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Robust portfolio optimization for electricity planning: An application based on the Brazilian electricity mix

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ABSTRACT

One of the major challenges of today's policy makers and industry strategists is to achieve an electricity mix that presents a high level of energy security within a range of affordable costs and environmental constraints. Bearing in mind the planning of a more reliable electricity mix, the main contribution of this paper is to consider parameter uncertainties on the electricity portfolio optimization problem. We assume that the expected and the covariance matrix of the costs for the different energy technologies, such as gas, coal, nuclear, oil, biomass, wind, large and small hydropower, are not exactly known. We consider that these parameters belong to some uncertainty sets (box, ellipsoidal, lower and upper bounds, and convex polytopic). Three problems are analyzed: (i) finding a energy portfolio of minimum worst case volatility with guaranteed fixed maximum expected energy cost; (ii) finding an energy portfolio of minimum worst case expected cost with guaranteed fixed maximum volatility of the energy cost; (iii) finding a combination of the expected and variance of the cost, weighted by a risk aversion parameter. These problems are written as quadratic, second order cone programming (SOCP), and semidefinite programming (SDP), so that robust optimization tools can be applied. These results are illustrated by analyzing the efficient Brazilian electricity energy mix considered in Losekann et al. (2013) assuming possible uncertainties in the vector of expected costs and covariance matrix. The results suggest that the robust approach, being by nature more conservative, can be useful in providing a reasonable electricity energy mix conciliating CO_2 emission, risk and costs under uncertainties on the parameters of the model.

1. Introduction

Working to ensure either energy security as a whole, or electricity security in particular, is a major responsibility of national governments. One of the major challenges of today's policy makers and industry strategists is to achieve an electricity mix that presents a high level of energy security within a range of affordable costs, considering environmental and economic scenarios. There is no doubt that an electricity shortage can severely harm economies. This was, for instance, what happened in Brazil in 2001 when, due to rationing, the total Brazilian electricity consumption decreased by 7.89%, while the GDP variation was still positive, by +1.3%. However, according to SPE — Secretaria de Política Econômica do Ministério da Fazenda (2001), the growth rate for the year 2001 would be in a range of 2.4% and 3.6%, without the crisis of the electricity sector. At the same time, the local industry had to deal with the scarce supply associated with skyrocketing electricity prices in the short term market, that ultimately transformed positive margins of electric intensive companies into negative ones. From January 2001 up to May of that same year the spot market price in the Southeast submarket increased by twelvefold, jumping from R$ 56.92 to R$ 684.00 in Brazilian reals, during the rationing period. Since the required infrastructure to provide electricity takes time to be in place, good planning is always critical in this industry, especially in large populated developing countries such as China, India, Indonesia, Brazil, and many others which present high increasing rates for their electricity demand.

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Mean-variance optimization, originally introduced by Markowitz (1959), is one of the most important models in portfolio optimization and also the basis for asset allocation. However, as pointed out in Rustem et al. (2000), for the optimal mean-variance strategy to be useful the set of expected return of the component assets and the covariance matrix should be sufficiently precise. Indeed it was shown by Black and Litterman (1991) that small changes in the expected returns can produce large changes in asset allocation decisions. In practice this lack of robustness with respect to the inherent inaccuracy of the expected returns and covariance matrix estimates prevents the widespread use of mean-variance optimization by practitioners. Due to that several robust versions of portfolio optimization problems, including mean-variance optimization, have been proposed in the literature, considering uncertainties on the expected returns and covariance matrix (see, for instance, Rustem et al., 2000; Bertsimas et al., 2011; Costa and Paiva, 2002; Costa and Nabholz, 2002; El Ghaoui et al., 2003; Fabozzi et al., 2007a; Goldfarb and Iyengar, 2003; Kim et al., 2014; Lobo and Boyd, 2000; Tütüncü and Koenig, 2004).

Nowadays the mean-variance optimization tools have been widely applied in energy policy, considering the trade-off between the risks and costs of using different energy generation technologies (see, for instance, Awerbuch, 2006; Awerbuch and Berger, 2003; Bazilian and Roques, 2008; Delarue et al., 2011; Doherty et al., 2006; Favre-Perrod et al., 2010; Liu and Wu, 2006; Mari, 2014; Marrero and Ramos-Real, 2010; Marrero et al., 2015; Roques et al., 2010; Roques et al., 2008; Shakouri et al., 2015). Usually the analogy with the financial market is to consider the random price per MWh of each technology instead of the returns of the assets, so that it is desired to minimize the expected cost of the energy portfolio for a given level of uncertainty obtained from the covariance matrix of the costs. Frequently these expected values and covariance matrix of the different energy technology costs are obtained from Monte Carlo simulations using the levelized cost of electricity (LCOE), which naturally yields to imprecision on these parameters.

To deal with the challenge of fostering a more reliable electricity mix, the main contribution of this paper is to workout the application of some of the results from robust asset portfolio theory (see for instance Costa and Paiva, 2002; Fabozzi et al., 2007a; Goldfarb and Iyengar, 2003; Kim et al., 2014; Lobo and Boyd, 2000; Fabozzi et al., 2007b) for electricity planning and policy-making. Similarly as considered in the robust financial portfolio literature, we assume that the expected costs and the covariance matrix for the different energy technologies are not exactly known but, instead, belong to some uncertainty sets (box, ellipsoidal, componentwise lower and upper bounds, and convex polytope defined by some known vertices). The motivation for that is, as pointed out above, Monte Carlo simulations are usually used for obtaining these parameters, which naturally yields to imprecision on them. Besides that, this approach gives room for the possible inclusion of different future scenarios for the expected energy costs and covariance matrices.

Three problems will be analyzed in this paper: the first one is to find an energy portfolio of minimum worst case volatility with guaranteed fixed maximum expected energy cost. The second one is to find an energy portfolio of minimum worst case expected cost with guaranteed fixed maximum volatility of the energy cost. The third one is a combination of the expected and variance of the cost, weighted by a risk aversion parameter. As in the robust financial portfolio literature (see for instance El Ghaoui et al., 2003; Fabozzi et al., 2007a,b; Kim et al., 2014) these problems can be written as quadratic, second order cone programming (SOCP) or semidefinite programming (SDP) (see the Appendix), so that the robust optimization numerical packages nowadays available for this class of problems can be used (see, for instance, Boyd and Vandenberghe, 2004). For the case in which the model distinguishes the energy coming from already existing plants (denoted by "old" energy) of the energy that comes from the new ones (denoted by "new" energy) the problems mentioned above can be simplified. In this situation all the old energy will be used in the energy portfolio so that any increase in size of each technology, must be with "new plants" (see for instance, Losekann et al., 2013), yielding to a reduction on the number of variables in the optimization problems.

This paper is organized in the following way: Section 2 presents the notation, basic results, and problem formulation that will be considered throughout the work. Sections 3 and 4 introduce the robust electricity energy mix optimization problems, the considered uncertainty sets, and the formulation of the robust portfolio optimization problems in terms of quadratic, SOCP or SDP optimization problems. Section 5 considers the situation in which all the "old" energy will be used in the energy portfolio so that any increase in size of each technology must be with "new plants", which yields to a reduction on the number of variables in the optimization problems. In Section 6 we illustrate the robust technique by analyzing the efficient Brazilian electricity energy mix considered in Losekann et al. (2013) with 8 energy technologies, classified as "new" energy and "old" energy. The paper is concluded in Section 7 with some final comments. We recall in the Appendix some basic facts on SDP and SOCP.

2. Preliminaries

2.1. Notation

We denote by $\mathbb{R}^m$ the m-dimensional euclidian space ($\mathbb{R}= \mathbb{R}^1$ for simplicity) and by $\|.\|_2$ the usual euclidian norm. We define by $\mathbf{1}$ the vector of appropriate dimension formed by 1 in all positions, and $'$ denotes the transpose of a vector or matrix. For symmetric matrices Q and R, and a matrix S, we write for notational simplicity $\begin{pmatrix} Q & S \\ \star & R \end{pmatrix} := \begin{pmatrix} Q & S \\ S' & R \end{pmatrix}$. By $P \succ 0$ ($P \succeq 0$ respectively) we mean that the symmetric matrix P is positive definite (positive semidefinite), and $P^{1/2}$ represents the square root matrix of P. For two matrices P and S with the same dimension we write $P > S$ (respectively $P \geq S$) if for each element of P and S we have $P_{ij} > S_{ij}$ ($P_{ij} \geq S_{ij}$). For real number x_i, $i = 1, \ldots, n$ we denote by $\operatorname{diag}(x_i)$ the $n \times n$ diagonal matrix with the element x_i on the entry (i, i), and zero elsewhere. Let $\mathbb{X}$ be a space of real vectors or matrices. For a collection of points $v^i \in \mathbb{X}$, $i = 1, \ldots, \kappa$, we define the convex polytope $Con\{v^1, \ldots v^\kappa\}$ as

$$Con\left\{v^1, \ldots v^\kappa\right\} := \left\{v \in \mathbb{X}; v = \sum_{i=1}^{\kappa} \lambda^i v^i, \sum_{i=1}^{\kappa} \lambda^i = 1, \lambda^i \geq 0\right\}.$$

Finally the expected value of a random vector V will be denoted by $E(V)$, its covariance matrix by $Cov(V)$, and for V, U random vectors we define $Cov(V, U) = E((V - E(V))(U - E(U))')$. If V is a scalar random variable we set $Var(V)$ as the variance of V.

2.2. Mean variance theory

Harry Markowitz (1959) developed the Theory of Portfolio Selection (TPS) in the 1950s to answer the question of how a risk averse investor should allocate resources among different investments. According to his theory, the investor should consider the trade-off between risk and return with risk being measured through the variance of asset returns. This model became a new paradigm in finance. Based on TPS approach, it is possible to construct an efficient frontier describing the optimal return for each possible level of risk. According to the investor's risk preference — or the investor's utility function — he or she will choose a point in the efficient frontier, and will obtain a specific portfolio. Formally, the mean variance