Mitigating Wind Exposure with (Lower and Upper Bound) Collars-type Insurance

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Abstract

Wind power generators typically enter into long term fixed price contracts with energy dealers in order to hedge against energy price risk. On the other hand, these contracts expose the generator to energy volume risk, as it requires them to deliver the full amount of energy contracted, even if energy production falls short of the expectation due to seasonality problems or low wind speeds. In this case, in order to meet its commitments, the generator must purchase any energy shortfall in the market, which may result in losses if the spot prices at such time happen to be higher than contracted prices. To mitigate these losses, wind generators can choose to purchase insurance against low wind speeds, but the appropriate type of insurance and parameters must still be determined. We propose a zero cost collar type insurance and develop a stochastic programming model to determine optimal strike price parameters and apply this model to a realistic case study. The results indicate that in all quarters there are possible strikes combinations

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that meets the objectives of both the generator and the energy dealer. In particular, the second and fourth quarters are those with the most common strikes points. Also, there exists a negative relationship between the risk to the generator and the expected value of the insurer.
Keywords: Wind Power, Energy Insurance Contract, Stochastic programming, Brazil

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1. Introduction

Brazil's energy matrix relies on renewable sources energy of over 40% of its needs, one of the highest proportion of clean energy in the world. But due to its significant reliance on hydro power, the electrical system is heavily dependent on adequate rainfall and reservoir levels. Unusually dry years leading to 2001 led to widespread energy rationing and a push to create a backup system based mainly on thermal sources of energy.

Nonetheless, these efforts have been insufficient, and more than a decade later, hydro power still accounts for 75% of the country's electrical energy needs, and below average rainfalls once more threaten its ability to meet the demand for energy. Thus, if Brazil is to truly diversify its energy matrix without expanding the use of fossil fuels, other renewable energy sources must come into play.

One alternative is the use of wind energy, which has the potential to generate up to 143 Gigawatts of electricity, which is greater than the current total installed capacity of the country. Not only is wind a clean and renewable source of energy, wind speeds are more intense during the dry season when rainfall and reservoir levels are at their lowest, making it a natural hedge for hydro power.

Wind power, on the other hand, has characteristics that make it significantly different from other energy alternatives. Unlike hydro power, it cannot store energy in reservoirs, and unlike thermal sources, energy production is highly variable and strongly seasonal. Wind power generators are also subject to uncertainty in energy prices and difficulties in predicting future wind conditions such as speed and direction. These uncertainties can have significant impacts on the returns of the wind energy generator.

Energy price risk can be eliminated by entering into forward contracts with energy dealers where a fixed volume and energy price are previously agreed upon by both parties. Such contract, on the other hand, exposes the generator to volume risk. If production exceeds the amount required, the generator can sell the excess on the market, but if production falls short, the generator must purchase this energy shortfall at current market prices, which may expose him to potential losses. To cover this additional uncertainty, the generator may choose to purchase volume insurance against low wind speeds, but the type and cost of this insurance must still be determined.

In this article we consider the case of a wind power generator in Brazil which purchases insurance to hedge volume risk as it is exposed to wind and price uncertainty throughout the year. We adopt a stochastic programming model to estimate the wind speeds to be insured that are acceptable to all parties involved assuming the insurance is a collar type contract. This contract assumes that there are two exercise points which we define as bottom wind and upper wind. Therefore, if it the observed wind level is lower than the bottom strike exercise level, the insurance firm covers any energy loss the generator may have; otherwise, if the observed wind level is above the upper strike exercise level, the excess energy goes to the insurer. Since there are no costs involved, this type of contract is known as a zero-cost collar insurance.

Pineda, Conejo and Carrion [1] analyzed the impact of an insurance contract on the decisions of an electric energy producer if some units fail. Braun and Lai [2] summarize the risks that energy companies face and analyze which one of these risks can be covered by insurance. Torrey and Russell [3] and Fumagalli, Black and Vogelsang [4] propose the use of a particular type of insurance to enhance the reliability of supply for consumers, with the objective allocating the risk of forced outages to the distribution provider, rather than to the consumer. Lien and Moosa [5] analyse the solution to the problem of choosing the parameters and determining the outcome of a currency collar. To the best of our knowledge, this is the first time that collars options are proposed for a wind power generation company in Brazil.

The results indicate that there are feasible strikes points (bottom wind, wind upper) in all quarters of the year during the contract period that are of interest of both companies simultaneously. Also we found a negative relationship between the values of the generator and the insurer. Note that, we estimate the strike points where both companies will be better with the insurance contract than without it. Therefore, it is important for these companies be aware of this information once it increases their bargaining power. Each company will choose those points that are in accordance with its decision rule.

The rest of this paper is structured as follows. Section 2 presents our methodology to find the contract region. Section 3 applies the proposed methodology to a case study. Section 4 shows the main results. Section 5 provides our final remarks.

2. The Model

The wind generator can either sell all his energy production in the short term market at prevailing prices, or enter into long term fixed price contracts with energy dealers in order to hedge against price uncertainty ([6]). This contract allows the energy generator selling a certain power quantity (e.g., 120 MW) during a given time period (e.g., next year) at a given price (e.g., 30$/ MWh).

However, if the production turns out to be lower than expected, the producer is required to purchase energy in the market and he becomes exposed to price risk. Then, in order to hedge against it, the energy generator can purchase an insurance contract. From an energy generator perspective, this contract is a financial instrument whereby he pays a premium to the insurer in exchange of receiving a certain amount from the insurer if financial losses occur. Consequently, according to Guay and Kothari [7] insurance is an important element of a firm's overall business strategy.

A recent risk management tool in the energy market is the collar insurance contract, which is used to hedge firms against exogenous risks. The primary goal of risk management is to eliminate the probability of costly lower-tail outcomes that would cause financial distress ([8]). In this sense, collar contracts reduce the likelihood of loss to the insured and increases the possibility of gains to the insurer, i.e., they set a floor and a cap ([9]) to the insured.

To clarify the collars concepts, Figure 1 presents an illustrative example of a collar insurance contract for one year. During this time horizon, the wind is forced out of the strike prices interval from week 18 and 23. If the producer has signed a forward contract for this period, he has to purchase the energy in the short term market to meet his selling obligations. However, if the producer has also signed an insurance contract, the insurer has to pay the producer the difference between the lower strike price and the insured wind times the market price in all the period. On the other hand, the insurance contract requires the producer to transfer any excess of wind revenues above the upper strike level to the insurer.

Mathematically, a collar option can be described as follows. Assume that the wind farm profits are represented by $\Pi(\Gamma|\gamma)$, where γ is the wind event and Γ is the set of resources used in the generation. Under this specification, $\Pi(\Gamma|\gamma)$ is determined by the input set, but the ultimate measure of profits is conditioned on the specific wind events. Profits are determined from revenues $P^{*}Y(\Gamma|\gamma)$ and the cost function $C(\Gamma|\gamma)$. The economic effect of wind risk is measured by both. It is assumed that Γ is predetermined so that marginal profits can be measured relative to γ alone.

We assume that $Y()$ is concave in γ while $C()$ is convex in γ which implies that as wind increases $\frac{dY}{d\gamma} > 0$ up to some point at which γ^{*} is optimal, $\frac{dY}{d\gamma} = 0$, and then $\frac{dY}{d\gamma} < 0$. This assumption guarantees that wind insurance does not apply to low wind conditions alone, but can also be applied to specific events of excessive wind. The convexity argument in the cost structure is justified by a symmetric argument. There will be some γ^{*} such that $\frac{dC}{d\gamma} = 0$. For $\gamma < \gamma^{*}$ costs will be increasing as the costs associated

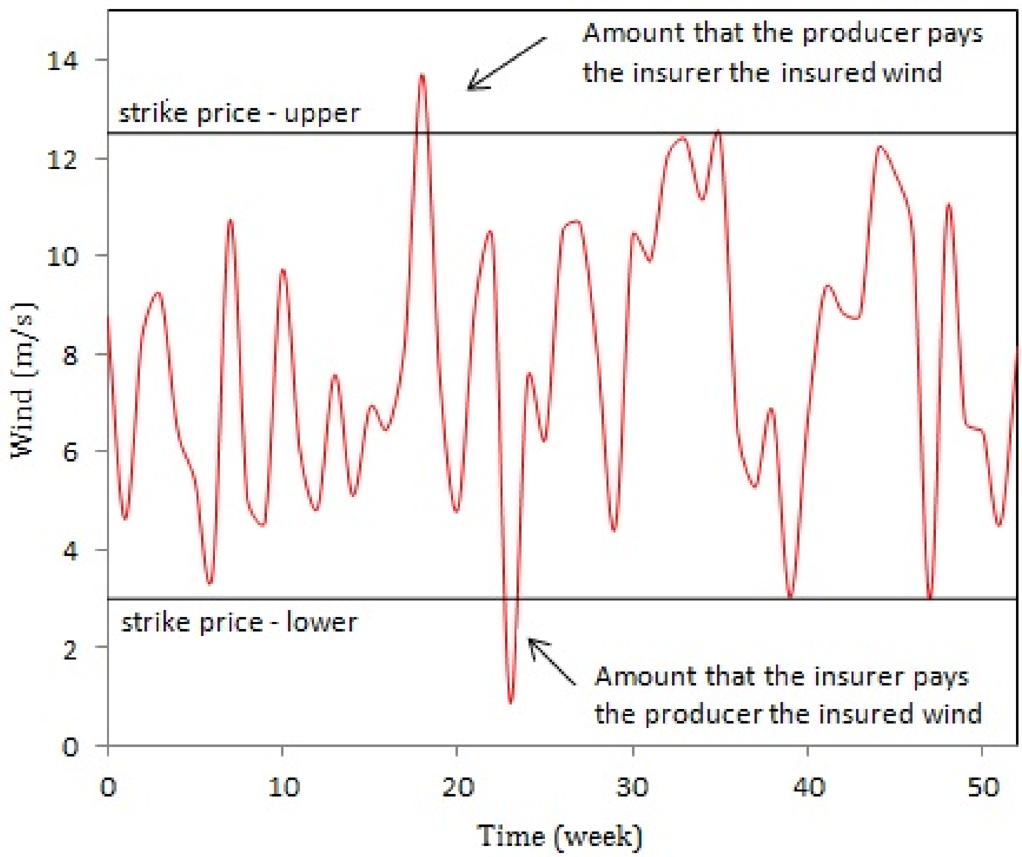

Figure 1: Insurance contract.

with low wind increase and for $\gamma > \gamma^*$ costs associated with excess wind are incurred. Marginal profits are then equal to equation 1.

$$\frac{\partial \Pi(\Gamma|\gamma)}{\partial \gamma} = P\frac{\partial Y(\Gamma|\gamma)}{\partial \gamma} - \frac{\partial C(\Gamma|\gamma)}{\partial \gamma} \tag{1}$$

This equation will be convex with $\frac{\partial \Pi()}{\partial \gamma} > 0$ for $\gamma < \gamma^*$, $\frac{\partial \Pi()}{\partial \gamma} = 0$ for $\gamma = \gamma^*$ or $\frac{\partial \Pi()}{\partial \gamma} < 0$ for $\gamma > \gamma^*$.

From the firms' perspective Π_{min} depicts a critical profit level which needs to be protected. Accordingly, the insured has three contract options. The insured can select a put option which would provide an indemnity if wind falls bellow γ_{lower}, a call option if wind exceeds γ_{upper}, or both (a collar). In general the price of these contracts would be:

$$V_{put} = \int_{-\infty}^{\gamma_{lower}} \Pi'(\gamma)(\gamma_{lower} - \gamma) f(\gamma) d\gamma \qquad for\ \gamma < \gamma_{lower} \tag{2}$$

and

$$V_{call} = \int_{\gamma_{upper}}^{+\infty} \Pi'(\gamma)(\gamma - \gamma_{upper}) f(\gamma) d\gamma \qquad for\ \gamma > \gamma_{upper} \tag{3}$$

Equations 2 and 3 rely on several factors to be priced. First, $f(\gamma)$ represents the probability distribution function; second the insured must have some idea of the specific event to be insured. For the put option in equation 2, the specific event is $\gamma < \gamma_{lower}$, and for the call option in equation 3 the specific event is given by $\gamma > \gamma_{upper}$, where γ_{lower} and γ_{upper} are, respectively, the bottom wind and the wind upper or the strike levels. Finally, the third element is the absolute value $\Pi'(\gamma)$ which will increase as wind moves away from the optimum. As written in 2 and 3, the pure-form derivative product would increase compensation at an increasing rate as the option moved further into-the-money.

Indeed, collars options allow for greater flexibility through some market responsiveness. A popular type of collar is the zero-cost collar (or costless collar). Zero-cost collars involve buying an out-of-the-money call (or put depending on the hedger's needs) and selling an out-of-money put (or call) of equal value with the same expiration date ([10]). The proceeds from selling the put offset the option premium on the call, so no upfront cash is required. The put provide insurance to the holder against any downward movement in the asset price below the strike price. Any movement above the strike price of the call is lost profit.

2.1. The Omega Performance Measure

The omega measure is a performance measure introduced by Keating and Shadwick [11]. Most indicators consider that the mean and variance completely describe the distribution of returns and these simplifications are valid if we assume a normal distribution of returns or values. However, it is generally accepted that the returns on investments do not have a normal distribution. The omega measure makes no such assumptions regarding the distribution of returns nor utility functions, but assumes that investors always prefer more to less, i.e., a higher value of omega is always preferred to a lower value.

This measure is a function of the return level and requires no parametric assumption on the distribution. Precisely, for any investor, returns below its specific exogenous threshold point (L) are considered as losses and returns above as gains. This is shown in Figure 2.

The omega measure provides a ratio of total probability weighted losses and gains that fully describe the risk-reward properties of the distribution. Therefore, for a random variable X defined on the interval $[a, b]$ and for a threshold point, L, the omega function is defined as:

$$\Omega(L) = \frac{\int_L^b [1 - F(x)]dx}{\int_a^L F(x)dx} \tag{4}$$

Where F is the cumulative distribution function of X. Note that the gain area in Figure 2 represents the numerator of equation (4) and the loss area

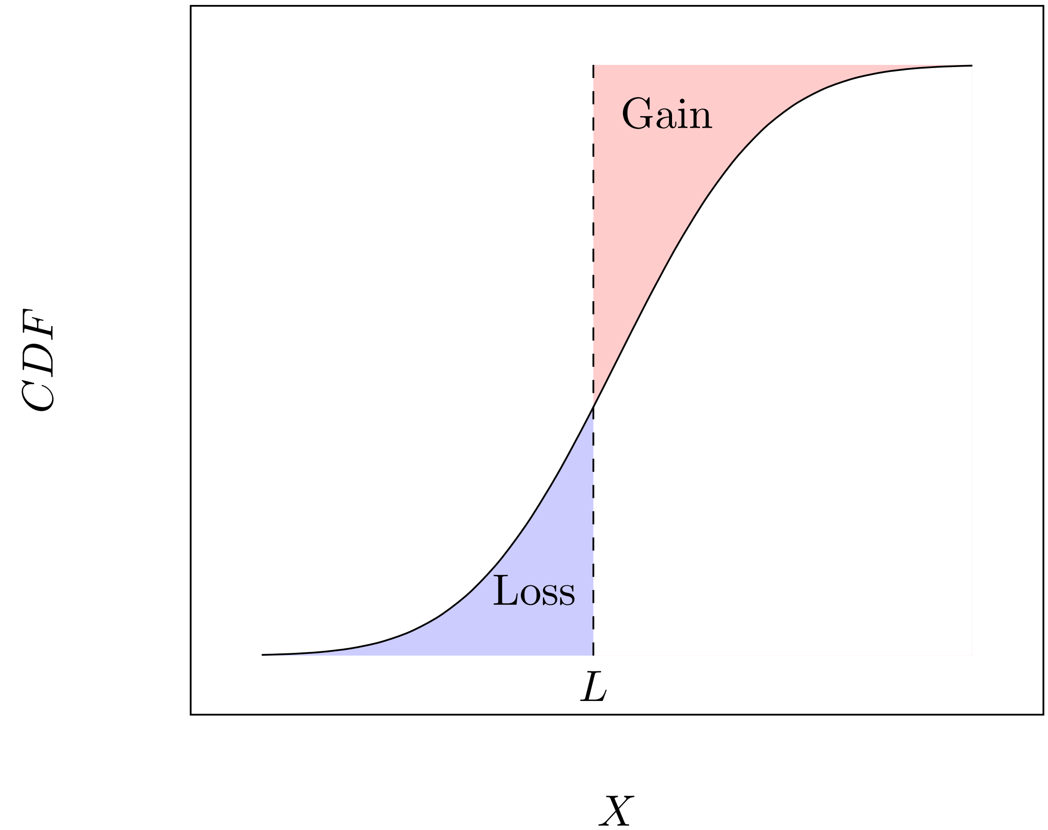

Figure 2: The omega performance measure.

is its denominator.

There is an alternative representation of the omega measure that is equivalent to equation (4), which, can be represented by the ratio between two expectations ([12]) as:

$$\Omega(L) = \frac{\int_L^b (x-L) f_x(x) dx}{\int_a^L (L-x) f_x(x) dx} = \frac{E[max(X-L;0)]}{E[max(L-X;0)]} \tag{5}$$

Equation (5) can be interpreted as the ratio between an undiscounted call option and an undiscounted put option, both with strike price L. Some studies that have employed this performance function can be cited as Eling [13] and Kaplan and Knowles [14].

As stated by Keating and Shadwick [11], when the returns are normally distributed or when higher moments are insignificant, omega tends to agree with traditional measures such as the Sharpe ratio. But, hedge fund returns differ significantly from a normal distribution ([13]) as well as wind insurance.

2.2. Decision framework

Energy producers can use insurance contract tools in order to stabilize revenues and profits. Especially, wind collars insurance contracts provide energy generators with protection by mitigating exposure to extremely adverse wind and price scenarios while giving up the upside potential profit resulting from extremely favorable wind scenarios.

In the case of wind insurance contracts, the parties involved must define agreed upon strike levels. This decision is very important and need to be taken based on all possible combinations of wind speed that generate the best results for both companies.

Therefore, our proposed model is run at the beginning of the time horizon in order to decide the insurance contracting boundaries. According to this model, the insurer will accept all combinations that generate a positive expected value, since it is risk-neutral, while the insured decides whether or not to sign the insurance contract according to the new omega's and the no-contract omega, since it is risk-averse.

To better understand this decision-making process, consider a contract that insures the company for losses: if profits are negative the insurance company covers the loss, but if profits are larger than its expected value, all the excess profit goes to the insurance company. If the company chooses to accept the contract, the expected value (EV) of the profit reduces from EV to $EV^{'}$. However the omega (Ω) increases from Ω to $\Omega^{'}$. Since the energy generator is risk averse, he will choose the distribution with the biggest omega, i.e. he accepts the contract. If there is no contract, the insurance company profit is 0. Since it is risk neutral, it will accept contracts with positive expected values. With the insurance contract the expected value increase to $EV^{''}$. Then, the expected value for the insurance company is positive, and the contract is also accepted.

Note that the decisions made by the generator and the insurer depend both on non-negotiable and negotiable variables ([15, 6]). In this article, the non-negotiable variables are market prices and wind speed as these are out of the control of both parties. On the other hand, the strike levels are negotiable variables since both parties must agree on their values for the insurance contract.

3. Empirical analysis

We study the case of the Amontada wind farm, located in the state of Ceara, Brazil. The managers of this wind farm have a long term energy contract with a national energy distributor, but if production is insufficient to fulfill their obligations they are required to purchase energy in the short term market, which may cause significant financial losses due to price risk.

As the Amontada manager's faces two main sources of uncertainty - short term electricity spot prices and wind speed levels - they are interested in signing a wind insurance contract. This contract could limit the generator financial losses and increase the insurer profits.

To sign the contract, the parties involved need to know the strikes points that could be signed, and this is not a trivial matter. Therefore, we run a stochastic programing model to determine the optimal pairs of bottom and upper wind speeds that would make both the generator company and the insurer be interested in a zero cost collar insurance contract.

It is important to note that this contract has a few particularities. First, it is modeled as a zero-cost collar contract, i.e., no premium is paid. Second, the contract period, i.e., the year of 2015, is analyzed by quarters. In other words, liquidations between the two parts occur every three months. Third, it is considered that the insurance contract is a European option. Then, at the end of each quarter if wind speed is below the lower bound the insurer covers the forward contract of the generator; otherwise, if speeds are above the upper bound, the excess of generation goes to the insurer. Within these boundaries no action is taken, and these boundaries are the strike points of the collar option. But, if the wind exceeds these boundaries, the option is deep-in-the-money.

3.1. The wind distribution of Amontada

We use examine the monthly database of the wind series for the period running from January 1990 to July 2014. Since the wind speed measurement in the wind farm only began in 2010, the data was combined with the Modern Era Retrospective analysis for Research and Applications (MERRA) wind speed measure at a nearby location. The correlation between the two series in this period is 98%.

Given that the turbine height is 90 meters and the MERRA wind speed data was measured at 50 meters, an adjustment was made using the wind profile power law ([16]), according to equation 6.

$$\overline{U}_{h_1} = \left(\frac{h_1}{h_2}\right)^{\alpha} \overline{U}_{h_2} \tag{6}$$

where

$\overline{U}_{h_i}$ = Wind speed;

h_i = height of each measure of wind speed;

α = wind speed vertical profile exponent, also known as the Hellmann exponent.

Following Kaltschmitt et al. [17], we adopted an alpha of 0.27 for unstable air and inhabited environments. Figure 3 illustrates the time evolution of the wind speed series in the full-sample period. The wind oscillates in short swings in a volatile regime with high speed values.

The descriptive statistics of the monthly wind data is presented in Table 1. The wind speed series is skewed to the left, platykurtic, and can be shown to follow a Weibul distribution.

Table 1 also evaluates the persistence of the wind series through a battery of testing procedures. It reports the p-values of the Augmented Dickey Fuller (ADF) and Phillips-Perron (PP) tests for unit root as well as the values of the KPSS test statistics for the null hypothesis of stationary. We select the number of lags in the ADF test using the Bayesian information criterion, whereas we run the KPSS test using the quadratic spectral kernel with bandwidth choice as in Andrews [18]. The null hypothesis of a unit root

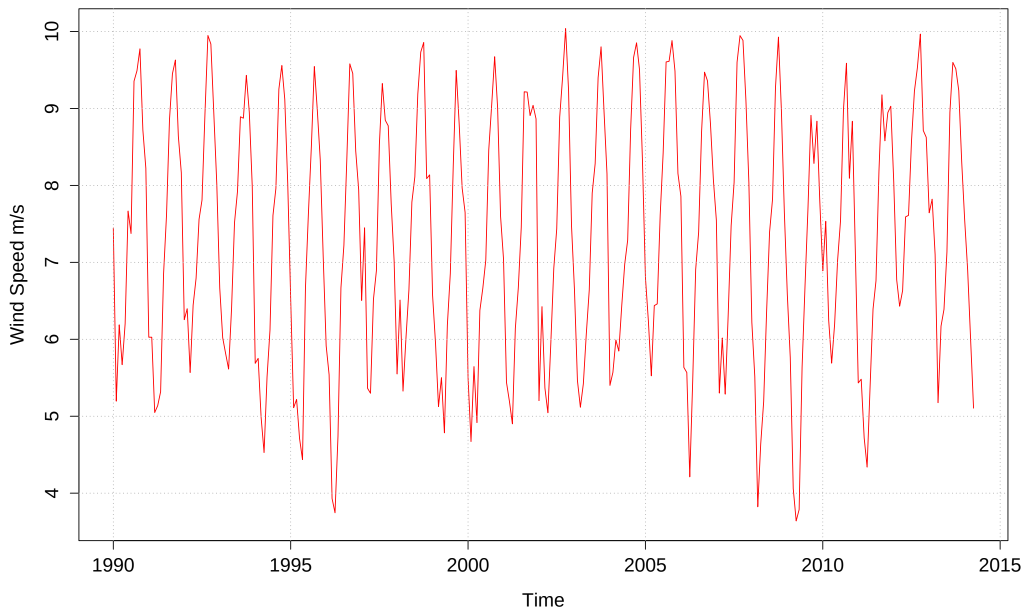

Figure 3: Historical wind series.

for the wind series with the ADF and PP tests is strongly rejected in each half of the sample as well as in the full sample. Similarly, the KPSS test cannot reject the null of stationarity.

We use the Auto Regressive Moving Average with monthly dummies as exogenous variables (ARMAX) model to forecast wind speeds. Two other models were tested, the simple ARMA and the SARMA. The best model was selected using the Bayesian information criterion (BIC). The best ARMA model was a ARMA(2,3), the best SARMA was a SARMA(1,0)(1,0,1,12) and the best ARMAX was a ARMAX(2,0) with dummies for months.

For each model we used a rolling window of 240 observations and we estimated the monthly prediction errors. The results showed that the AR-

Table 1: Descriptive statistics for wind.

Sample Statistic	Full Sample
Mean	7.297
Median	7.447
Minimum	3.639
Maximum	10.04
Standard deviation	1.610
Skewness	-0.119
Kurtosis	-1.058
Jarque-Bera	0.000
ADF	0.010
PP	0.010
KPSS	0.100

MAX is equal or better than all the other models on all statistics. Then, we chose the ARMAX to generate the scenarios, but we also tested the simple ARMA and the SARMA and the forecast errors were bigger. The sample autocorrelation and partial autocorrelation functions presented in figure 4 corroborates this choice.

Using the wind simulated time-series, we draw the wind distributions of the Amontada wind farm for each quarter of the insurance contract. These distributions are presented in Figure 5. This figure shows a regular distribution of the wind throughout each quarter of the year 2015.

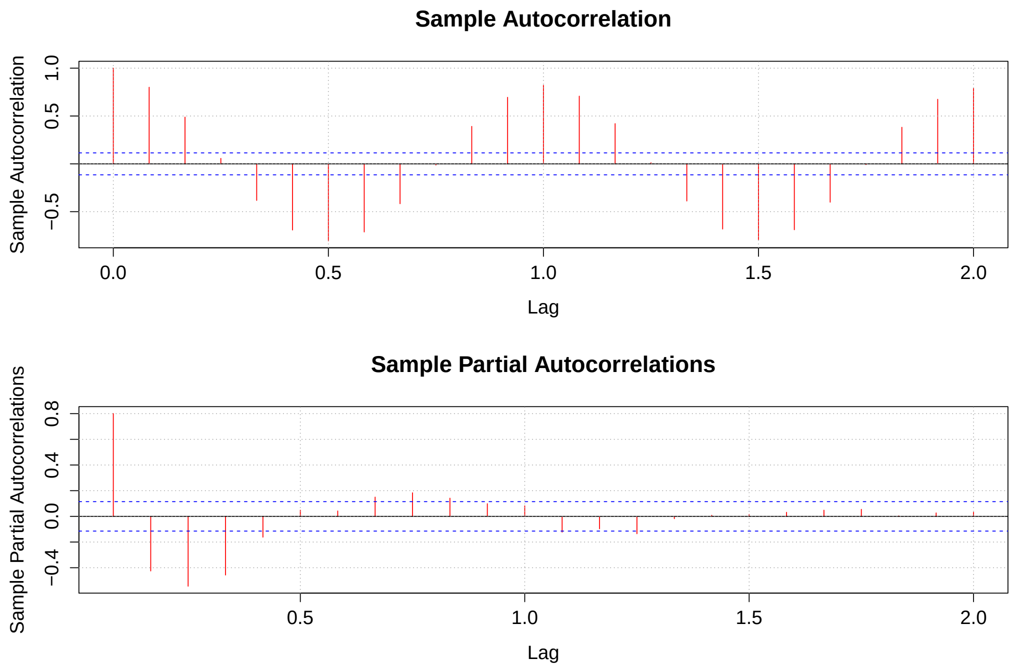

Figure 4: Sample autocorrelation and partial autocorrelation functions of the wind.

Figure 5 shows that the Amontada wind farm is characterized by constant winds throughout the year, but with some seasonal adjustments. The first and second quarters are the periods with the strongest winds. In these quarters, the wind can reach high speeds. The last two quarters are characterized by low wind speed. Note that, the wind speeds observed in the dry seasons (two first quarters) show a higher capacity of power generation at the moment that the hydrological affluence in hydroelectric reservoirs is reduced.

Considering these distributions, the generator has higher gain expectations over the period that the winds are stronger. Thus, in the firsts quarters the generator considers as lost very high values and, therefore, the threshold

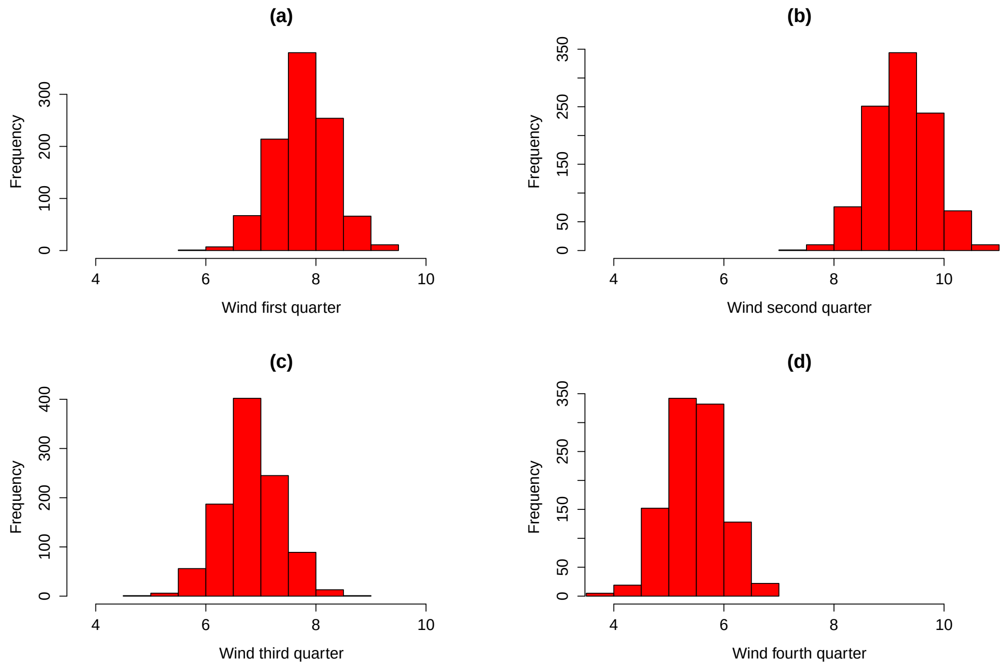

Figure 5: Wind distributions.

(L) is high. In the lasts quarters, the gain expectations is lower, then the loss threshold is lower too. Note that, the choice of L will determine the omega measure, which have an impact in the amount of points that could be in the contract, i.e., depending on L the generator may have more strikes options to choose. Then, we did some sensitivity analysis on L to see the size of this impact. The results are presented in Figure 6 and 7. We noted from these figures that, as the generator increases his loss threshold the less is the omega measure and the contract possibilities [1]. In other words, if the wind farm

[1] The omega measure is calculated on the distribution of profits and both the L and the distribution are in millions of BRL.

managers have very high loss level tolerance, they will be more susceptible to risks and, therefore, they will not be very interested in the wind insurance contract.

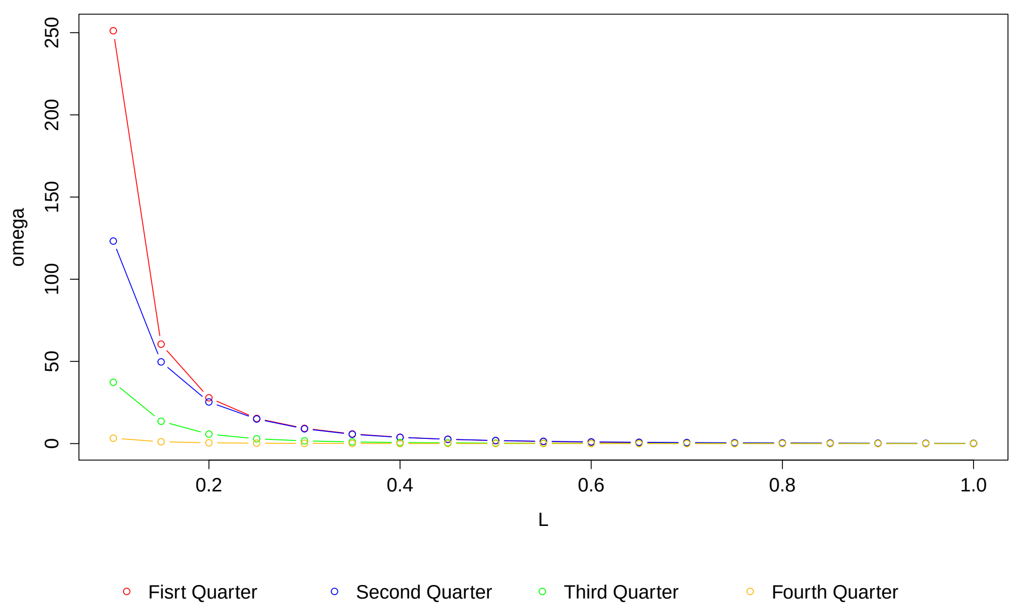

Figure 6: Omega measure.

4. Results

For each quarter of the year 2015 we found all wind speed combinations that both enterprises would be willing to sign the contract. The entire process took approximately 10 seconds to be calculated using the @Julia programming language.

We assume that the proxy for spot market energy price is the "Preço de Liquidação de Diferenças" (PLD) determined by the Electrical Energy

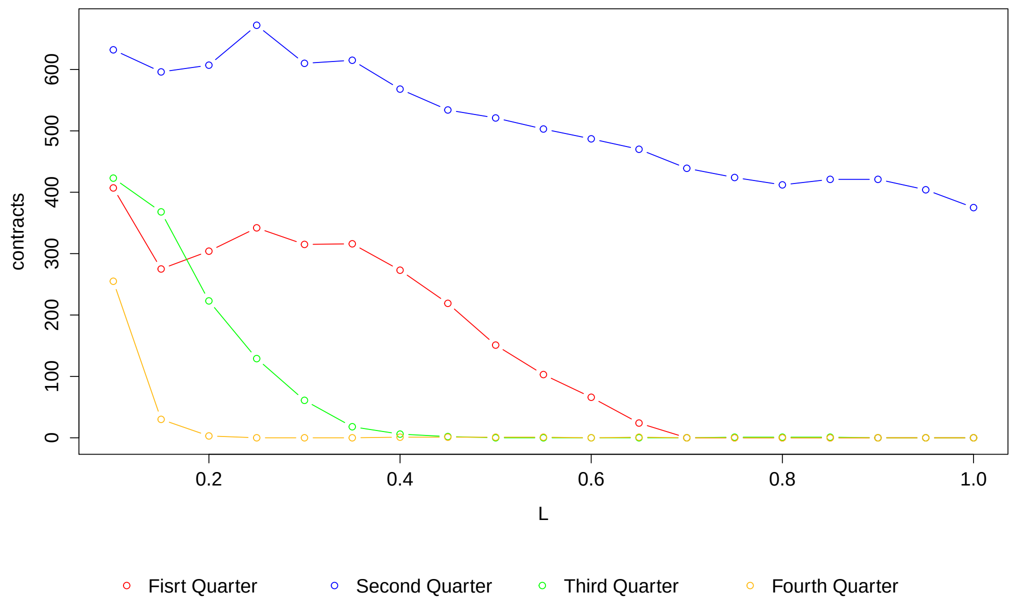

Figure 7: Possible contracts.

Clearing Chamber (CCEE) and use the monthly simulation made by the National System Operator (ONS) in August 2014 for the year of 2015 for each of the four energy submarkets in Brazil. As we consider a wind generator in the Brazilian northeast, the corresponding time-series for that submarket was used.

The results of descriptive statistics of wind, spot prices and thresholds are presented in Table A.2 attached for each quarter of the contract period. These results are on scale of a single wind turbine, but the wind farm has 28 turbines [2]. We note from this table that while the firsts quarters are marked

[2]We did the analysis for a single turbine because the values are easier to understand

by strong winds, the last two quarters are marked by light winds. Besides, the prices are higher in the first and fourth quarters and the thresholds are higher in the first two quarters [3].

These characteristics are considered in forward contracts and the generator expects to earn more profits in the first two quarters of the year than in the last two. Therefore, if the energy production is lower than expected, the generator will face the following scenarios. A low production in the first or third quarters will result in major financial losses, since the market price is higher in these periods. If the low production occurs in the second or fourth quarters, despite the more controlled price, the generator must purchase energy in the market to meet his obligations, which will also generate large losses.

Thus, there exists an interest in the wind insurance contract in all quarters of 2015. Then, we need to find all possible (bottom wind, upper wind) points where both companies would be willing to sign the contract. Figure 8 shows these results [4]. The points in this figure were determined from the intersection of those points that generates a positive expected value for the insurer, since it is risk-neutral, with those points that generates a higher omega (with the insurance contract) for the generator, since he is risk-averse.

[3] Is important to note that, since Brazil is passing through an energy crisis, prices are having an unusual behavior. The water storage is very low, during the end of the raining season (January to March) there is a lot of speculation on the energy price caused by the expectation of rains.

[4] The results are presented in wind, but the omega measure was calculated considering also the uncertainty on energy prices and the conversion of wind speed in into MWh.

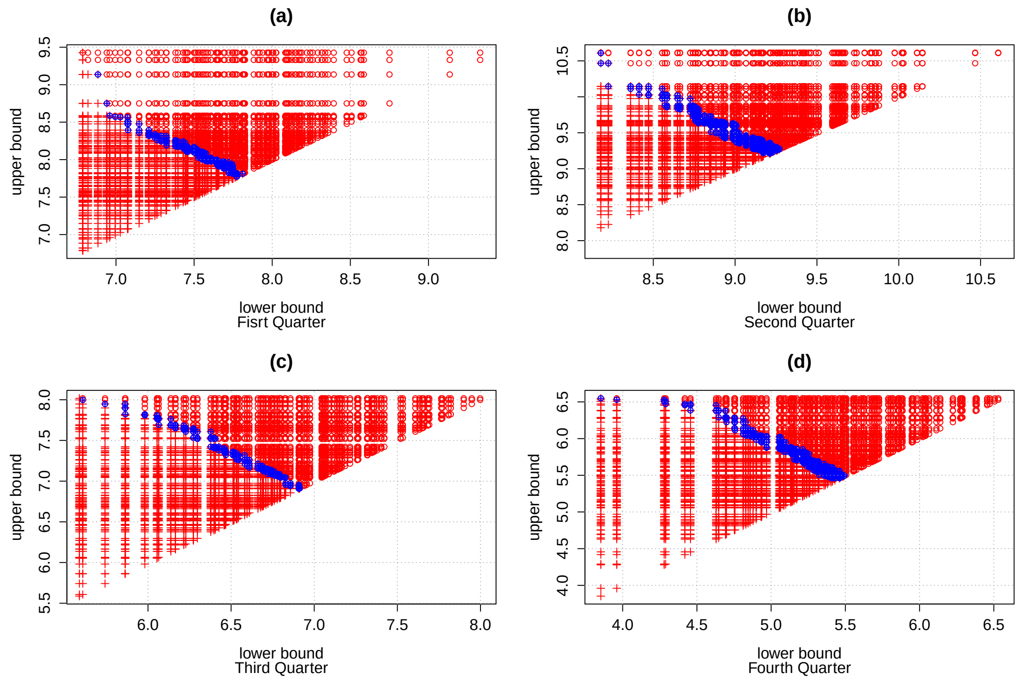

Figure 8: Wind combinations.

The red part in these figures shows a combination of bottom wind and wind upper for each of stakeholders. The region bellows the blue points refers to all wind combinations that the insurer is willing to accept. The region above the blue points represents all wind combinations that the power generator is willing to accept. The part highlighted in blue color shows the intersection of these points, i.e., the combinations of wind speed that are acceptable for the insured and the insurer. In other words, it has a positive expected value and higher omega at same time.

We note that in all quarters there are points where both companies accept sign the wind insurance contract. In particular, there are more opportunities for agreement on the second and fourth quarters than in the first and third quarters. Besides, we note that the generator has more interest in the contract in the first two quarters, which are those with the highest number of points above the blue region than in the last two quarters. Note that the insurer has many optimal points close to the generator interest, which makes this intersection region larger.

The position of these points over the wind mean is demonstrated by Figure A.11 attached. The parts a-b of this figure show the variation of the omega measurement in each boundary. The parts c-d show the variation of the expected value for the insurer in each boundary. Note that the first and third quarters are those with larger distances between the bottom wind and the upper wind. In the other quarters these intervals are small. Furthermore, in all quarters most of wind combinations have lower bound below the mean and upper bound above it. Only in some scenarios wind points are simultaneously below or above the wind mean.

Note that depending on the period, the distance between bottom and upper may vary greatly. In this sense, Figure A.12 attached shows the boxplot of the wind points in each quarter. The location of the quartiles indicates if there is a concentration of the wind points close to the wind mean. The first and second quarters are those with the highest accumulation of the points of lower bound and upper bound around the wind mean. In the third and fourth quarters was observed a greater dispersion of these points from the wind mean.

Each of these points generates a result for the insurer and the insured. Figure 9 shows the benefits of the insurance contract for both companies. In this illustration the color changes from dark blue to dark red as the benefit of the option is more advantageous for either company. Dark blue color is related to those combinations of wind speed that are more advantageous for the power generator. Dark red color shows a better result for the insurer. A merge of two colors means that both companies would be good, but could be better. The points have a descending spiral shape, which means that for wind combinations very favorable for the generator, the insurer has expected value close to zero; otherwise, the opposite occurs. Under a different optical Figure 10 shows the relationship between the omega measure of the generator and the expected value of the insurer. We note that the third and fourth quarters are those periods in which the generator earns higher omega with the insurance contract. This figure also evidences the fact that the expected value of insurer is higher in the second and fourth quarters.

Finally, it was shown that when the generator has some contract obligations, uncertainties about wind and market prices make the wind insurance contract becomes valuable for both companies. There are several possibilities for agreement between the generator and the insurer. Which of these possibilities will be the chosen strike of the insurance collar option contract depends on the bargaining power of these companies and it is not in the scope of this paper.

The bargaining power is the ability to secure an agreement with another agent on their own terms, i.e., the agent with the greater bargaining power is more likely to achieve his goal than the agent with the least power. In cases of difference of opinion, an assumption is that the principal has the bargaining power when designing the contract. According to Inderst [19] this may be reasonable if there is competition between various and sufficiently

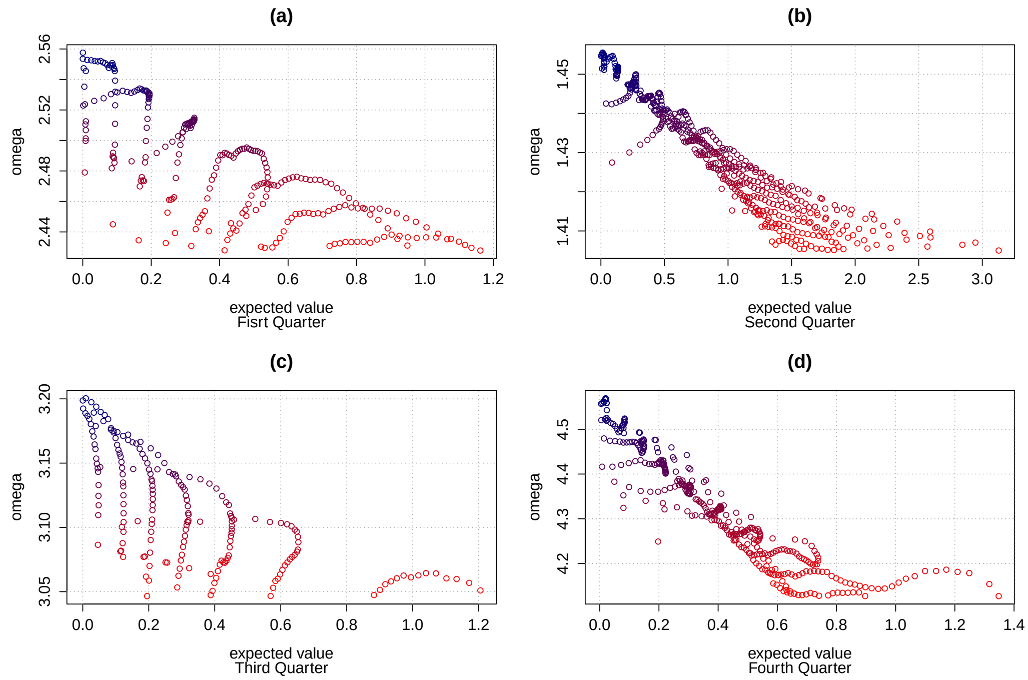

Figure 9: Comparison of the best contract to both companies.

homogeneous agents. Some papers like Lien and Moosa [5] study the relation between bargaining approach and operational hedging technique of currency collars, but they ignore how to estimate the combinations of strikes points that will be analyzed by the bargain holders, which is the target of this work.

5. Conclusion

A Brazilian wind power generation company has a long term energy contract and wants to protect itself against a low energy production and huge financial losses. In order to fulfil its obligations, due wind uncertainties, the managers may need to buy the energy deficit in the pool, which exposes the company to price volatilities. Then, this company is seeing the opportunity

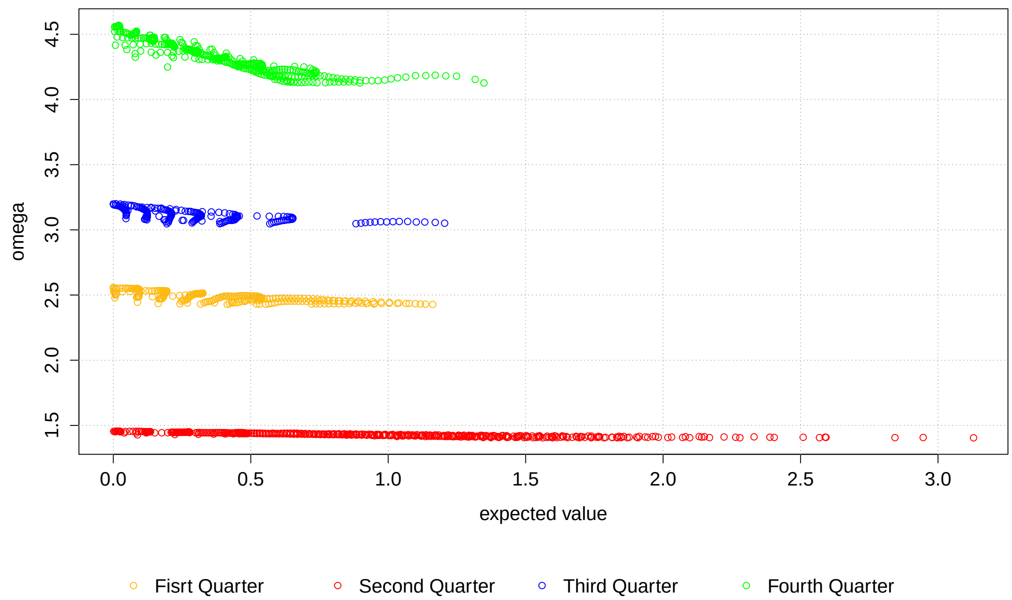

Figure 10: Comparison of Omega and Mean in each quarter.

to sign a wind insurance contract with an insurer.

This contract is zero-cost collar type, which means that there are two wind strikes that are considered in the agreement. One of these boundaries is called lower wind or lower strike, which means that if blows below the lower wind the insurer fulfil the generator obligations. The other boundary is called wind upper or upper strike, which means that if blows above the wind upper the generator is required to give a part of the energy for the insurer. We note that, the determination of the contract agreement points is challenging and that, to the best of our knowledge, this is the first time that this kind of insurance contract model is proposed for a Brazilian company.

This paper presents a methodology to find all possible contract points that would make both companies best with the contract than without it. To estimate the optimal strikes points we propose a stochastic programming model that follows five steps: 1) determine the market price for the period in analysis; 2) forecast the wind for the insurance contract period; 3) consider all forward contracts of the generator; 4) Determine the characteristics of the insurance contracted; 5) Consider the risk aversion of each company and its decisions framework, i.e., the optimal points consider all those scenarios with higher omega and positive expected value. This process took approximately 10 seconds to be calculated.

The results showed that in all quarters there are opportunities for both companies signing the wind insurance contract. The regions with more contract opportunities are on the second and fourth quarters. The second quarter is marked by strong winds, low prices and great expectation of generating high profits in future markets. In this period, if the energy production be lower than expected the insurer will have to compensate the generator with relatively low spot prices, but, even then, if the production is much lower than expected the financial losses can be huge; otherwise, if blows above the expected, the insurance company will bill. Thus, in the second quarter the insurer has the highest expected values, while the omegas are small. The fourth quarter is marked by light winds, low prices and low futures contracts. During this period the insurer has many contracting options and its expected values are high, while the generator has the largest omegas with the insurance contract.

In the first quarter the winds are strong, but if the energy production fails the generator must to purchase the energy deficit in the market at very high prices and, thus, the insurance contract is desirable. In this period, omegas and expected values are low. The third quarter is marked by light winds, but if the generator needs to buy power in the market to meet his obligations, he will faces high prices and, therefore, the contract is also justified in this period. In this period, the omegas are high, but the expected values are low.

Finally, we found a negative relationship between the omega measure of the generator and the expected value of the insurer in all quarters of the year. The largest omegas values are associated with the smaller expected values, and vice-versa. The determination of which of these points will be chosen for the contract depends on the bargaining power of the companies that are interested in the insurance contract, but it is not in the scope of this paper. The insurer can achieve the highest expected values in the second and fourth quarters. The generator reaches the highest omegas values in the third and fourth quarters.

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Appendix A.

Table A.2: Descriptive statistics.

Wind Simulations (m/s^3)					
	μ_w	$median_w$	σ_w	min_w	max_w
First Quarter	7.77	7.63	0.63	4.54	11.24
Second Quarter	9.23	9.42	0.66	6.87	11.55
Third Quarter	6.82	6.51	0.64	3.94	9.92
Fourth Quarter	5.48	5.40	0.63	3.23	7.90
Prices Simulations (US$) *					
	μ_p	$median_p$	σ_p	min_p	max_p
First Quarter	105.66	83.25	74.91	5.21	274.3
Second Quarter	78.44	60.60	65.35	5.21	274.3
Third Quarter	85.22	64.17	68.44	5.21	274.3
Fourth Quarter	72.30	51.35	67.32	5.21	274.3
Threshold (L) **					
	1 Turbine	All Turbines			
First Quarter	0.42	11.76			
Second Quarter	0.52	14.56			
Third Quarter	0.21	5.88			
Fourth Quarter	0.07	1.96			
Total	-	34.16			

* We use an exchange rate of 3 USD/BRL.

** L is the percentile of 10% of the generator profit distribution without the insurance contract.

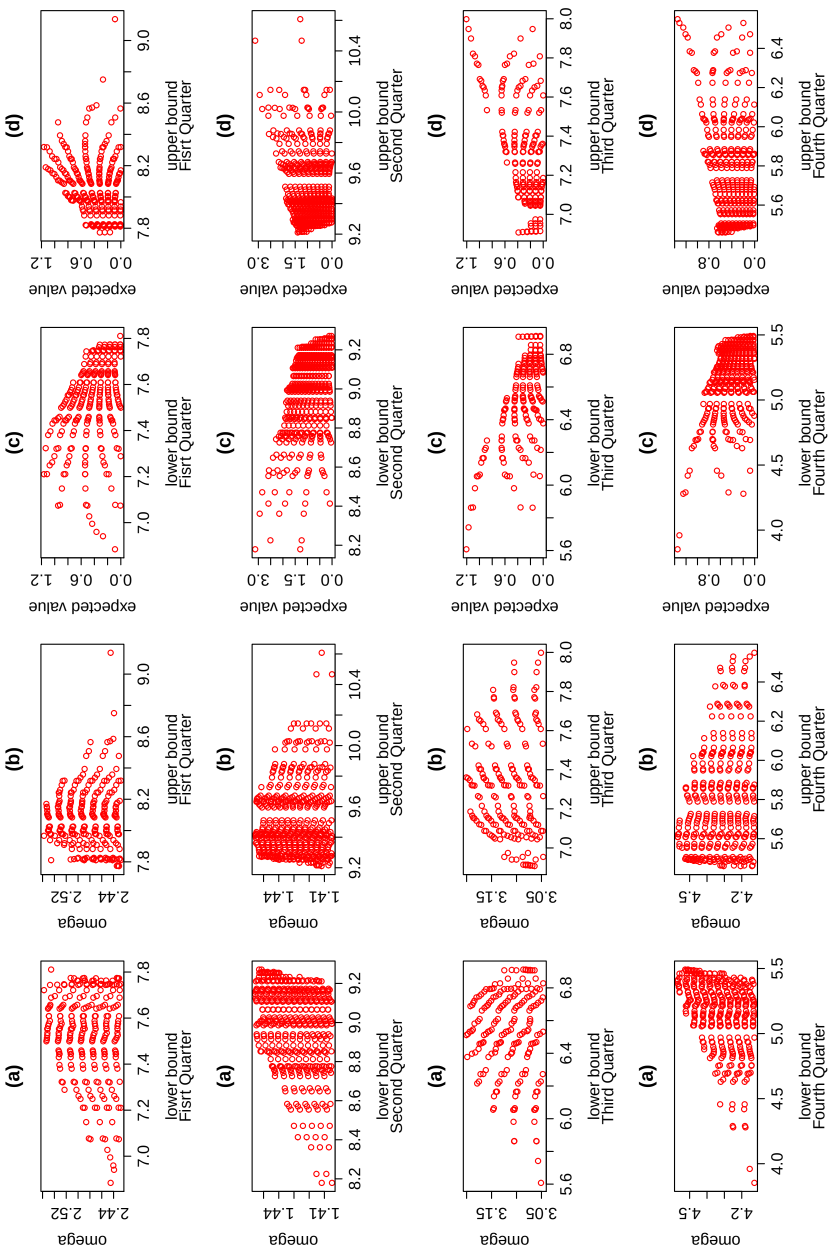

Figure A.11: Comparison between wind pairs and the insurer expected value and the generator omega.

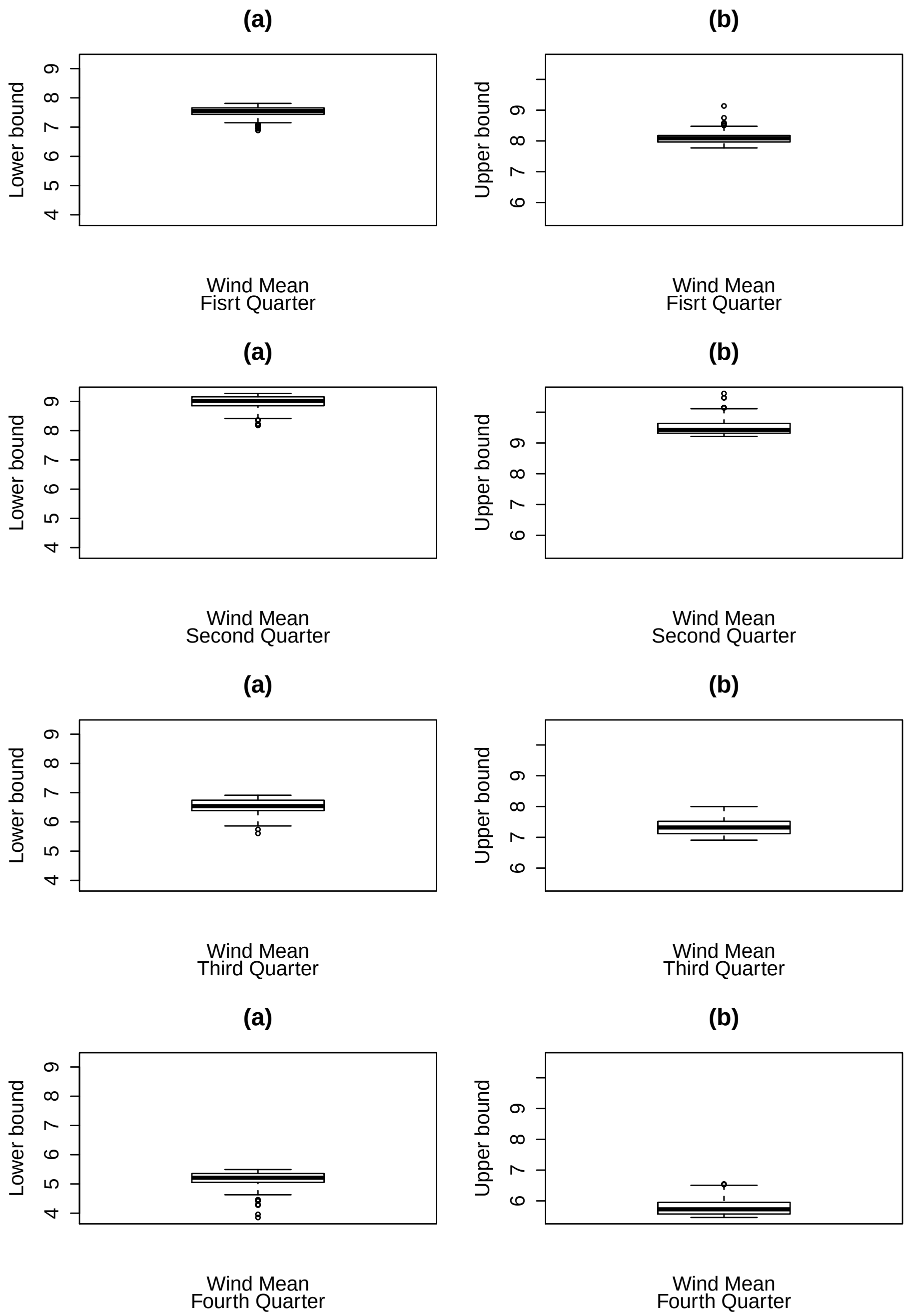

Figure A.12: Boxplot.

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