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Construction of an efficient portfolio of power purchase decisions based on risk-diversification tradeoff

Javier Contreras [a], Yeny E. Rodríguez [b,c,*], Aníbal Sosa [d]

[a] Universidad Castilla – La Mancha, E.T.S. de Ingenieros Industriales, 13071 Ciudad Real, Spain
[b] Universidad ICESI, Financial and Accounting Department, Cali, Colombia
[c] Universidad de los Andes, School of Management, Bogota, Colombia
[d] Universidad ICESI, Mathematics Department, Cali, Colombia

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ABSTRACT

We present a methodology based on the tradeoff between risk and diversification in order to evaluate a purchase portfolio of energy, where the assets refer to purchasing strategies of a retailer-generator of electricity in three markets: spot, regulated and non-regulated markets. We use two measures of diversification: i) entropy based on factors, constructed by principal components analysis, and ii) entropy based on asset risk. In each case, weights for each strategy are estimated by using the interior point method, for which monthly forecasts of returns are calculated a year ahead for each market. Spot prices are modeled using an ARIMA model and bilateral contracts are modeled using growth rates. We compare risk-diversified portfolios with mean-variance portfolio. Although diversification does not necessarily mean a lower risk, we show that the mean-variance portfolio's risk is not always lower than the risk-diversified approaches. Also, we show that diversification converges to one for the highest risk portfolio, but this does not happen in the case of entropy based on factors, because one asset can participate in more than one principal component. Clearly, the mean-variance approach is unable to perform a diversified allocation. These results are useful for retailer-generators who want combine the criteria of risk and diversification.

1. Introduction

World interest in risk management for electricity markets started 20 years ago with the introduction of competition in these markets, caused by the liberalization undertaken. These processes introduced economic regulation and led the organization of spot markets into the activity of generation.

Among the risks that the agents who participate in spot markets bear is price risk. This risk refers to the significant fluctuations of electricity prices in spot markets all over the world. These high fluctuations are explained because there are shocks between supply and demand, which cannot be softened, since energy storage is usually a costly process. Managing price risk is done through both the development of price models and the use of bilateral contracts.

Electricity price forecasting requires prior knowledge of price's features, such as seasonal patterns, peak rates, mean reversion, price-dependent volatilities and non-stationarity in the long term (Burger et al., 2007). Forecast techniques for electricity spot prices that have been used in different studies are: Markov regime changes (García-González et al., 2005; Haldrup and Orregaard, 2006; Becker et al., 2007; Weron, 2009), GARCH models (Contreras et al., 2005), ARIMA-GARCH (Contreras and Rodríguez, 2014), neural networks (Catalão et al., 2007), and stochastic processes (Geman and Roncoroni, 2006; Benth et al., 2007).

Bilateral contracts, between retailers (retailer-distributors) and generators, are commonly classified depending on their destination (regulated and non-regulated markets) and payment methods. The prices of bilateral contracts exhibit a more stable behavior than those of spot prices, where the level of the latter depends on the destination. The contract price for a non-regulated market is lower than the contract price for a regulated market, which is explained by the larger volumes of energy that can be traded in the former.

A company may be interested in managing price risk signing of bilateral contracts and investing in the spot market, therefore, spot prices need to be modeled. The interest usually focuses on the estimation of the purchase of energy through bilateral contracts and the spot market. The financial literature provides different approaches for the efficient creation of an investment portfolio and its risk management.

Different approaches exist in terms of the type of assets in the portfolio and the optimization criteria used. A financial portfolio can be composed of assets or asset classes (factors), and there are different

* Corresponding author at: Universidad ICESI, Financial and Accounting Department, Cali, Colombia.
E-mail addresses: Javier.Contreras@uclm.es (J. Contreras), yerodriguez@icesi.edu.co, ye.rodriguez395@uniandes.edu.co (Y.E. Rodríguez), uasosa@icesi.edu.co (A. Sosa).

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asset (factors) allocation methodologies that try to balance risk and return optimization criteria are different.

Markowitz's (1952) minimum-variance strategy requires inputs as asset returns, standard deviations and correlations. Although this approach analyzes the concept of portfolio diversification, clearly the mathematical model does not involve a specific measure for it (Benoît et al., 2015), which is its main weakness, because it produces portfolios conformed by a small subset of low-volatility assets (Bera and Park, 2008). Besides going against the principle of diversification, this approach presents out of sample underperformance, and it is known that errors of estimation of inputs used in the optimization produce changes in asset weights so that the portfolios involve extreme positions (Jobson and Korkie, 1980). On the other hand, a well-diversified portfolio presents benefits when investing in risky assets because it is immune to shocks produced by one or more assets (Frahm and Wiechers, 2011).

In order to reconcile mean-variance and diversification approaches Pola (2014) shows a remedy to produce more diversified allocations at a negligible cost in terms of portfolio risk-return efficiency; based on this remedy we propose a mathematical formulation to provide a novel strategy to find weights that take into account both risk and diversification.

The goal of this paper is to propose a methodology for constructing an efficient portfolio of power purchase, where the assets are not physical but based on purchase decisions.

The main contribution of this paper is to present a theoretical development about the construction of an efficient portfolio that maximizes power purchase diversification subject to a given return. We apply this theoretical development to the case of an electricity retailer-distributor located in the south west of the country, which is a typical retailer-distributor. In Colombia, there are 24 retailer-distributors dedicated to distributing and retailing energy in each region in an independent way. Given that they do not produce energy, retailer-distributors need to hedge spot market price risk by signing bilateral contracts, therefore it is interesting for this type of agents to maximize the diversification of their power purchase portfolios for a given return. In addition, it is assumed that a retailer-distributor sells electricity in the spot market when the estimated demand is greater than the real one, but the surplus is marginal, producing a small amount of volatility in the selling price.

This paper is organized in four sections. Section 2 presents the literature review necessary to provide the background on price models and portfolio theory. Section 3 presents the methodology used to construct an efficient portfolio taking into account risk and diversification. Section 4 presents a realistic case study from the situation of a Colombian's electricity retailer-distributor, and Section 5 provides conclusions.

2. Literature review

This Section focuses on the progress of literature regarding two main issues: development of pricing models and description of the methodologies used in portfolio allocation.

2.1. Price models

Different approaches have been used to elaborate appropriate forecasts for spot prices, such as ARIMA and GARCH models, which are mentioned in Contreras and Rodríguez (2014). It is important to highlight that ARIMA models present a good fit of data when the series is stationary, otherwise ARIMA-GARCH models must be used in order to capture this kind of behavior. Therefore they are widely applied to forecast prices. The authors use an ARIMA-GARCH model for the daily spot prices in the Colombian electricity market and apply a methodology composed of five steps for the monthly electricity prices forecasting model, following Contreras and Rodríguez (2014).

The ARIMA model was introduced by Box and Jenkins (1976) and provides a wide class of models for univariate time series forecasting. In 1986, Bollerslev (1986) introduced GARCH models, which consider the moments of a time series as an invariant. In these models the error term is assumed to be serially correlated and can be modeled by an autorregresive process (Contreras et al., 2005). Following the notation in Contreras et al. (2005), the ARMA(p,q)-GARCH(P,Q) model can be expressed as:

$$\left(1-\sum_{i=1}^{p}\phi_i L^i\right)p_t = c + \left(1+\sum_{i=1}^{q}\theta_i L^i\right)\varepsilon_t, \tag{1}$$

where p_t denotes the electricity price at time t, L represents the delay operator acting on variable p_t so that: $Lp_t = p_{t-1}$. The ϕ_i's terms denote the p autoregressive parameters, c is a constant term, θ_i's terms represent the q moving average parameters, and ε_t denotes the error term, which is Normally distributed, i.e., $\varepsilon_t \sim N(0,1)$. Also, the square of the error is given by $\varepsilon_t^2 = \upsilon_t^{2*}\sigma_t$, where υ_t^2 represents a Normally distributed white noise, i.e., $\upsilon_t \sim N(0,1)$, and σ_t represents the variance term which is time dependent and it is expressed as:

$$\sigma_t = c + \sum_{i=1}^{P}\alpha_i\sigma_{t-i} + \sum_{i=1}^{Q}\beta_i\varepsilon_{t-i}, \tag{2}$$

where c is a constant, α_i's represent the p lagged variance parameters and β_i's denote the q lagged error parameters. To estimate the parameters of the mean (1) and variance (2) models we use the maximum likelihood method.

2.2. Portfolio theory

Portfolio construction and risk management are the focus of many studies by academics and practitioners. Therefore, knowing efficient approaches of asset allocation is relevant for investors interested in risk management in presence of uncertainty in the financial markets.

The most popular approaches are minimum-variance, risk parity and risk diversification. The mean-variance approach of Markowitz (1952) minimizes the variance of a portfolio to construct an efficient portfolio. The risk parity approach allocates capital such that all assets have the same marginal contribution to the total portfolio risk (Qian, 2006; Qian, 2011; Maillard et al., 2010). Finally, the diversification approach is based on the notion of asset segmentation, which can be based on: i) similarity of asset types, ii) correlation of assets, or iii) similarity of asset dependency on macroeconomic factors (Pola, 2014).

2.2.1. Mean-variance approach

This approach requires estimating the returns, standard deviations and covariances of the assets that compose the portfolio. The efficient portfolios are obtained by maximizing returns for a given level of risk, and, with these efficient portfolios, the efficient frontier, in which the best returns for a given risk are located, is built. The mathematical formulation is:

$$w_{MV}^{*} = argmax_{w\in C}(E(R) - \lambda V(R)), \tag{3}$$

where the return of the portfolio is defined as the weighted average of the asset's returns:

$$R_{MV} = \sum_{i=1}^{n} w_{MV}R_i, \tag{4}$$

and

$$E(R) = w^t\mu_R, \tag{5}$$

where μ_R is the vector of expected asset returns and $V(R) = w^t\Sigma_R w$ is the matrix of asset covariances. Therefore, these are minimum-variance