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Sharing Quotas of a Renewable Energy Hedge Pool: A Cooperative Game Theory Approach

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***Abstract*—Renewable sources play an important role in the current climate world policy, emerging as an efficient way to reduce greenhouse gas emissions that cause global warming. Despite their appeal, renewable sources bring to the fore important challenges on the economic side. In Brazil, the three main renewable sources are wind power, small run-of-river hydro and cogeneration from sugarcane waste. Their highly seasonal yet complementary availability makes individual energy selling through contracts a dangerous option. By taking advantage of the resource mix, the optimal joint risk-adjusted trading strategy creates financial surplus value that can be studied using cooperative game theory. Therefore, the objective of this work is twofold: first, to propose a risk-averse renewable energy hedge pool to jointly sell a single complementary renewable generation portfolio and, second, to analyze different schemes of sharing the financial gains, namely quotas, between the members of such a pool from a cooperative game theory point of view. Results using realistic data from the Brazilian system are discussed and four different quota allocation strategies are analyzed: Energy Proportional, Shapley value, Nucleolus and Proportional Nucleolus.**

***Index Terms*— Cooperative game, Conditional Value-at-Risk, forward contract, risk-aversion, renewable energy.**

I. Introduction

Renewable sources appear as an opportunity to achieve CO_2 emission goals worldwide. However, the challenges currently faced on the economic side represent the most impeditive issue for the massive development of such sources. Wind power plants and small run-of-river hydros are typical intermittent sources having their generation profiles dictated by their respective availabilities: wind speed and water inflow. Both types of resources follow an uncertain pattern and, due to that, a significant amount of work has been done to optimize their short-term operation planning ([1]). On the other hand, the medium/long-term energy commercialization through contracts, recognized as being an efficient way to reduce generators' cash flow volatility and to ensure system long-run supply adequacy, can be too risky for generators with intermittent and/or seasonal generation patterns. The contract delivery obligation, as reported in previous works ([2]), can lead to high purchase expenses in the spot market in the case of low production scenarios.

As shown in [3], there is a joint risk-averse optimal trading strategy for selling contracts backed up by the mix of two complementary renewable sources, small hydros (SH) and cogeneration from sugarcane biomass waste (BIO) that reduces the risk of high expenditures in the spot market. In the present work, we make use of this concept to develop a renewable hedge pool that aims at trading energy optimally with the three main renewable sources available in Brazil, namely SH, BIO, and wind power (WP), acting as a portfolio. Since, in a risk-averse setting, the joint trading strategy risk is lower than the individual-based ones, the *value* of the portfolio strategy should be greater than the sum of the *values* of the individual strategies. By recognizing that the appropriate framework to deal with the problem of allocating benefits among players is cooperative game theory ([4]), four different *quota* allocation methods to share the income revenue of such pool will be analyzed. We will finally use realistic data from the Brazilian power system to test our framework.

II. Renewable Generation Profiles

In the Brazilian power system, the regulatory framework states that all contracts should be covered by *firm energy certificates* (FEC)[1]. A FEC represents the maximum amount of energy that each generator can sell through contracts. This is because the Brazilian power system is mainly hydro-based and, therefore, energy-constrained (see [5] for further details). However, in the case of the three renewable sources studied in this work (not dispatched by the system operator due to their intermittent/inflexible nature), the amount of FECs is provided, and periodically revised by the regulator, based on its historical average value.

As shown in [3], a SH suffers from an intermittent and seasonal generation profile, with dry and wet periods alternating within a year. The production of a run-of-river SH results from the up-coming water inflow release, which is unknown and, therefore, can be modeled as stochastic process. On the other hand, BIO power plants suffer from a highly seasonal and inflexible (must-run unit), yet assumed deterministic, generation profile. The production from

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[1] The FEC of a dispatchable generator is a share of the overall system *firm energy*, which is the amount of energy that can be supplied under very adverse conditions.

sugarcane waste placed in the southeastern zone of Brazil is fairly complementary to the generation profile of SH in the same zone. The harvest period, when there are sufficient available resources for the BIO plant, coincides with the dry period, when there is resource scarcity for SHs. A similar complementary pattern exists between a SH in the SE zone and a WP placed in the northeastern (NE) zone ([6]). In Fig. 1, the three renewable profiles of generation are illustrated on a p.u. (of FEC) basis. While SHs are traditionally employed in the Brazilian power system, WP generation is quite new and, due to that, it suffers from a lack of historical data.

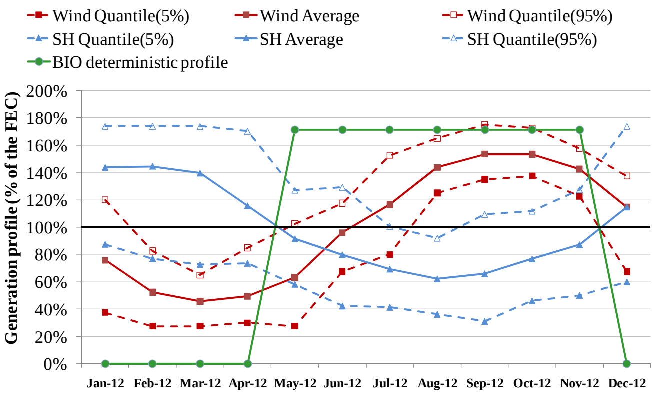

Fig. 1. Simulated generation profile in % of the FEC (long-term average) for the three main renewable sources present in Brazil.

III. Game Setting

A cooperative game is characterized by means of a set of players, $N = \{BIO, SH, WP\}$, generally called the grand coalition, and a *value function*, generally called characteristic function (or imputation), which is also *superadditive* in our case.

For the purposes of this work, we assume only one generation unit per source type, called player hereinafter. The proposed game of sharing renewable hedge pool *quotas* characterizes a stochastic cooperative game ([7]), where what is allocated to each player is, in fact, a future stochastic cash flow. Each player's cash flow is a percentage, or a *quota*, of the future random net revenue obtained by optimally trading the grand coalition generation profile through medium-term contracts (see [3] for a complete description of such model). Therefore, a *value function*, also known as Certainty Equivalent (CE), is needed to assess the *value* each player assigns to its shared *quotas* in order to apply classic cooperative game theory ([7]).

We use a well-known coherent risk measure ([8]) called Conditional Value-at-Risk (CVaR) to play the role of the *value function* (see [9] for the hypothesis and properties of this association). The coherence property will provide us with a *superadditive value function*.

We will adopt the approach established in [10] to assess the CVaR of the random outcomes by means of linear program (LP). For the sake of tractability, we use Monte Carlo simulation approach to estimate CVaR (see [10]).

A. *Players' Characterization*

For a player we mean a generation unit equipped with a given generation technology (source type) with a certain energy generation profile and its corresponding FEC amount.

We assume that players have only access to the following markets: forward market, where medium-term contracts are negotiated, and spot market. In the forward market we only consider standard forward contracts, also known as two-sided forward contracts for differences ([11]), or *quantity* contracts (see [3]), in which the seller has a positive or negative payoff depending on the difference between the contract price and the spot price. Such a contract is a pure financial instrument and does not impose a physical commitment on the energy production (see [2] for more details); it is mainly used as a hedge instrument to protect against spot price volatility (see [11] and [5]). Therefore, all the physical energy production is assumed to be sold in the spot market. In this sense, for any player, here identified by index i, the random net revenue of selling Q average-MW through a financial forward contract at a price P (in \$/MWh) has the following form (see [2] for further details):

$$\tilde{R}_t(Q, \{i\}) = (P - \tilde{\pi}_t) h_t Q + \tilde{G}_{it}(\tilde{\pi}_t - c_{it}) \;\; \forall\, t \in T, \qquad (1)$$

where $\tilde{\pi}_t$ is the random spot price in period t (in \$/MWh), h_t is the number of hours in each period t, $\tilde{G}_{it}$ is the random (intermittent) generation amount produced by generator i in period t (in MWh per period), and c_{it} is the average production cost of unit i in period t. Finally, T is the set of periods that defines the contract time horizon.

The extension of expression (1) to consider the existent contract portfolio of each generator, as well as other market opportunities, is straightforward. However, such features would bring to focus many issues that are out of the scope of this work and, therefore, we let such extensions for future researches. For the sake of simplicity, we will assume only one contract.

In the case of Brazil, where there is no bid in the short-term (spot) market and all differences between produced energy and contract amounts are automatically cleared at the short-term price, (1) can be directly used (see [2], [3], and [5]). Depending on the market rules, (1) may be adjusted accordingly to incorporate specific and relevant features needed to provide a realistic description of the opportunities available. It is worth mentioning that the extension of the proposed methodology for different power systems is possible mainly by changing (1).

Finally, the optimal contract strategy of an individual player is obtained through a risk-averse maximization problem. Such a problem aims at finding the optimal quantity Q^* for a given market price opportunity P by maximizing the CE of the net revenue stream (see [2] for more details). The main hypothesis of our work is that every player agrees with the adopted CE, namely the α-CVaR, which is the left-tail conditional expectation for values lower than the quantile (also known as Value-at-Risk – VaR) of $(1-\alpha)$%. The risk level $(1-\alpha)$ is generally set between 1% and 5% in order to provide a pessimistic view of the results. Fig. 2 illustrates the VaR and

CVaR for a general continuous probability mass function.

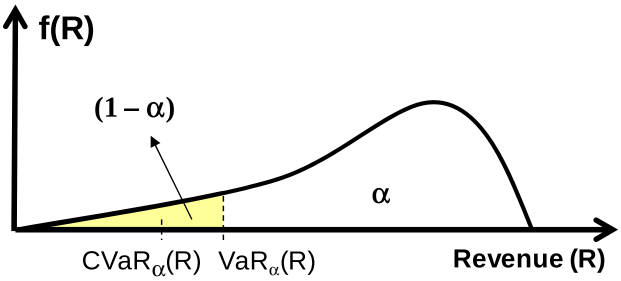

Fig. 2. Conditional Value-at-Risk of a general revenue probability mass function.

B. *The Value Function*

The value function is a map from the set of all coalitions (all subsets of players given by the power set of N, denoted by 2^N) to the set of real numbers, $v: 2^N \rightarrow \mathbb{R}$. In order to obtain it we need to measure the monetary value of a given coalition. A given coalition $S \subseteq N$ is a set of generators capable of jointly trade their FECs through a contract at a known market price, P. Since this ultimately leads to a stochastic cash flow stream, the value function of S should measure the future cash flow with respect to the CE of its players.

Moreover, depending on the coalition, a different trading strategy (Q^*) might take place: each coalition would jointly maximize its CE to take advantage of the synergy between the generation profiles of its members ([2]). For instance, the total amount that should be sold when considering coalition $S_1 = \{BIO, SH\}$ should differ from the amount that should be sold when considering coalition $S_2 = \{BIO, WP\}$. Roughly speaking, this is possible because in the former case there is a complementary pattern between generation profiles, whereas in the latter there is not. Therefore, one should not be surprised if S_1 exhibits a more aggressive trading strategy than S_2. This example will be analyzed in more detail in the case study section.

With these previous considerations in mind, the value function of a given coalition $S \subseteq N$ can be defined as the CE of the stochastic cash flow due to the optimal joint trading strategy of the FECs and generation profiles of its players. Thereby, the proposed value function assumes the following form:

$$v(S) = \max_{Q \geq 0} \left\{ \rho_\alpha \left(\sum_{t \in T} \frac{\tilde{R}_t(Q,S)}{(1+K)^t} \right) \middle| \; Q \leq \sum_{i \in S} FEC_i \right\}, \quad (2)$$

where

$$\tilde{R}_t(Q,S) = (P - \tilde{\pi}_t) h_t Q + \sum_{i \in S} \tilde{G}_{it}(\tilde{\pi}_t - c_{it}) \quad \forall\, t \in T \quad (3)$$

is the joint revenue expression, for each period in the contract horizon, that considers the generation profiles of all players in coalition S.

In (2), K is the risk-free opportunity cost of money measured in percentage per period, $\rho_\alpha(.)$ is the α-CVaR of the net present value of the cash flow stream as defined in [3] and [9], and FEC_i is the amount of FEC in average-MW of each player i in the coalition S. Note that the *value function* in (2) is *superadditive* (see [9], Properties 1 - (c)).

C. *Sharing-Quota Methods*

Four different methods are presented to allocate the pool *quotas* to each player. The first one is called *Energy Proportional*, which allocates *quotas* based on the contribution of each player to the total FEC (tradable energy) amount of the pool. The second method is based on the Shapley Value. The Shapley Value of each player can be obtained through its average marginal contribution in all possible coalitions where it may participate (we refer to [4] and [12] for related works). The third and fourth methods, namely Nucleolus and Proportional Nucleolus, are both based on the concept of *Core* of a cooperative game ([4]).

The *Core* is the set of *quota* vectors (allocations), $\boldsymbol{x} = [x_{SH}, x_{BIO}, x_{WP}]$, under which no coalition has a *value* greater than the *value* allocated through the *quotas* to its players when participating in the pool. That is,

$$C(v) := \left\{ \boldsymbol{x} \in [0,1]^N \;\middle|\; \begin{array}{c} \sum_{i \in N} x_i = 1 \\ v(N) \cdot \sum_{i \in S} x_i \geq v(S) \quad \forall\, S \subset N \end{array} \right\}. \quad (4)$$

In (4), the allocation vectors are constrained to add up to 1 as a requirement to be a share among participants. The second constraint enforces the aforementioned *gain condition*, which must hold for all sub-coalitions of the pool. Therefore, in *Core*-based methods (Nucleolus and Proportional Nucleolus), the *quotas* can be allocated by means of a linear optimization problem. It can be done by maximizing the worst case gain of the worst coalition in the pool in absolute and relative terms, respectively, as follows:

$$\boldsymbol{x}^{Nuc} \in \arg\left\{ \max_{x \in C(v)} \left[\min_{S \subset N} \left(v(N) \cdot \sum_{i \in S} x_i - v(S) \right) \right] \right\}, \quad (5)$$

$$\boldsymbol{x}^{Prop.Nuc} \in \arg\left\{ \max_{x \in C(v)} \left[\min_{S \subset N} \left(\frac{v(N) \cdot \sum_{i \in S} x_i - v(S)}{v(S)} \right) \right] \right\}. \quad (6)$$

According to (5), the gain of a subset S of participants in the pool can be defined as the difference between the total *value* allocated to such participants and the *value* that would be achieved if they formed a coalition by themselves. It is worth mentioning that (5) does not take into account that a small-value coalition may be “over optimized” in a percentage basis. To solve that, expression (6) defines the nucleolus considering the relative gain. The worst-case coalition gain (or relative gain) might be understood as a measure of the pool stability, since the larger the worst-coalition gain is, the smaller the willingness to give up this *value* should be.

It is important to note that in the context of a stochastic game – where the payoffs are stochastic and defined as a percentage of the net present value of the pool future cash flow, $\sum_{t \in T} \frac{x_i \cdot \tilde{R}_t(Q,N)}{(1+K)^t}$ – the *value* associated to any subset S of the pool is the CE of the sum of the revenue shares allocated to its participants:

$$x(S) := \rho_\alpha \left(\sum_{i \in S} \sum_{t \in T} \frac{x_i \cdot \tilde{R}_t(Q,N)}{(1+K)^t} \right). \quad (7)$$

Since the adopted CE measure (ρ_α) is based on a coherent risk measure (CVaR - see [8]), the homogeneity property allows us to rewrite (7) as the left-hand side of the second constraint in (4):

$$x(S) = v(N) \cdot \sum_{i \in S} x_i. \tag{8}$$

Note that the final form of (8) allows us to write our game *Core* set by means of a set of linear constraints, as is done in deterministic cooperative game theory, which would not be possible in the case of a general concave expected-utility functional[2].

D. Pool Design Hypotheses

In the following we present five hypotheses (H1 to H5) in order to design the pool rules. Those hypotheses allow us to define a measure of gain when participating in the pool, which is key to develop the proposed sharing *quota* scheme.

- H1: There is a common open market opportunity for contracting energy at a given known price *P* ($/MWh).
- H2: Such opportunity is able to consume all the energy (FEC) of all the players.
- H3: There are no market opportunities other than the ones from the electricity spot and forward contract markets.
- H4: All the players are known before forming the pool and there is a common acceptance on the generation scenarios of every player. Thus, there is a complete absence of ambiguity in the estimated probabilities of each player's generation profile.
- H5: Every player agrees with the CE adopted to measure the *value* of the future (stochastic) cash flow stream of a given contract trading strategy.

While H1-H3 deal with market opportunities that can be generally observed[3], H4 can be justified in the following cases: (i) if there is a single-owned set of generators, and (ii) if there are detailed reports of historical generation profiles associated with compensation penalties (refunds) to the pool for not reaching a certain margin that is (statistically) likely to be achieved. Finally, H5 may sound the hardest hypothesis on first sight. In that sense, it deserves a more detailed explanation as follows.

Despite being widely used by researchers and in industry, it is clear that different decision makers may exhibit different risk attitudes. Notwithstanding, practical decision making, such as forward contracting under uncertainty, requires a practical measure of risk. The proposed CE measure, CVaR, has been proven to possess a set of good features (see [9], Remark 3 and Properties 1 – (f)). Generation companies composed of different stakeholders' preferences usually make decisions according to *ad hoc* procedures. However, in the last 20 years, they have adopted more risk management tools. In this regard, we believe that a pool designed according to H5, for a reasonable α that produces a risk-averse attitude, may be seen by these companies as an opportunity not only to acquire a new and practical risk management tool, but also to gain access to a hedge tool that is not easy to obtain in the market. Moreover, if a company has a different risk level or a completely different risk-attitude (preference), this pool can also be attractive if, under the agent preference, the allocated *quotas* provide a higher gain with respect to the other available coalition opportunities. Since the future cash flow can be simulated, due to H1-H3, and since H4 holds, a player can always assess its own CE and, therefore, its gain.

Finally, H5 can be seen as a *seal* for the pool, which provides every player with an α-CVaR index higher than the one that would be obtained outside the pool. Thus, it may attract players with compatible risk-attitudes and may repel those with incompatible ones. It is beyond the scope of this work to develop or discuss the players' willingness to participate in that pool for different risk-attitudes rather than the one in H5. However, we recognize its importance as an interesting extension of our research.

IV. Case Study

For the sake of simplicity, we assume that each player possesses 1/3 avgMW of FEC, which leads to a pool with a unitary FEC. In addition, for illustration purposes, it is assumed that there is a market opportunity to sell a contract at a price of 140 R$/MWh[4].

The short-term operation in Brazil is centrally coordinated and the Independent System Operator makes use of a least-cost dispatch model to determine the generation of each unit [13]. A byproduct of this model is the operational marginal cost, which plays the role of short-term price ("spot"). The small hydro stochastic generation profile is simulated according to the Paraibuna river (located in the Southeastern zone) inflow embedded in the Brazilian system dispatch model [3]. The WP generation profile is simulated according to historical data (Northeastern zone) by means of a bootstrap procedure preserving the annual seasonality pattern according to Fig. 1. The BIO unit generation profile is assumed to be deterministic following the typical harvest period in the Southeastern zone. The number of simulated scenarios is 200 for each random variable. In Fig. 1, the average and the 90% confidence interval of the three simulated generation profiles are depicted.

The main results for a hedge pool with a 5% risk level $(1-\alpha)$ are shown in Table I, where the allocated *quotas* are presented for each player and sharing method.

TABLE I
METHODS FOR QUOTAS ALLOCATION (%)

Unit	Energy Proportional	Shapley Value	Nucleolus	Proportional Nucleolus
SH	33.3	33.5	35.0	35.8
BIO	33.3	33.6	33.3	33.0
WP	33.3	32.9	31.7	31.1

In Table II, the optimal trading quantities (as a percentage of the total FEC in the coalition) and the value of each coalition are presented. Also, the relative gain for each coalition per sharing *quota* method is provided. The Energy-

[2] Concave expected utilities are not guaranteed to be homogeneous. Therefore, the value of the summation of allocated revenues is not guaranteed to meet the summation of the values, as is the case of the adopted measure.

[3] For instance, in Brazil there is a free trading environment where generators and consumers negotiate bilateral contracts. In more sophisticated markets, forward price information is available in the internet.

[4] 1 R$ ~ 1.7 US$ on October 2010.

Proportional method provides an intuitive solution for the sharing *quotas* problem, *"what you give is what you get"*. However, according to Table II, this method leads to the least stable solution, considering the relative coalitions' gain. Although, in this case, the Shapley Value and the Energy Proportional methods belong to the *Core*, this is not always guaranteed.

TABLE II
COMPARISON OF FOUR DIFFERENT METHODS FOR QUOTA ALLOCATION

S	Q^* ($\%FEC$)	$v(S)$ ($\$\ 10^3$)	$relative\ gain(S) = \frac{x(S)-v(S)}{v(S)} \cdot 100\%$			
			Energy Proportional	Shapley Value	Nucleolus	Proportional Nucleolus
{SH}	73.1	261.8	28.0	28.5	34.2	37.6
{BIO}	83.3	290.9	15.2	16.0	15.2	14.1
{WP}	76.7	296.5	13.0	11.7	7.5	5.5
{SH,BIO}	85.4	664.3	0.9	1.5	3.3	4.2
{SH,WP}	81.6	646.1	3.7	3.3	3.7	4.2
{BIO.WP}	79.1	619.0	8.3	8.0	5.6	4.2
{SH,BIO,WP}	86.4	1005.1	-	-	-	-
		Worst case:	0.9	1.5	3.3	4.2

By analyzing the generation profile during the year in Fig. 1, it's possible to see that the WP unit provides the pool with a seasonal pattern quite similar to the one provided by the BIO. Thereby, both sources compete for the SH perfect marriage in terms of complementarity. However, the BIO profile provides a better fit in terms of complementarity and uncertainty reduction (see Fig. 1). Consequently, for the first two methods the coalition {SH, BIO} presents the worst-case gain when participating in the pool (see Table II), putting at risk the stability of the grand coalition. In this way, one can find the allocation that maximizes the worst-case gain, also known as Nucleolus. Such a solution is guaranteed to belong to the *Core*, if it exists, and provides the most stable allocation. In Table II, two versions of this concept are presented: Nucleolus and Proportional Nucleolus. It can be seen that, despite having the highest payoff among all the players (individual coalitions), the WP receives the lowest *quota* allocation and gain compared to the other players, mainly because its synergy with the complementary player (SH) is lower than the synergy between the BIO and the SH. Notwithstanding, the complementarity synergy effect can also be observed in the optimal trading quantities: the complementary two-player coalitions, namely {SH, BIO} and {SH, WP}, both exhibit more aggressive trading strategies (higher values of Q^* in a percentage of the total FEC in the coalition) than their individual players alone.

Finally, in Fig. 3, the *Core* of the game and the set of allocations provided in Table I are depicted in a two-dimensional projection on the sum-one plane (drawn with [14]). The outer triangle limits the set of allocations in which only individual gains are ensured. As can be seen, both Nucleolus and Proportional Nucleolus allocation methods provide points that pursue the interior of the *Core* set, the internal polyhedron inside the triangle, which is coherent with (5) and (6), i.e., being as far as possible from the closest constraint.

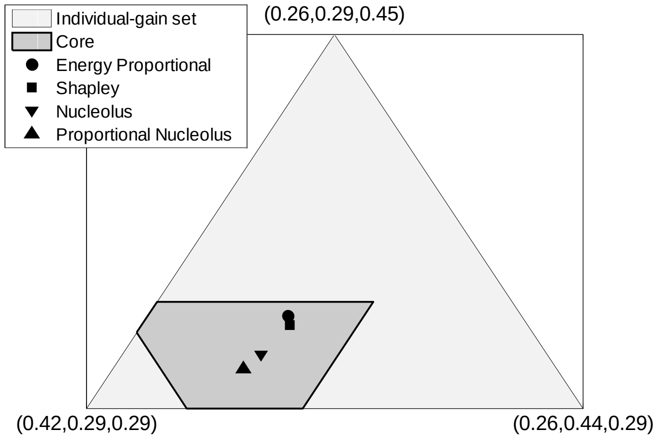

Fig. 3. Quotas-allocation plot.

V. CONCLUSION

In this work, a cooperative game approach is employed to analyze different schemes of sharing the *quotas* of a renewable hedge pool. Four methods are studied and compared: Energy Proportional, Shapley Value, Nucleolus and Proportional Nucleolus. The concept of a contract-based renewable hedge pool presented in this work provides a new methodology to jointly trade renewable energy. This methodology is based on portfolio diversification and on the complementarity between seasonal generation profiles of three well-known renewable sources in Brazil. It proposes an alternative strategy for decision makers and investors to become more competitive, which ultimately might help in fostering the penetration of such sources in the market.

Future work will involve the development of a portfolio model for generators to select their optimal FEC distribution among different pools with different risk levels.

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VII. BIOGRAPHIES

Alexandre Street (S'06–M'10) holds an M.Sc. and a D.Sc. in Electrical Engineering (Operations Research) from the Pontifical Catholic University of Rio de Janeiro (PUC-Rio), Rio de Janeiro, Brazil.

From 2003 to 2007 he participated in several projects related to strategic bidding in the Brazilian energy auctions and market regulation at the Power System Research Consulting (PSR), Rio de Janeiro, Brazil. From August 2006 to March 2007 he was a visiting researcher at the Universidad de Castilla-La Mancha, Ciudad Real, Spain. In the beginning of 2008 he joined PUC-Rio to teach Optimization in the Electrical Engineering Department as an Assistant Professor. His research interests include: strategic bidding in energy contract auctions, energy markets regulation, optimization methods, and decision making under uncertainty. He is also involved with gas-energy integrated portfolios studies and renewable energy trading strategies.

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His research interests include power systems planning, operations and economics, and electricity markets.

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