the other hand, the inclusion of risk measures in the model provides the decision maker with a tool to hedge against possible extreme scenarios. The model developed in this paper extends the deterministic model in [1] to a STO problem that deals with uncertainty, in order to overcome the drawbacks of a deterministic approach using average values for stochastic parameters, see [2]. The multi-stage stochastic model eventually adopted is explained in depth in Section 2.

Adding uncertainty to the model and optimizing the total expected cost is a way to reduce risk, mainly making the model robust (feasible) for a wide range of scenarios. However, models in which risk is not specifically modeled are *risk neutral*. Ignoring risk management might result on an optimal average value for the objective function, but providing very bad outcomes for some extreme scenarios. In the case at hand, the *optimal* investment plan leading to the minimum expected cost could be poor for the actual scenario that eventually occurs. To overcome such drawback, in Section 3 a risk measure is added to the formulation.

To avoid repetition with the previously published work, we do not give details regarding energy technologies modeling. Instead, the complete model can be found in Appendix A. The description of the deterministic model equations can be found in [1] whilst the stochastic-specific aspects are in Section 2.

1.2. Background

The model has been developed within the Energy Efficiency and Risk Management in Public Buildings (EnRiMa) research project [3].

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The result of the project is a Decision Support System (DSS) for building managers and operators, which helps making decisions for energy efficient buildings. This DSS deals with both strategic and operational decisions. Thus, in addition to the strategic model presented in this paper, an operational model was also developed, see [4,5]. 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 contract selection.

STO has been extensively used in energy markets modeling, mainly from the utilities perspective. We can find the use of STO and risk measures at the generation level in [6,7]. In [8], uncertainties and their impact are captured by scenario trees to optimize building operation. Further techniques such as simulation and enumerative algorithms can be found in [9,10]. The use of STO at the building level for strategic decision making is a novelty, hence the model and approach presented in this paper cover a gap in the sector.

Regarding risk measures, the simplest one that can be used is the variance. A mean-variance model that minimizes the risk (variance) requiring a given average objective was proposed in [11]. It can be found in the literature detailed descriptions and comparisons between risk measures, see for example [12,13]. However, the minimization of Conditional Value at Risk (CVaR) method [14] has proved to be a breakthrough risk measure since its publication. It has desirable properties [15] to be a *coherent* risk measure. More recent advances on risk measures include stochastic dominance, see for example [16–19]. Risk management is tackled in [20], focusing on Value at Risk (VaR) for investment analysis but ignoring the building-specific performance. In this paper, the CVaR risk measure is extended beyond the typical economic use, which is a novelty in the field.

2. Modeling

2.1. Stochastic optimization framework

The starting point of the stochastic model is the deterministic model in [1], which contains a complete set of features regarding energy systems in a building, including both systems deployment (strategic) and systems use (operational). Such deterministic models are usually extended to their stochastic version through the deterministic equivalent linear program, i.e., (i) approximating the probability distribution of stochastic parameters through a finite set of scenarios; (ii) requiring constraints to be fulfilled for all scenarios; (iii) optimizing the mathematical expectation of the objective. In this section we provide details of this transformation including links to the deterministic model in [1] and the new exhaustive formulation and nomenclature in Appendix A.

2.2. Scenario trees

The uncertainty structure is modeled by means of scenario trees. Scenario trees are widely used in stochastic programming to discretize the huge, usually infinite, number of possible outcomes of the random variables in a stochastic model. Thus, a scenario tree gathers the most probable scenarios resulting from a combination of all random variables. Several size-reduction techniques can be used in order to make the problems computationally tractable, see for example [21].

A scenario tree can be graphically represented as an acyclic graph consisting of nodes and arcs where each node may have one or more children, and each node can only have one parent (except for the root). The number of terminal nodes (leaves), which do not have children, determines the number of scenarios considered. Each scenario is a path from the root node to a leaf node. Nodes represent states of the system at a particular time, e.g., the beginning of a year, where decisions are made. The root node corresponds to the beginning of the planning horizon. Arcs represent the precedence relationship between nodes with an associated probability of occurrence. Therefore, in addition to the node identifier ν, which substitutes the index p in [1], the following information is required: (i) The parent node of each node ν, which is mapped by the expression $Pa(\nu)$; (ii) the probability of each node, represented by the PR^{ν} parameter; and (iii) the time period of each node, represented by the PT^{ν} parameter.

Fig. 1 shows a simple scenario tree with all the symbols and expressions used in the model. Circles represent nodes with the node index ν displayed inside. Nodes in the same column correspond to the same time period, and each one has a probability associated to its parent's branching. For example, for node $\nu = 8$, $PT^{\nu} = 1$, $Pa(\nu) = 1$, and PR^{ν} is the probability of occurrence of the second branch after node 1. The represented tree corresponds to a three-stage stochastic problem, where new information arrives at periods 1 and 4. The tree contains thirteen nodes which lead to six scenarios. An illustrative, simplified example at the building level could be: After first stage decisions, i.e., investments in efficient technologies, at node $\nu = 1$ $(PT^{\nu} = 0)$, the stochastic parameters energy cost and energy demand might evolve in two directions in $PT^{\nu} \in \{1, 2, 3\}$: (i) low demand and same cost (node $\nu = 2$); and (ii) high demand and increase in cost (node $\nu = 8$). Such possibilities having a given probability, say $PR^2 = PR^8 = 0.5$. In the fifth year, i.e., $PT^{\nu} = 4$, three new possibilities are considered for each *branch* above: (i) low demand and same cost; (ii) high demand and same cost; (iii) high demand, increase in cost. Again, probabilities for each possible outcome are to be considered.

Note that the stochastic model needs knowledge about uncertainties, that is to say, the probability distribution of the stochastic parameters. Using this knowledge, a DSS for STO needs an appropriate *scenario generator* in order to generate as many scenarios as the optimization software is capable to solve. Scenario generation is out of the scope of this paper. Nevertheless, in Section 4 the scenario generator in the EnRiMa DSS has been used. The strategy followed by this tool relies in the assumption that short-term stochastic parameters vary over the long-term, but can be modeled within each long-term period by means of profiles, using a multi-horizon approach. This scenario generation approach can be consulted in [22], along with discussions on tree sizes (stages, branching, periods). In any case, the tree structure very much depends on the problem at hand. A market-based possibility would be branching after four and ten years, taking into account futures for electricity and gas prices from the European Energy Exchange,[1] which are available up to six years.

A two stage generic model was initially proposed in [2]. However, instead of using the two-stage model with a *by-scenario* representation of the uncertainty, a multi-stage approach was eventually adopted within the EnRiMa project. Thus, uncertainty is modeled through the use of scenario trees gathering the uncertainty throughout the decision horizon. A *by-node* notation is followed, which basically means that, in contrast to the deterministic model presented in [1], a new time-related index representing the node is used instead of the one for long-term periods, e.g., years, as remarked above. This index applies: (i) to parameter and variable symbols; (ii) to constraints, so that they are fulfilled for all the nodes and thereby making the model robust for all scenarios; and (iii) to the objective function, in order to compute the expected value. Thus, Eqs. (A.1)–(A.28) represent the stochastic problem complete

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[1] http://www.eex.com