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Risk Metrics Modeling As Applied To Electric Energy Commercialization Problems

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***Abstract*— In order to deal with uncertainties in energy prices, coming from market and natural conditions, electricity companies started to use risk metrics applied by the financial market to quantify the risk to which they are exposed on energy trading. Different risk metrics have respective areas of applicability and generates different results for the same portfolio. This paper highlights some risk metrics used for risk management in electric energy trading. It evaluates each metric individually and proposes an aggregation of metrics using linear weighted sum (LWS) method, for the construction of an aggregated risk measure, which assists in elaborating decisions related to the choice of portfolios for electricity sector companies in conditions of uncertainty.**

***Keywords*— Energy Trade, Multiobjective Optimization, Risk Management**

NOMENCLATURE

This paper uses common symbols and acronyms for energy markets that are widely used in the literature. Table 1 presents the nomenclature used in this work.

TABLE I. NOMENCLATURE

Symbol	Description
ΔC	Contracting variation
τ	Reference level
Aux	Auxiliary contracting of the agent
CT_m	Total bought of month m
$CVaR$	Conditional value at risk
Exp	Exposition
GSF	Generator Scaling Factor
i	Confidence level
j	Objective function index
LPM	Lower Partial Moment
LWS	Linear Weighted Sum
m	Month index
p	Order of the lower partial moment
R_i	Revenue at confidence level i
R_m	Revenue for month m
RC_m	Revenue from all bought energy for month m
$RContratAux_m$	Revenue of the auxiliary contracting
$REsp$	Expected revenue
RV_m	Revenue from all sales for month m
sc	Scenario index
VaR	Value at Risk
VT_m	Total sales of month m
w_j	Weight coefficient for objective function j

I. INTRODUCTION

Electric power is a commodity that has high volatility and uncertainty in its price [1]–[3]. Due to factors such as large-scale storage difficulties and the need to balance generation and consumption, electricity needs structured markets to establish all its business relationships. With the increase in the number of transactions in the energy markets, companies began to worry about quantifying the risk they were exposed [4], [5].

The regulation initiated in 2004 in the Brazilian market establishes two environments for the commercialization of energy: Regulated Hiring Environment (ACR – *Ambiente de Contratação Regulada*) and the Free Hiring Environment (ACL – *Ambiente de Contratação Livre*). All agents that are connected in the national interconnected system (SIN – *Sistema Interligado Nacional*) are connected in either of these two regulatory regimes. In ACR, contracts are established by energy auctions. While in the ACL, contracts are made bilaterally often be extensively customizable.

When observing the energy price in the Brazilian market, it is perceived that it is sensitive to the amount of energy stored (water available for generation) in the reservoirs of the hydroelectric power plants, and to the prediction of affluent natural energy in the SIN. In order to avoid assuming a position that exposes the company to the price of energy, some risk metrics have been used by market agents, such as: value at risk (VaR) [2], conditional value at risk (CVaR) [3] and lower partial moments (LPM) [6].

Works such as [4], [7], [8] sought to answer the question of how to build a portfolio in order to consider the company's risk vision. While [9], [10] are concerned with the performance of each metric, and establish comparisons between them.

Each metric has its own peculiarities and responds differently to the same problem. In particular, CVaR has a greater sensitivity to the tail of price distribution than other metrics and is thus more influenced by the worst-case scenario [3]. The VaR metric, on the other hand, is concerned with the potential loss of a present value of an investment, while the LPM focuses its analysis on the distribution format of any unwanted part of the revenue [2], [5], [11].

Considering the above, this work proposes the creation of a new risk metric from the aggregation of existing metrics, with the approach exposed in [12], in order to reduce the discordance between responses. With this metric, you can find a robust risk decision and thus help energy companies build their portfolio.

This work was structured as follows. Section 2 presents the work related to this research. Section 3 is devoted to the theoretical framework and methodology. Section 4 reflects the experiment associated with the aggregation of metrics and their results. Finally, Section 5 contains the conclusion of the paper and possible lines of its development.

II. Related Works

The portfolio optimization problem has its origin in the financial market [10], [14], [15]. To optimize the purchase and sale of shares, several methodologies were developed and applied in investment funds.

Analogously to the purchase and sale of shares, energy trading deals with the same type of uncertainty in price variation. Price projections are constructed, and uncertainties are modeled to construct an optimization model in order to find optimal bids in the energy market, as proposed by [16].

Market monitoring is essential, since the position of other agents is key to price. Works such as [9], [17], [18] and [19] have used game theory and robust optimization to address this kind of market uncertainty.

The diversification of the energy matrix with the insertion of renewable sources of generation also brings uncertainty to the energy price. Since this type of generation is intermittent due to climatic conditions, a new approach is needed to address this volatility, exposed in the works of [9] and [7].

To address the uncertainties, the electric sector has adapted some financial risk methodologies to the problem of energy commercialization. Works such as [1] and [5] presented the state of the art on the treatment of risk in the energy market, in addition to exposing some approaches used by companies in the electricity sector. Both papers explain, as well as the work of [2], why energy prices are a volatile variable, and justify financial engineering approaches to measuring risks in the energy market.

The results presented in [2] also addressed the modeling of the VaR metric. They explain how the methodology should be used, presenting requirements as predictions of returns. VaR is also covered in the work of [5], as well as other metrics such as CVaR. In it, some examples and comparisons of results of the methods used were presented.

The LPM approach in energy trading is carried out in the work of the author [20], who presented a methodology of maximizing the return while minimizing the risk, applying it in the Turkish energy market. In the same way as [20], other researches such as [17], [21] and [22] addressed the problem of multi-objective decision-making at risk.

Works such as [10] and [23] focused on establishing comparisons between risk metrics, in order to establish differences between the models. They presented financial market applications with stock purchase and sale portfolios.

To aggregate the risk methodologies, the methodology presented in [12], which is an *a priori* approach to deal with more than one objective. Some examples of the technique shown in [12] can be seen in [24] and [25] to solve multiobjective problems.

The work presented in this paper also has a multi-objective view on the portfolio construction problem. However, instead of establishing comparisons between the metrics, as done in the works of [10], it aims to aggregate the methodologies of risk, as discussed in the works of [26]–[28], for a robust view of risk.

III. Risk Analysis in the Brazilian Market

Risk can be generically set with a probability of an unexpected outcome occurring. From the point of view of a hydraulic generator, it is possible to classify them into hydrological risk and market risk [29].

The hydrological risk is related to the climatic conditions of the region. In order to a hydroelectric plant have generation conditions, it depends on the affluent natural energy and stored energy, that is, on the inflow to the plant, on the expected precipitation in the river basin, on evaporation of the reservoir, among others. In the event of a sudden drought, an energy can be sold without the power plant having generation capacity. In the Brazilian energy market, there are some agreements that reduce hydrological risk, such as the Energy Reallocation Mechanism (MRE – *Mecanismo de Realocação de Energia*), which can be summarized as an exchange of energy between the hydraulic generators that decide to participate in the mechanism; and clauses to reduce the supply of energy in case of rationing. The market risks that usually bring exposure to energy companies are generally the renewals of contracts that have already been established with customers, and the settlement price of differences (PLD – *Preço de Liquidação das Diferenças*).

Since both (hydrological and market) risks are strongly connected and have a direct influence on energy prices, agents participating in the free-hiring environment (e.g. energy companies) use financial risk metrics to plan and monitor their risks. positions in the short-term settlement market. From these metrics, it is possible to quantify the amount of revenue that can be lost due to uncertainties in the price of energy.

A. NEWAVE

In order to get a price distribution, the Brazilian electric sector uses NEWAVE. This program is used by the National System Operator to dictate as a steering operation, minimizing the marginal cost of operation of the whole SIN.

NEWAVE consists of a periodic autoregressive model, where several data about the electrical system are considered, such as: transmission limits, stored energy in reservoirs, availability of power plants, load forecasting and inflows, among others.

Among the responses that NEWAVE returns are 2000 scenarios, over a five-year horizon, of energy prices and GSF, which are used to build the company's revenue forecast.

B. Revenue modeling

Among the uncertainties that are present in the revenue of a hydraulic generator are the amount of energy allocated by the MRE and the PLD. Hydrological uncertainty affects the amount of energy verified by the generator, by decreasing or increasing the physical guarantee by the generation scalability factor.

In order to model the exposure and revenue of people, an auxiliary variable was used to increase or reduce the contracting of the portfolio. Thus, the exposure of the agent to the corresponding month can be represented by:

$$Exp_{m,sc}(\Delta C) = CT_m + gFis * GSF_{m,sc} - \Delta C - VT_m$$
(1)

the exposure to the market price (1) should be weighted with the amount of purchases and sales, according to the company's PLD forecast, since the impact on revenue can stand as a form of regret or cost.

If the market price is expected to be below the sales price, it is a good choice to sell as much as possible to avoid being exposed, but if the price goes up, the best option for the generator is to increase your exposure.

$$R_{m,sc}(\Delta C) = 720 * \left(RContratAux_m + RV_m - RC_m + \left(Exp_{(m,sc)} * PLD_{(m,sc)}\right)\right)$$
(2)

The monthly income of the sc scenario as a function of auxiliary contracting is described by (2). The 720 coefficient in this equation is a result of the consideration that every month has the same number of hours.

C. Value at Risk

The paper [2] defines that VaR estimates how much of a set of investments can be lost, given a probability (α%) considering normal market conditions in a given period, such as day, month or year.

This metric refers to the expectation of variation of market value over time. Mathematically, the VaR of a date with the confidence interval $(1 - \alpha)$ % is defined as:

$$VaR(\Delta C) = REsp(\Delta C) - R_\alpha(\Delta C)$$
(3)

VaR originated in the late 1990s and is one of the most popular risk measures. However, despite being a consolidated metric, it has undesirable mathematical characteristics such as lack of subadditivity and convexity.

D. Conditional Value at Risk

This metric is defined as the expected return on a portfolio in the worst α% scenarios (expected deficit at a level α%). Also known as *expected shortfall*, *average value at risk* or *expected tail loss*, CVaR is a metric used to measure the market or credit risk of a portfolio [3], [9].

$$CVaR(\Delta C) = REsp(\Delta C) - \frac{1}{\alpha}\sum_{i=1}^{\alpha} R_i(\Delta C)$$
(4)

This metric estimates the risk of an investment in a more conservative way and focuses on less profitable situations. It is an alternative to other metrics since it is more sensitive to the tail shape of the distribution.

E. Lower Partial Moments

The LPM metric, also known as *Downside Risk*, evaluates the behavior of assets falling below an acceptable minimum level of return [20].

$$LPM_p(\Delta C, \tau) = \sum_{i=1}^{\tau}(\tau - R_i)^p$$
(5)

The special case when the reference level τ is equal to the mean of the distribution is called the central moment. The first moment around zero is the mean of the distribution and the second center point is the variance. Asymmetry is the normalized central moment of the third order. The fourth central moment is a measure of the tail weight of the distribution, compared to the normal distribution of the same variance.

F. Linear Weighted Sum Method

Considering the following normalized single-objective optimization problem [12]:

Maximize:

$$f(x) = \sum_{k=1}^{l} \omega_k Q_k^0(x), \quad (6)$$

Subject to:

$$x \in X \quad (7)$$

where the weights w_i, i = 1, ..., l corresponding to objective functions satisfying the following conditions:

$$\sum_{i=1}^{l} \omega_i = 1,\ \omega_i \geq 0, i = 1, \dots, l \quad (8)$$

where $Q_k^0(x)$ is normalized k-th objective function $Q_k(x), k = \overline{1, l}$.

For the case of the linear weighted sum with linear objective functions, we have the next form:

$$Q_i(x) = \sum_{k=1}^{l} a_{ki} x_i, \quad a_{ki} \in R \quad (9)$$

Consequently, normalized objective functions have the following forms:

$$Q_k^0(x) = \frac{Q_k(x)}{S_k} = \frac{a_{k1}}{S_k} x_1 = \frac{a_{k2}}{S_k} x_2 + \dots + \frac{a_{kn}}{S_k} x_n \quad (10)$$

In which case the floating-point values S_k are evaluated in the following way:

$$S_k = \sum_{j=1}^{n} |a_{ki}| \neq 0, \quad (11)$$

In most of real problems, various measure units represent the objective functions. For this reason, the objective functions normalization is required transforming the range on a segment between 0 and 1. It carry us for a programming linear problem that could be easily solved using the approaches detailed on [28].

IV. Experiment and Results

In order to solve the multiobjective portfolio risk minimization problem, the linear weighed sum method was used to construct an aggregation of the functions and later the function aggregated by the method was minimized.

The variation in energy contraction considered was $-gFis$ to $+gFis$, using the auxiliary contracting variable. And to analyze the impact of the energy contracting variation on revenue, we used the risk metrics VaR, CVaR and LPM with the parameters described in Table 2.

TABLE II. Parameters of the Simulation

Parameter	Value
α	5%
τ	Expected income for current portfolio
p	2
w_{CVaR}	0,33
w_{LPM}	0,33
w_{VaR}	0,33

The algorithm constructed for the development of the proposed work is represented by the Figure 1.

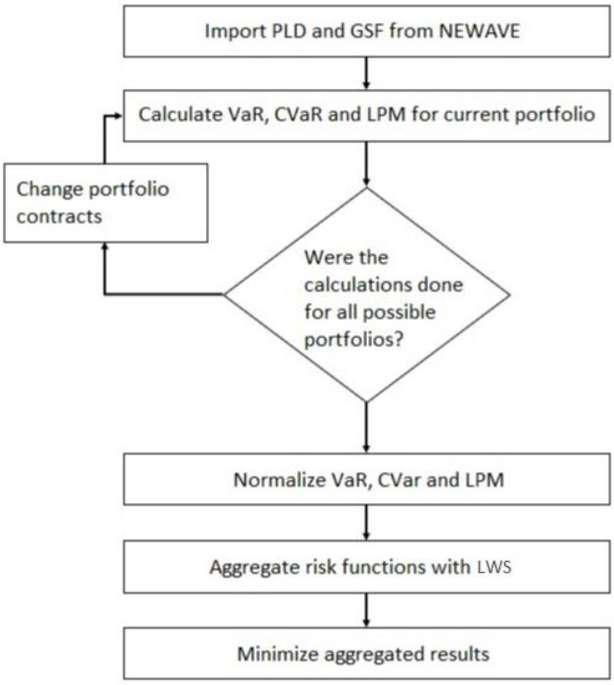

Fig. 1 – Algorithm

To normalize the response of the risk functions was used (7), which was also employed by [28] and [30]:

$$f_p(x) = \frac{\max F_p(x) - F_p(x)}{\max F_p(x) - \min F_p(x)}$$

(7)

Where the objective function $F_p(X)$ in minimized, and $f_p(X)$ is the normalized value of the function.

The experiments consisted of using the 2000 PLD and GFS scenarios as initial data to construct the revenue forecast for 48 months. With the implementation in MatLab, it was possible to evaluate the behavior of the revenue when the contracting of energy of the generating agent is varied. The portfolio used in the experiment is composed of:

- $gFis$: $100\ MWm$;
- bought 1: 70 MWm with 70 $R\$/MWh$;
- sale 1: 70 MWm with 150 $R\$/MWh$;
- sale 2: 90 MWm with 130 $R\$/MWh$;

In this work, we used the average revenue from the analysis horizon of each scenario for the construction of the revenue distribution, as shown in Figure 2. The purpose of the experiment is to evaluate the company's energy contracting for each risk metric. The question that is intended to answer is: what happens to the company's revenue at risk, when the amount of energy bought and sold changes?

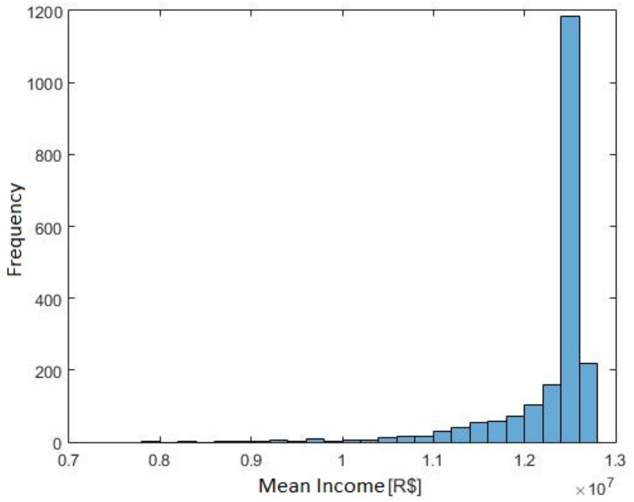

Fig. 2 – Histogram for $\Delta C = 0$

The risk profile for the buying and selling composition is represented by Figure 3, which shows the dispersion of the average revenues of each scenario by the average PLD of the scenario. In red, the 5% worse agent revenues are highlighted.

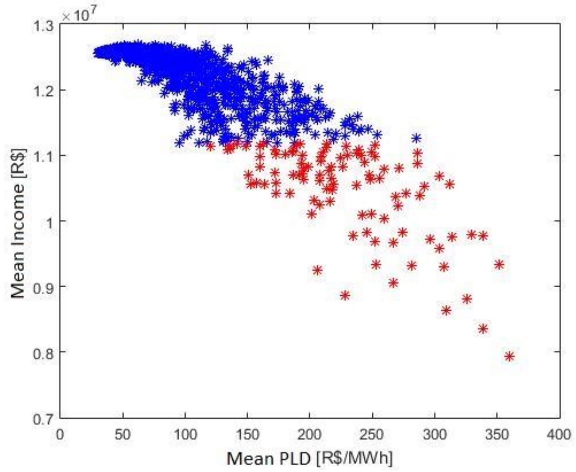

Fig. 3 - Risk Profile

The intrinsic risk to the energy price of the hydraulic generator for the considered purchase and sale configurations is represented in Figure 4. As this figure shows, each metric has its respective revenue at minimum risk, and indicate different contracting variance positions.

The response of all the figures is similar, the agent is exposed to high PLD values, which indicates that he is very hired and there is a possibility he will sell a lot now and regret it. However individually, each metric has a respective contraction of energy in order to minimize the risk in revenue. The VaR metric, according to Figure 4, tells us that the minimum revenue at risk can be $\$\,274{,}000$, reducing contracting by $14.4\,MWm$. CVaR, in turn, estimates that the minimum risk is $R\$\,490{,}000$, when contracting is reduced by $18.2\,MWm$. While LPM returns us $R\$\,191{,}000$ minimum risk when reducing $14.9\,MWm$.

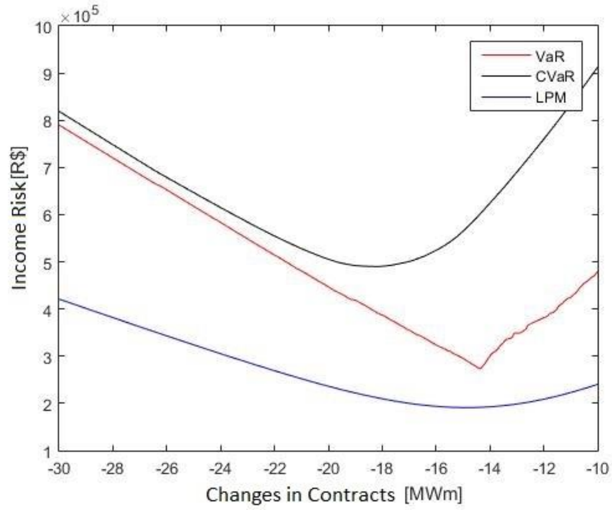

Fig. 4 - Intrinsic Risk

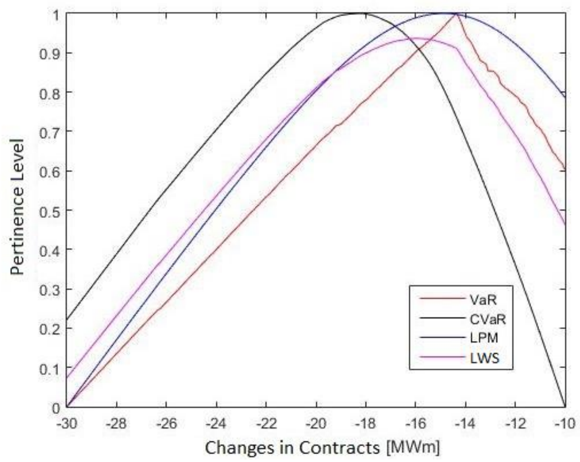

Fig. 5 - Comparison of Metrics

The aggregation of the risk metrics using the OWA operator, as shown in Figure 5, returns a range of options where the risk remained practically constant, in contracting variations between $-15.8\,MWm$ and $-16.1\,MWm$, the level of relevance of the function remained constant at 0.93.

V. Conclusions

The paper proposed a unified view of risk, considering metrics already consolidated by energy and financial agents to measure risk. Although responses from all metrics indicate that the hydraulic generator should reduce its contracting, each individually indicates that it must reduce its quantity in order to achieve the minimum risk. The difference between the metrics presented by Figure 4 and 5 results in different positions if the agent chooses an individual metric.

The aggregation of risk metrics by the linear weighted sum method eliminates this mismatch of positions by allowing an analysis that considers all risk views, thereby validating the initial proposal. This integrated view, offered by the aggregation of metrics, returns not only a position that is not as conservative as CVaR but also eliminates the limitations of VaR and is not as weak as LPM.

A great advantage of the proposed work is, with the possibility of integrating risk metrics, to be able to overcome uncertainties in the initial data of the problem when carrying out analyzes with more than one risk function. However, with the increase in the number of metrics, aggregation can result in several optimal position possibilities.

A proposal for future work is the use of new metrics for aggregation, making possible new positions of contracting of energy. Another proposal is the use of the proposed methodology for generators of renewable sources such as wind power plants, for this, it is necessary to create generation scenarios from the wind velocity distributions to change the modeling of the revenue. It is also possible to use the work for portfolio analysis of free consumers.

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