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Risk Constrained Portfolio Selection of Renewable Sources in Hydrothermal Electricity Markets

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***Abstract*—Renewable sources have recently emerged as a generation option for many countries in order to promote clean energy development. In the case of Brazil, small hydro plants and cogeneration from sugarcane waste (bagasse) have been attractive alternatives during the past years, with hundreds of MW installed since 2004. Despite their advantages, both alternatives are hindered by seasonal yet complementary availability. This forces producers to discount (or price) the risks faced when selling firm energy contracts and may ultimately lead to projects being commercially unattractive. We propose a stochastic optimization model that defines the optimal composition of a portfolio based on these two renewable sources in order to maximize the revenue of an energy trading company. At the same time, this model mitigates hydrological and fuel unavailability risks, thus allowing the participation of both sources in the forward market environment in a competitive manner. A case study is presented, based on data from the Brazilian system.**

***Index Terms*—Energy trading, portfolio selection, renewable generation, risk management, stochastic programming.**

I. Introduction

MOTIVATED by the need to curb emissions of greenhouse gases that cause global warming, renewable energy has recently emerged as a generation option for many countries, in order to provide clean energy development [1]. Wind power has been the prime low carbon source for several continental European countries, especially Denmark, Germany, and Spain. In North America, although federal authorities both in the United States and in Canada have been less proactive in the reduction of greenhouse gas emissions [2], [3], several state and provincial administrations have taken steps to increase the diffusion of wind power and other renewable generation technologies. On the *technical* side, the strong development of wind power in these countries has stimulated the investigation of alternatives and improvements to current short-term power system operation planning methods, in order to cope with a power source that cannot be dispatched in the classical sense—because of its intrinsic dependence on constantly-varying weather conditions. For example, in [4] a stochastic security approach to perform secure economic short-term scheduling of generation with uncertainty in wind production was developed.

In the case of South America, the strong presence of hydropower has relieved the pressure to develop new renewable energy sources. Even so, the region has followed developments in Europe and in the USA, and started to develop wind power, although results so far have been are modest. However, the region is characterized by the presence of other types of renewables, which have indeed been exploited at a faster pace. For example, in Brazil, small hydros (SH) and cogeneration using sugarcane bagasse (sugarcane cogen) have been the most attractive options during the past few years, with hundreds of MW installed since 2004 (see [5] and [6]).

The main challenge to the massive development of these two clean generation options in Brazil lies less on the *technical* side—as the plants operation is dispatchable rather than intermittent (such as wind power commented above) but on the *commercial* side: both alternatives are impaired by the seasonal nature of their resources. The small storage capacity makes inflow variability critical for small hydros, and sugarcane congeneration plants have a seasonal (inflexible) energy production, which occurs only during the harvest period. Producers are then forced to price the market risks faced when selling firm energy contracts (i.e., the risks of purchasing in the spot market whenever their production is smaller than the contracted amount) and this may ultimately lead each of the projects to not being as commercially attractive by itself as the resulting joint portfolio.

The commercial feasibility of renewables is a relevant topic and a lot of work on this subject has been recently developed. Because of its large diffusion, most of this work relates to wind power and to its association with other production sources, in order to mitigate revenue uncertainty or to devise bidding strategies. For example, [7] and [8] have investigated the benefits of a risk-neutral portfolio composed of a wind farm and a pumped-storage hydro plant when developing bidding strategies for the Spanish day-ahead spot market. A mixed integer linear programming model has been constructed to verify the attractiveness of the joint optimization in day-ahead markets. In [9] the physical hedging of a wind farm, again with a pumped-storage hydro facility, is compared to the financial hedging by using call/put options under a risk-neutral real options approach.

A. Objective

This work is based on the similar concepts of [8] and [9] and develops a mathematical model to explore synergies due to the seasonal complementarity of a biomass cogeneration power

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plant and a small run-of-river hydro unit generation patterns. The proposed model aims at composing an optimal portfolio of these two sources and jointly determines the risk-constrained optimal trading strategy for an energy trading company (ETC) in the forward contract market. The energy production of biomass cogeneration plants occurs only during the sugarcane harvest period,[1] which coincides with the dry season of the hydro system. Small hydros face the hydrological risk during dry periods, but can make up for the biomass cogeneration unavailability during the rest of the year. In other words, there is a natural synergy between these two production sources that might make it possible to develop a portfolio able to mitigate hydrological and fuel unavailability risks and thus allow a competitive firm energy delivery.

Our model is based on two-stage stochastic programming and solved directly through its linear programming (LP) deterministic equivalent. The same optimization approach was used in [10] to establish the optimal forward trading strategy of an ETC in the Spanish Market and in [11] for an optimal portfolio of interruptible and firm gas supply contracts to a consumer.

B. Contributions

The main contributions of this work are not in the algorithmic or methodological fields, but in extending and complementing recent work on renewables ([8] and [9]) by modeling a new problem defining a business model that makes a portfolio of renewable sources economically viable. We summarize the main contribution of this work as follows: 1) to extend and to complement previous analyses developed for portfolio of wind power and hydro plants to portfolios of small hydro and sugarcane cogeneration, 2) to consider the agent risk-aversion by means of the CVaR risk measure, and 3) to provide a practical decision support tool based on a medium/long term forward contract trading model ([8] and [9] concentrate on day-ahead bidding strategies) that would allow an ETC to build a willingness-to-supply curve (WSC), which gives the firm MWs that can be sold in forward contracts at given prices considering risk constraints. The WSC concept is new and was not discussed in references [7]–[9]. We believe that it may help to foster the development of renewable energies in Brazil and in other countries where these energy sources are available.

The remainder of this work is organized as follows: Sections II–IV describe the market environment, drivers and constraints for energy commercialization. Section V presents the problem faced by the energy trading company, while Section VI presents the portfolio optimization model. Finally, Section VII presents a practical case study, with data from the Brazilian system and Section VIII provides the final conclusions.

II. Brazilian Power System Overview

This section provides an overview of the Brazilian power system and of the Brazilian electricity market.

A. Power System

The Brazilian power system is the largest in Latin America, with an installed capacity of 105 GW (2008). Almost 90% of the energy is produced by hydroelectric plants and the remaining generation sources mix includes natural gas, coal, nuclear and oil. Bioelectricity (co-generation from ethanol production, using sugarcane bagasse as a fuel) is emerging as a competitive new source. Because of Brazil's large area, the hydroelectric basins have a wide variety of weather patterns. In order to take advantage of climate diversity, the independent system operator (ISO) dispatches the whole hydro system as a "portfolio," with transfers of huge energy blocks from the "wetter" regions to the "drier" ones. Hydro plants are dispatched based on their expected opportunity costs ("water values"), computed by a multistage stochastic optimization model that takes into account a detailed representation of hydro plant operation and inflow uncertainties (see [12] and [13]). As a result, the overall supply reliability is increased and the use of fossil fuels in the thermal plants is minimized.

B. Regulatory Framework

The basic rule in the Brazilian regulation is that all consumers, both regulated and free, should have contracts that back up 100% of their loads. The contract coverage is verified ex-post, comparing the cumulative MWh consumed in the previous year with the cumulative MWh contracted. If the contracted energy is smaller than the consumed energy, the user pays a penalty related to the cost of building new capacity. All contracts, which are financial instruments, should be covered by "firm energy certificates" (FEC).[2] For example, in order to sign a contract for 1000 average MW[3] (avgMW), the generator (or trader) must show that it possesses FEC that add to the same amount. The FEC are tradable and can, along the duration of the contract, be replaced by other certificates; the only requirement is that the total firm energy of the certificates adds up to the contracted energy. Note that the Brazilian approach bundles two products: the FEC and the energy contracts.

The yearly FEC are issued by the regulator to each generating plant in the system and reflect its firm energy production capacity in dry years. The FEC defines the maximum amount of energy a project can sell through a bilateral contract. The joint requirement of 100% coverage of loads by contracts and 100% coverage of contracts by FEC creates a link between the load growth and the construction of new capacity.

In the case of regulated consumers, the procurement of new capacity is carried out through public auctions. In these auctions, long-term contracts are offered to meet future demand. There is another important segment, however, called free market (or free trading environment—FTE), in which loads and generators can freely negotiate short, medium and long-term contracts. Although this segment is restricted to consumers with loads greater than 3 MW, it has been growing very significantly in the last years, and today it has a share of about 30% of the market. It will be the focus of this work.

C. Energy Spot Price Volatility

Energy spot prices are based on the water values, calculated by SDDP tools as described earlier [12]. In other words, there is no competitive market based on bid-based dispatch.

[1]In the southeast of Brazil, the harvest period runs from May to November.

[2]This is because the Brazilian system is 85% hydro and is energy-constrained, not peak-constrained.

[3]$\text{Average MW} = \text{MWh}/(\text{number of hours})$.

Spot prices are very volatile and negatively correlated with the system's hydrological conditions. The system is designed to supply the load under very adverse inflow conditions, which do not occur frequently. As a result, most of the time (when inflows are in their "normal" pattern) demand is covered by hydro generation and the marginal demand cost or the spot price is very low. But in contrast, when the system's future reliability is in danger, the water value increases very fast and the marginal cost can reach its price cap in a period shorter than a month.

III. Contracting Risks

The main risk management tool used in the Brazilian market is a financial forward contract (in Brazil it is named "contract by quantity"). The energy delivery risk is on the producer's hands, who is not obliged to physically produce the contracted amount, but must clear in the spot market the difference between produced and contracted energy. In this sense, the spot market turns to be a clearing house in which energy shortfalls and surpluses are negotiated at spot price, and contracts are good mechanisms to hedge spot price volatility.

The revenue for each period t and scenario s of a generation company (Genco) or ETC selling E (avgMW) in a financial forward contract for a price P (R$/MWh) can be obtained by the following expression (neglecting production costs):

$$\mathrm{R_{ts}} = \mathrm{P}\cdot\mathrm{E}\cdot\mathrm{h_t} + (\mathrm{G_{ts}} - \mathrm{E}\cdot\mathrm{h_t})\cdot\pi_{\mathrm{ts}} \quad \forall \mathrm{t} = 1,\ldots,\mathrm{T} \text{ and } \mathrm{s} = 1,\ldots,\mathrm{S} \tag{1}$$

where

$\mathrm{h_t}$ number of hours in period t;

$\mathrm{G_{ts}}$ generation (MWh) in each period t and simulated inflow scenario s;

π_{ts} spot price (R$/MWh) in period t and dispatch scenario s.

In expression (1) there are two types of revenues: 1) the fixed (deterministic) contract payment, $\mathrm{P}\cdot\mathrm{E}\cdot\mathrm{h_t}$, paid by consumers, and 2) the variable spot market clearing, which is stochastic (i.e., depends on scenarios of the future spot price and energy production) and may assume negative values in energy shortfall scenarios, for which $\mathrm{G_{ts}} < \mathrm{E}\cdot\mathrm{h_t}$.

Therefore, one key aspect to model the future behavior of forward contracts is the forecasting of future spot prices. In the presence of a competitive spot market, prices can be addressed through statistical models such as seasonal auto-regressive models [10], [14], in which the relevant lags will depend on the specific market characteristics. However, in the presence of a centralized scheduling system—as in the case of the Brazil—scenarios of future spot prices may be generated through the same long-term dispatch models [12], [13]. These models simulate the optimal system operation for a given time horizon considering inflow uncertainty [15] and, thus, allowing the production of scenarios of future energy spot prices (based on marginal costs) and plant production, in a Monte Carlo-based approach.

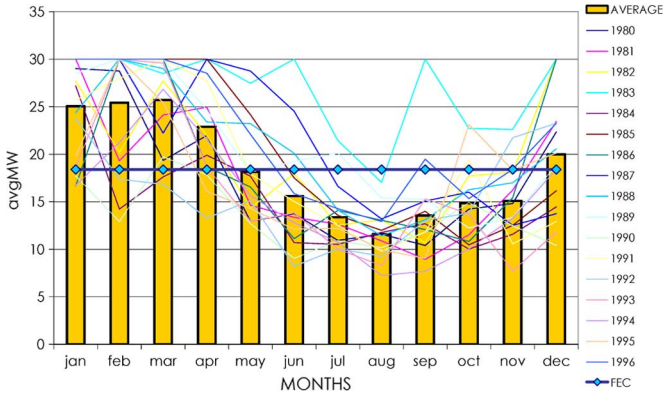

Fig. 1. Historical inflow data converted into hydro generation for a small hydro unit with 30 MW available power. FEC obtained by means of the estimated generation average (18.4 avgMW).

IV. Small Hydros and Sugarcane Cogeneration Risk

A. Small Hydros

Small hydros in Brazil are plants with installed capacity below 30 MW and reservoir area less than 2 $\mathrm{km^2}$. Their production results from the inflow release for each period (run-of-river units) since they have very limited storage capacity. For this type of units, the FEC is obtained through the time average of the historical inflows, transformed into energy generation by considering the project average productivity coefficient and its maximum available power. For example, Fig. 1 shows the total energy production of a 30 MW small hydro located in the Paraibuna River, in the southeastern part of Brazil. The plant simulation is carried out for the historical record of inflows (each year of the historical inflow is shown) and its average energy production is 18.4 avgMW, which then becomes its FEC. In this figure it is also possible to observe the effect of the dry period (May to November) in this specific inflow pattern, as well as that of the inflow variability, which results in a very volatile production pattern. These facts, together with the negative correlation between hydro production and spot prices, make it risky for an individual small hydro to sell a yearly firm energy contract. The reason is that spot purchases to compensate deviation between physical production and the contracted amount might be frequent and take place in high spot prices scenarios, thus introducing an undesirable volatility, and an eventually negative component in the project cash-flow.

B. Cogeneration from Sugarcane Bagasse

As discussed in [5], Brazil is a producer and exporter of ethanol. Its ethanol production comes from sugarcane, which is cultivated by more than 350 mills spread all over the country. The sugarcane bagasse is used as a fuel to produce electricity by means of a steam turbine. This makes the ethanol production process self-sufficient in terms of electricity. Since several producers are installing efficient high-pressure boilers, the amount of MWh produced is higher than the ethanol plant consumption and this surplus energy is being sold to the grid.

A cogeneration plant that uses the sugarcane bagasse (BIO) produces a constant energy amount during the harvest period, which, in the southeast of Brazil, occurs from May to November. This plant can sell its surplus energy through a long or medium-term quantity contract, but it will have a shortfall to clear in the spot market during the months with no production. The BIO plant's yearly FEC is equal to its total annual energy production in avgMW. Since it runs at 100% full power during seven out of twelve months (and has no production in the remaining five months of the year), this leads to a FEC equivalent to 58% of its available capacity (constant yearly energy production). In the case of a 30 MW plant, the FEC would then be 17.5 avgMW.

An interesting aspect is that the harvest period of sugarcane *coincides* with the system's dry period of inflows. Consequently, spot prices tend to be higher in this period than in the others, leading to a *favorable* synergy with the overall system characteristics: in the exact period in which all hydros are facing a low energy production, the congeneration from sugarcane is selling its constant generation surplus and receiving a high remuneration due to high spot prices.[4] But despite this upside, a well-known result of risk-averse behavior in decision theory says that an agent is much more sensible to its downsides than to its upsides [23], and since there are some periods in which there is no production (from December to April), the spot purchases during this period turn out to be an impeditive expenditure component for any individual risk-averse investor. Therefore, the practical consequence is that sugarcane congeneration plants are very reluctant to sign forward (quantity) contracts because of the risk of being exposed to the spot market during the non-harvest months.

C. Complementarity Between Sugarcane Cogeneration and Small Hydro Production

Fig. 2 shows the generation profile for both power plants (SH and BIO) in percentage of their FEC amounts. In this figure it is possible to observe the risk that both plants are exposed to if they sign a contract to supply 100% of their FEC throughout the whole horizon (January 2010 to December 2011): whenever the future generation is below the 100% FEC level (highlighted by a bold line), the plant will be exposed to spot purchases. Thus, if on one hand the SH faces its deficit production periods during dry periods—when spot prices are high—and the BIO plant is profiting by selling its surplus on spot market, on the other hand, during the non-harvest period (from December to April), the situation reverts to the exact opposite position in which the BIO plant is totally in deficit (with no production) and the SH presents an expected energy production surplus.

Therefore, as done in [7]–[9] for the case of wind power and pumped-storage hydro, a natural consequence is to study the hedging potential of a combined portfolio composed by these two sources, thus exploiting the possibilities of synergies. In Brazil, several ETCs have emerged as buyers of these two energy sources and are creating a third product, which is a flat

[4]Due to that, the seasonal production may lead to a positive annual expected spot revenue surplus compared to the annual expected value of the average production (FEC constant amount) spot sales.

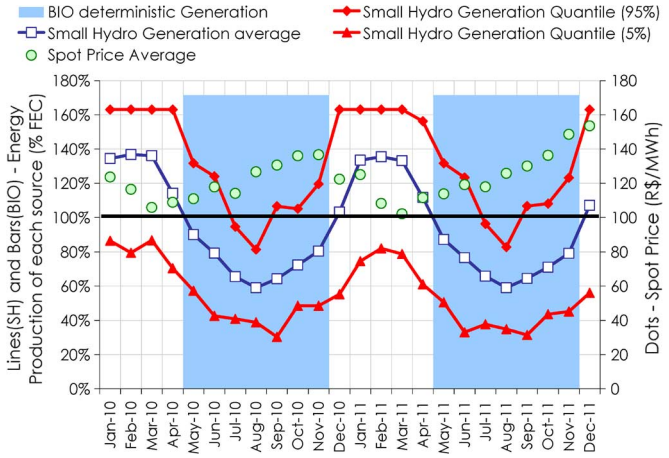

Fig. 2. Energy production profile (BIO plant surely production versus stochastic small hydro generation—scenarios for SH generation and spot prices follow the case study data presented in Section VII). Values in % of the total FEC amounts of two 30 MW available power capacity plants.

contract that is cross-hedged by a "blend" of these production patterns. This will be addressed next.

V. New Business: Mix of Two Production Patterns

Energy trading companies play an important role in competitive electricity markets. These companies basically act by buying and selling electricity contracts from/to both generators and consumers. By operating as portfolio managers, ETCs may also develop strategies that mitigate risks associated with individual projects, and consequently, may provide incentives which, otherwise, would be nonexistent.

The particular case studied in this work deals with the combined trading of the production from renewables. A recent Brazilian law determines that free consumers are entitled to a reduction of 50%+ in their distribution fees if they sign contracts with wind, biomass or small hydro generators. In the FTE, participants may then work out deals that allow both generators and consumers to take advantage of this benefit. However, the fact that the majority of contracts negotiated in the FTE are forward contracts by "quantity" gives rise to a series of uncertainties and risks from the point of view of generators. They are subject to spot price exposure during unavailability periods, as mentioned before, which is exactly what gives the opportunity for ETCs to come into play.

The proposal is then to create a new business model by which the ETC buys the production rights of the small hydro and of the sugarcane congeneration to sell it back as a firm energy quantity contract. The purchase of the SH and BIO production is done by a capacity contract, or an energy call option [17] and resold as a contract by quantity to a free consumer. The problem faced by the ETC is then to determine the amount of energy to purchase from each source so that it will be able to re-sell this energy and sign quantity contracts with free consumers to fulfill their demand, as shown in Fig. 3.

This contracting scheme transfers all production and delivery risks from the renewable generators to the ETC, since it is equivalent to the ETC renting $x\%$ of the available generation capacity and the respective percentage of the FEC amounts of both

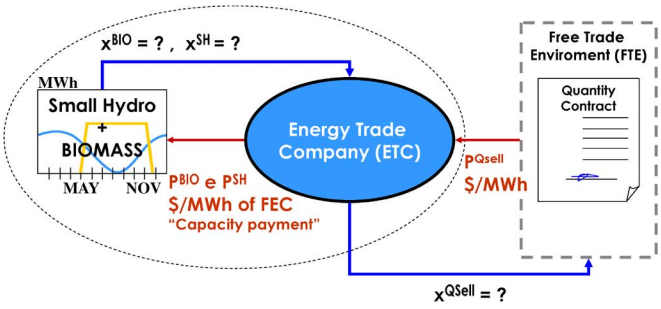

Fig. 3. ETC contract scheme.

sources, in exchange for a fixed "capacity" payment. The total FEC amount can then be re-sold to consumers by means of firm delivery obligation contracts (flat quantity contract). In this context, the ETC is representing some percentage (x^{BIO} and x^{SH}) of each generator in the FTE: it profits during the upsides due to the spread between the selling and purchase prices, and assumes the risks during the downsides, which occur in scenarios of low energy production. The ETC should then hedge against the production risk by over contracting a surplus (or reserve) capacity, so that the resulting portfolio production deficit is mitigated.

The purchase expenditure incurred by the ETC when signing capacity contracts with the generating agents is the following:

$$\mathrm{Exp_t} = \mathrm{P^{SH}} \cdot \mathrm{E^{SH}} \cdot \mathrm{x^{SH}} \cdot \mathrm{h_t} + \mathrm{P^{BIO}} \cdot \mathrm{E^{BIO}} \cdot \mathrm{x^{BIO}} \cdot \mathrm{h_t} \quad \forall \mathrm{t} = 1, \ldots, \mathrm{T} \tag{2}$$

where

$\mathrm{P^{SH}}$, $\mathrm{P^{BIO}}$	price (in \$/MWh) required by each source;
$\mathrm{E^{SH}}$, $\mathrm{E^{BIO}}$	firm energy certificates (FEC in avgMW) of each source, which play the role of maximum contract amount of each source, as described in Section II;
$\mathrm{x^{SH}}$, $\mathrm{x^{BIO}}$	percentage of FEC and production capacity purchased by the ETC of each source;
$\mathrm{h_t}$	number of hours in period t.

The revenue received by the ETC from selling a quantity contract of a given amount, defined as $\mathrm{E^{Qsell}} \cdot \mathrm{x^{Qsell}}$ (in avgMW) at a price $\mathrm{P^{Qsell}}$ (in \$/MWh), is

$$\mathrm{R_{ts}^{sell}} = \mathrm{P^{Qsell}} \cdot \mathrm{h_t} \cdot \mathrm{E^{Qsell}} \cdot \mathrm{x^{Qsell}} + \left(\mathrm{G_t^{BIO}} \cdot \mathrm{x^{BIO}} + \mathrm{G_{ts}^{SH}} \cdot \mathrm{x^{SH}} - \mathrm{h_t} \cdot \mathrm{E^{Qsell}} \cdot \mathrm{x^{Qsell}}\right) \cdot \pi_{\mathrm{ts}} \quad \forall \mathrm{t} = 1, \ldots, \mathrm{T} \text{ and } \mathrm{s} = 1, \ldots, \mathrm{S}. \tag{3}$$

In expression (3), $\mathrm{E^{Qsell}}$ represents the total consumer demand (the maximum selling contract opportunity) and $\mathrm{x^{Qsell}}$ is the ETC's decision variable, defined in the interval [0,1], which expresses the percentage of such amount that the ETC will be actually willing to supply. In addition, $\mathrm{G_t^{BIO}}$ and $\mathrm{G_{ts}^{SH}}$ are the production profiles (in MWh), in each period t, of the biomass and small hydro plants. The latter has also a scenario (s) index due to its uncertain nature (as outlined in Section III).

As previously mentioned, according to the regulation, any contract has to be backed by FEC amounts. Since we consider that the ETC does not own any generating capacity, the amount of energy it sells to free consumers has to be less or equal to the amount of energy certificates it acquired from the generators. This condition may be expressed by the following inequality:

$$\mathrm{E^{Qsell}} \cdot \mathrm{x^{Qsell}} \leq \mathrm{E^{SH}} \cdot \mathrm{x^{SH}} + \mathrm{E^{BIO}} \cdot \mathrm{x^{BIO}}. \tag{4}$$

As already pointed out, the decisions that must be taken by the ETC are not straightforward. By acting as a risk manager and as an intermediary between generators and consumers, it is exposed to the production and price risks, and this fact must be taken into account during the decision-making process. This topic will be further investigated in the following section.

VI. Risk Aversion and Optimum Renewable Portfolio Problem

We choose to represent the risk profile of the ETC by constraining the profit α-conditional value at risk (α-CVaR) [18], which corresponds to setting requirements on the expected value of the $(1-\alpha)100\%$ worst profit scenarios. Both theoretical and practical features have made the use of the CVaR widespread in portfolio allocation problems. It combines a set of virtues such as an intuitive parameter specification process, all needed coherence properties (see [19] and [20] for further explanations)—in which sub-additivity is included, the advantage of capturing the averseness to high-impact with low probability losses and it may also be incorporated into linear programming problems as a set of linear constraints [18].

Mathematically, the CVaR of a random variable R (net revenue or operative profit) with cumulative probability function F_R is given by

$$\mathrm{CVaR}_\alpha(R) = \mathrm{E}(R|\Psi) \tag{5}$$

where Ψ is the set of net revenue outcomes below the associated α-value-at-risk, $\mathrm{VaR}_\alpha(R)$, defined as the $(1-\alpha)$ quantile, $\mathrm{VaR}_\alpha(\mathrm{R}) = \inf_{\mathrm{r}}\{\mathrm{r}|\mathrm{F_R(r)} \geq 1-\alpha\}$, having α typically ranging from 95% to 99% in practical applications. As shown in [18], the α-CVaR of a random variable may also be written as a linear programming (LP) problem and can be easily inserted into a two-stage stochastic profit maximization problem by adding a set of linear constraints. Thus, the following linear maximization problem should find the optimal contracting amounts: $\mathbf{x}^* = [\mathrm{x^{SH^*}}, \mathrm{x^{BIO^*}}, \mathrm{x^{Qsell^*}}]^{\mathrm{T}}$ so that it maximizes the expected net present value (NPV) of the final net profit, or net revenue cash flow, defined as $\mathrm{R_{ts}} = \mathrm{R_{ts}^{sell}} - \mathrm{Exp_t}$, subject to a set of per-period α-CVaR constraints. Expressions (2)–(4) will make part of the remaining constraints of the portfolio problem and will be indicated in the following model:

$$\text{Maximize} \sum_{\mathrm{t}} \sum_{\mathrm{s}} \mathrm{p_s} \cdot \mathrm{R_{ts}} \cdot (1+\mathrm{K})^{-\mathrm{t}}$$

$$\text{s.t.} \tag{6}$$

$$\delta_{\mathrm{ts}} \geq \mathrm{z_t} - \mathrm{R_{ts}}, \qquad \forall \mathrm{t}, \mathrm{s} \tag{6.1}$$

$$\mathrm{z_t} - \sum_{\mathrm{s}} \mathrm{p_s} \cdot \delta_{\mathrm{ts}}/(1-\alpha) \geq \mathrm{R_t^{min}}, \qquad \forall \mathrm{t} \tag{6.2}$$

$$\mathrm{R_{ts}} = \mathrm{R_{ts}^{sell}} - \mathrm{Exp_t}, \qquad \forall \mathrm{t}, \mathrm{s} \tag{6.3}$$

$$\text{Expressions (2) to (4)} \tag{6.4}$$

$$x^{SH}, x^{BIO} \text{ and } x^{Qsell} \in [0,1] \tag{6.5}$$

$$Exp_t \text{ and } z_t \in \Re_+, \quad \forall t \tag{6.6}$$

$$\delta_{ts} \in \Re_+ \text{ and } R_{ts} \text{ and } R_{ts}^{sell} \in \Re, \quad \forall t, s. \tag{6.7}$$

In order to account for the CVaR constraints in model (6), we need to use some additional auxiliary decision variables:

- z_t — α-CVaR auxiliary variable that will achieve the net revenue α-value-at-risk for each period at the optimum solution;
- δ_{ts} — α-CVaR auxiliary variable that represents the left deviation of the net revenue scenario s to the variable z_t in each period t.

The model parameters are:

- K — capital opportunity cost for the ETC (% per-period);
- R_t^{min} — minimal profit requirement for each period t;
- p_s — s scenario probability;
- t — discrete time period index in the set $\{1, \ldots, T\}$;
- s — discrete scenario index in the set $\{1, \ldots, S\}$ of simulated scenarios.

In the above LP problem, constraint (6.1) together with the nonnegative bound for δ_{ts} represents a two-segment piecewise linear function, which computes in δ_{ts} only the violations for the scenarios whose net revenue do not exceed the threshold z_t. As shown in [18], these thresholds will reach, in the optimum solution, the α-value-at-risk of each period and, thus, (6.2) will provide a lower bound for the conditioned[5] expected VaR violations (which is the CVaR). Constraints (6.3) and (6.4) have been presented before and relations (6.5)–(6.7) indicate the domain of the decision variables. The proposed LP model solves the deterministic equivalent form of the two-stage stochastic programming problem, having the buy and sell contract percentages $(\mathbf{x})$ as the here-and-now decisions, and the spot clearing transactions as the wait-and-see decisions. These are taken according to the realizations of the uncertainties, which are implicitly represented by the production and contracted amount difference on the second term of expression (3). The model was solved by the commercially available linear programming solver XPRESS-MP [22].

VII. Case Study

A. Case Study Description

The base case for our computational example assumes that the ETC is able to sign capacity contracts with the small hydro and biomass generators at a price of R$140/MWh.[6] The selling price of the "quantity-based" contract sold to free consumers is set at R$165/MWh, based on the following rationale: if we consider a free consumer which currently pays its supplier R$115/MWh plus an additional R$135/MWh for the distribution fee (a total of R$250/MWh), by purchasing its demand from renewable sources, he would be able to receive a discount of up to R$75/MWh on the distribution fee and, thus, with the new energy price, reach a total cost of R$225/MWh. Assuming a 15 avgMW consumer, this 10% decrease on the total fee would represent R$4.3 millions in savings[7] over a two-year period, e.g., 2010 to 2011.

TABLE I
Business Opportunity Prices and Energy Amounts

E^{Qsell} (avgMW)	P^{Qsell} (R$/MWh of FEC)	P^{SH} (R$/MWh)	P^{BIO} (R$/MWh)
15	165	140	140

The stochastic formulation of our problem requires a set of scenarios to model the uncertainties present in the problem. These scenarios were generated through a Monte Carlo simulation by means of a scheduling model, and a sample of 200 simulated dispatch and spot prices scenarios were obtained for a time horizon of 24 months (January 2010 to December 2011).

The business opportunity, summarized in Table I, will be analyzed in annual steps, but taking into consideration the seasonality by means of the correct month-to-month composition of the total annual revenue. We also consider that both generation sources (SH and BIO) have 30 MW of installed capacity and 18.4 and 17.5 avgMW of FEC amounts, respectively, and agree to contract their energy certificates for a fixed R$140/MWh capacity payment during the whole time horizon. For a 10% per year ETC's nominal capital opportunity cost ($K = 10\%$ p.y.), problem (6) will be run first with no risk constraint (risk-neutral profile) and then, with minimal per-year α-CVaR constraints (risk-averse profile), in order to highlight differences between the solutions obtained through the probability distributions of the resultant portfolios.

B. Results: Risk-Neutral Analysis

The risk-neutral optimal buying and selling decisions—obtained by solving problem (6) dropping constraints (6.1) and (6.2)—resulted in the fulfillment of the total consumer demand of 15 avgMW covered by 15 avgMW of biomass energy certificates. This result can be understood considering the advantageous relation that exists between the generation profile of the biomass plant and the periods of the year during which spot prices are expected to be high and low, as discussed in Section IV-B. For a risk-neutral ETC, each MWh of purchased FEC would provide an R$1.8 expected annual spot benefit due to its associated seasonal power production.

However, the next two figures reveal the potential annual losses of this portfolio in terms of annual net revenue and the resulting net present value.

The potential losses for the 5% worst scenarios (see Figs. 4 and 5) suggest the need of a risk constraint requiring a minimum net revenue lower bound for this set of scenarios. For this purpose, we can use model (6) with $\alpha = 95\%$ to impose a constraint in which the 5% left-tail average of the annual profit is bounded

[5]The $(1-\alpha)$ term, in the LHS of expression (6.2), is normalizing the probabilities of the scenarios that do not exceed the VaR amount, providing thus, a conditional expectation of the $(1-\alpha)100\%$ worst scenarios.

[6]1 US$ = 2.3 R$ on January 2009.

[7]This value is obtained by the savings in tariffs (25 R$/MWh) × 15 avgMW × 2 years × 8760 hours×0.66 (due to income tax reduction) =4.3 Millions of R$.

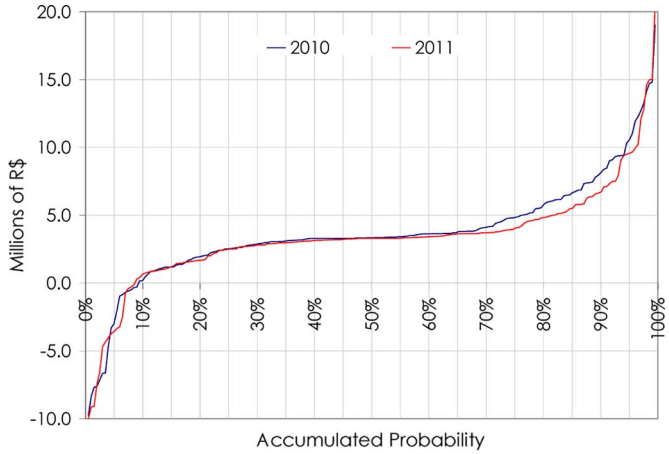

Fig. 4. Inverse accumulated probability function for the annual profit resulting from the risk-neutral optimal portfolio.

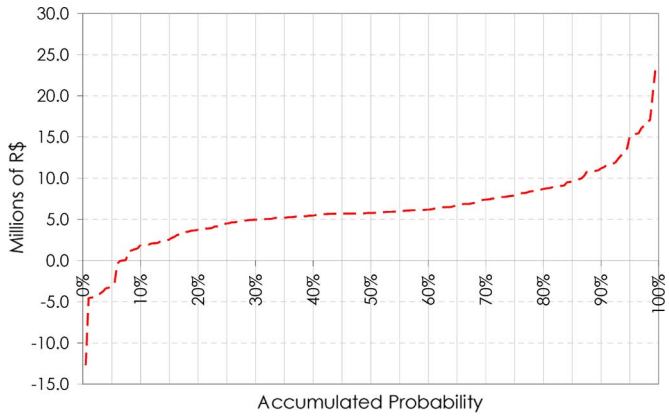

Fig. 5. Inverse accumulated probability function for the net present value of the two-year profit resulting from the risk-neutral optimal portfolio ($\mathrm{K} = 10\%$ per year).

TABLE II
CONTRACTED ENERGY AMOUNTS

Type of Solution	$E^{Qsell}.X^{Qsell*}$ (avgMW)	$E^{SH}.X^{SH*}$ (avgMW)	$E^{BIO}.X^{BIO*}$ (avgMW)	Total Purchased (avgMW)	Surplus Hedge (avgMW)
Risk Averse	15.0	10.6	5.8	16.4	1.4
Risk Neutral	15.0	0.0	15.0	15.0	0.0

below by R$-1 Million. In other words, a maximum annual loss of the average 5% worst scenarios would be accepted to be R$1 Million.

C. Results: Risk-Averse Analysis

The resulting optimal risk-constrained portfolio has chosen a mix between the two generation sources (see Table II) in order to achieve the minimal profit CVaR constraints while maximizing the expected value of the discounted cash flow.

In Table III, the expected NPV for the risk-averse solution is shown to be lower than for the risk-neutral portfolio, which is somewhat reasonable, as the first deals with a constrained version of the second. This objective function reduction is the

TABLE III
FINANCIAL RESULTS

Type of Solution	Expected NPV (M R$)	NPV α-CVaR (M R$)	CVaR for t=1 (M R$)	CVaR for t=2 (M R$)
Risk-Averse	5.1	1.4	0.1	-1.0
Risk-Neutral	6.1	-4.8	-6.5	-6.3

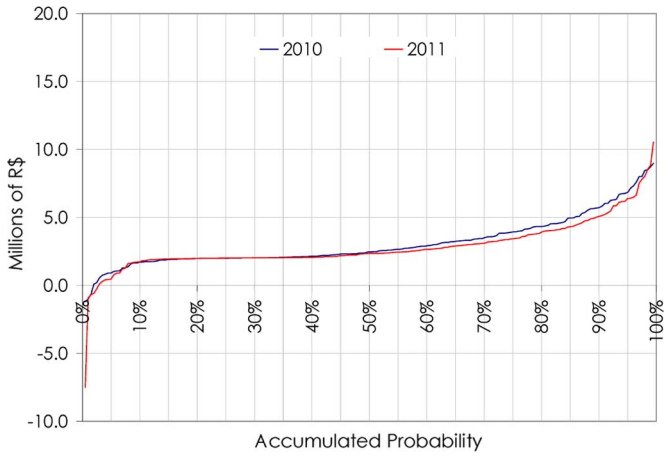

Fig. 6. Inverse accumulated probability function for the annual profit resulting from the risk-averse optimal portfolio.

consequence of the imposed annual CVaR constraints, which have decreased the annual losses, mitigating the production and spot market exposure risk through a surplus hedging amount of purchased FEC—defined as the difference of the total FEC purchases minus sales (see Table II, last column). Furthermore, such expected NPV decrease of R$1 Million from risk-neutral to risk-averse solutions is compensated by an increase of R$5.2 Million in NPV's α-CVaR, as summarized in the second and third columns of Table III. For a graphical visualization, Fig. 6 shows the inverse cumulative probability function of the annual profit, while Fig. 7 compares the NPV quantile functions for both solutions, risk-neutral and averse.

The advantage of the use of a CVaR constraint, in order to guide the optimization model for a safe portfolio, has shown to be straightforward to understand, bounding the worst scenarios average losses, and quite easy to implement, by adding constraints (6.1)–(6.3) to a common LP expected maximization portfolio problem. Furthermore, it is clear from the analysis of Fig. 7 and Tables II and III that an ETC can profit in this business taking a reasonable risk level, by forming a risk-averse portfolio comprising these two renewable sources.

D. Willingness to Supply Curve

From the framework presented it is possible to calculate a willingness-to-supply curve (WSC), which would relate the optimal risk-averse portfolio vector $\mathbf{x}^*(\mathbf{P})$ for each negotiated price vector $\mathbf{P} = [P^{SH}, P^{BIO}, P^{Qsell}]^T$. Fig. 8 shows such curve for the case in which P^{SH} and P^{BIO} remain at their original values and P^{Qsell} varies from 140 to 169 R$/MWh. For the considered range of P^{Qsell}, the optimal percentage

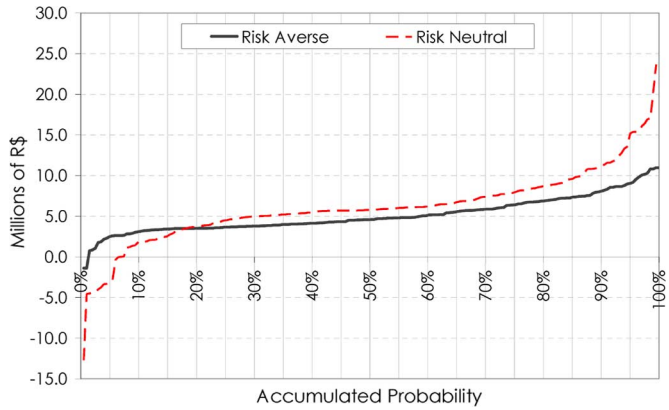

Fig. 7. Inverse accumulate probability function for the net present value of the two years profit resulting from the risk-neutral and risk-averse optimal portfolio solutions ($\mathrm{K} = 10\%$ per year).

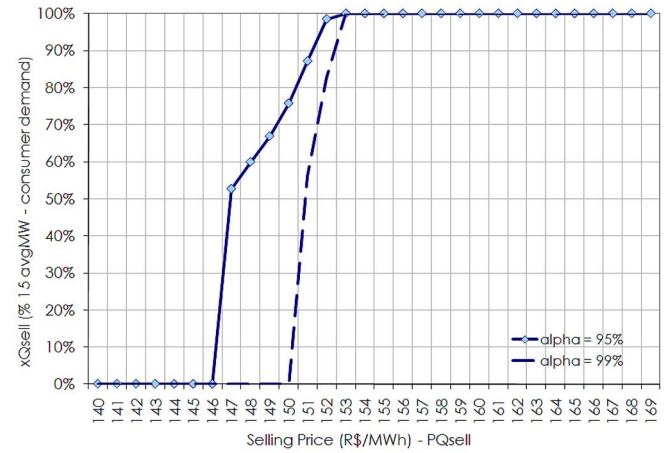

Fig. 8. Willingness-to-supply curve: optimal selling decisions for a range of selling prices (risk aversion parameter $\alpha = 95\%$ and 99%).

$\mathrm{x}^{\mathrm{Qsell}^*}$ of the total firm energy demand ($\mathrm{E}^{\mathrm{Qsell}}$) to be supplied is shown. This would be an important strategic information for the ETC when negotiating the selling price with consumers or during multi-round contract auctions [16], where it can be used as a bidding rule. Since the shape of such a curve will depend intrinsically on the risk aversion of the decision maker, Fig. 8 shows the WSC for $\alpha = 95\%$ (adopted during the whole case study) and also for $\alpha = 99\%$.

Depending on the selling price opportunity, e.g., varying from 140 to 152 R$/MWh, the only way to maintain feasibility regarding the maximum risk budget is to reduce the size of the business (firm energy sale). These cases happen whenever the price spread (between selling and buying contracts) is unable to support the maximum risk constraint on the optimal portfolio and, thus, the ETC should supply only a fraction of the consumer demand. Finally, by analyzing Fig. 8, it is possible to see that a R$13/MWh spread is needed to make this business 100% attractive for this risk-averse ETC.

VIII. Conclusions

This work presented a stochastic optimization model to devise portfolio trading strategies combining two sources with complementary energy production patterns. The model maximizes the revenue of an energy trading company, while mitigating hydrological and fuel unavailability risks and providing a safe and competitive firm energy delivery over a given time horizon. A practical case study was shown, with data from the Brazilian system. This model is being used by several trading companies in Brazil to develop their trading strategies, taking advantage of the potential of small hydros and cogeneration from sugarcane bagasse, in an attempt to provide clean energy development in the country.

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