Mitigating Wind Exposure with Zero-Cost Collars Insurance

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Abstract

Renewable energy generation worldwide has relied increasingly on wind farms where wind energy is transformed into electricity. On the other hand, electricity prices are uncertain and wind speeds are highly variable, which exposes the producer to risks. Typically wind power producers enter into long term fixed price contracts in order to hedge against energy price risk, but these contracts expose the wind farm to energy volume risk, as it requires delivery of the full amount of energy contracted, even if energy production falls short due to low wind speeds. To mitigate this risk, wind producers can purchase insurance. In this article we propose a zero-cost collar insurance and develop a stochastic model to determine the feasible range of wind strikes for both the wind farm and the insurer. The results indicate there is a set of possible strike combinations that meets the objectives of both parties.

Keywords: Wind Power, Energy Insurance Contract, Stochastic models

JEL: G22, D81, G17, G11

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1. Introduction

Wind energy is a growing and increasingly popular source of clean and renewable energy, especially due to environmental issues. In recent years (Kim et al., 2014), many countries put an emphasis on the development and deployment of new and renewable energy sources to cope with the global environmental crisis and among these sources, the wind power energy is one of the core areas for investments. Nonetheless, investment in wind energy generation requires application of large amounts of resources and there are many risks associated with. This energy source is subject to environmental uncertainties (Reuter et al., 2012), it depends on the behavior of climatic variables (e.g. wind regime). Thus, it is important to mitigate wind exposure of this type of investment.

Accordin to Reuter et al. (2012), renewables-based technologies such as wind energy suffer from uncertain loads depending on environmental conditions. Unlike hydro power it cannot store wind power generation in reservoirs, and unlike thermal sources, is highly variable and strongly seasonal. In addition, there are difficulties in predicting future wind conditions, and there are financial risks due to pool price volatility. Then, to hedge against these risks the wind power producer can choose to sell its energy through forward contracts. However, due seasonality some periods shows overproduction while than at other times indicate energy lack. If production falls below expected levels, the energy shortfall must be purchased from the pool at prevailing prices. But, it extremely exposes the producer to pool prices variations. Moreover, if a price peak coincide with periods of generation deficit it may cause financial losses. This is known as volume risk. Therefore, it is important to create mechanisms to protect the producer from this risk.

In this sense, the wind farm could sign an insurance contract to minimize volume risk. Jin et al. (2014) explains that the wind power industry has high risks and since insurance is an effective instrument to control risks, it can contribute to the healthy development of the industry. According to Pineda et al. (2010), under an insurance contract the insurer receives a premium at the beginning of the contract period in exchange for a contingent liability over future energy shortfalls. The authors also analyze the impact of an insurance contract on the decisions of an electric energy producer if some units fail and conclude that insurance reduces the financial risk associated with the failures of the production units and allows the producer to sell a greater amount of energy in the futures market. A similar analysis is made by Jiang et al. (2006) who conclude that insurance can be an attractive hedge contract against financial losses caused by forced outages. In a different line, Mills (2003) states that if properly applied, energy insurance can potentially reduce the net cost of energy-saving projects by reducing the interest rates charged by lenders. Braun and Lai (2006) analyzed energy firms and determined which risks can be covered by purchasing insurance. On the other hand, none of these papers address the issue of how one determines a feasible set of strikes for an insurance contract, and the best our knowledge, this is an innovation of this article.

This paper proposes a special type of insurance contract that contributes to mitigate low production risk, i.e, we propose a zero-cost collar contract where no premium is paid. The wind mitigation is carried out by selecting a range of wind strike levels for a zero-cost collar insurance contract where both the wind energy producer and the insurance firm are better off by entering into the contract. The collar contract requires two strike values, thus we calculate all combinations of a lower bound wind strike level below which the insurance firm covers any energy shortfall the producer may have, and an upper bound wind strike level above which the excess energy goes to the insurer.

There is obviously a conflict between the interests of the wind farm and the insurer. While a very low lower strike level is in the interest of the insurer, as it minimizes the potential payments it may have to make, it is ineffective in protecting the producer against low wind speeds. Similarly, a low upper strike level may provide the insurer with significant returns at the expense of the producer. On the other hand, a high lower strike level provides maximum protection for the producer, but may be costly to the insurer, while a high upper strike level minimize the revenues the producer may be required to hand over to the insurer. Thus, while the producer is interested in high lower and upper strike levels, the insurer is interested in the opposite in both cases. Thereby, in order to find the strike levels we run a stochastic model that takes into account the firms risk aversion and the uncertainty associated with pool prices variations and possible energy shortfalls. Our model seeks to determine a set of upper and lower strike levels that provide sufficient protection for the producer considering his risk attitudes while at the same time, providing the required return for the insurer in a contract region where the insurance is possible with zero cost.

The main advantage of a zero-cost collar contract is that it provides protection for the energy producer with no upfront outlay of cash. While the particular pair of wind strike levels that both parties may choose will depend also on the bargaining power of the producer and insurer, our model determines the complete set pairs of acceptable lower and upper wind strike level that they will choose from.

Our main results show a set of contract possibilities, i.e., there are feasible strikes points (lower wind, upper wind) in all contract period. The final result (strike combination that will be signed) will depend on the bargaining power of each party. The results also presents a negative correlation between the values of the producer and the insurer. We note that in the contract region, both parties are better off with the contract, but for each pair of strike levels one party is individually better off than the other. Therefore, it is important that each of these firms be aware of this information as it increases their bargaining power.

The rest of this paper is structured as follows. After this introduction we explain the concept of a zero cost collar option contract and introduce the risk metric used to assess the insurance contract. In section 3 we present the stochastic model adopted to determine the contract region and next we apply this to the case of a wind farm in northeastern Brazil. In section 5 we discuss the main results. In section 6 we run some robustness tests and after that we conclude.

2. The collar insurance option

A collar insurance is a financial derivative instrument that can be used to hedge firms against exogenous risks. In particular, a collar option involves buying an out-of-the-money call (or put depending on the hedger's needs) and selling an out-of-money put (or call) with the same expiration date (Vander Linden, 2005). If the proceeds from selling the put are offset by the option premium on the call such that no upfront cash is required, then this derivative is a zero-cost collar.

Figure 1 illustrates a typical collar strategy. In this example, the lower and upper wind strike levels determine the bounds for the option exercise. If wind speeds are below the lower bound, such as in week 9, the insurance firm pays the energy producer any revenue shortfall incurred. Similarly, if wind speeds reach levels above the upper bound, as in week 41, the producer transfers any excess revenues to the insurer.

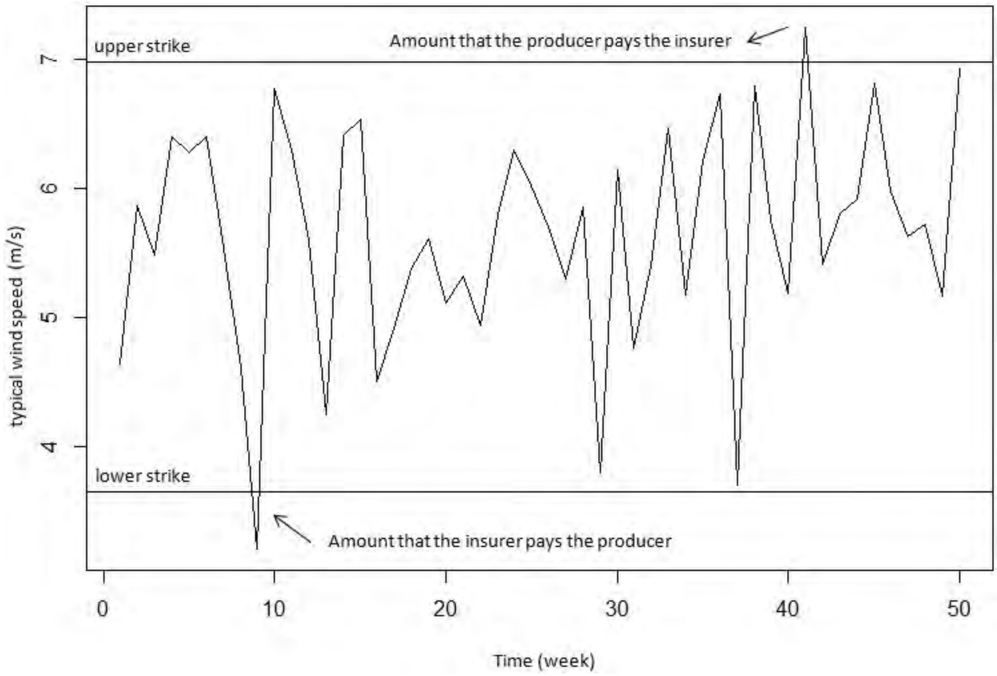

Figure 1: Collar strategy example.

Mathematically, a collar option can be described as follows. Assume that the wind farm profits are represented by $\Pi(G|\omega) = P{*}Y(G|\omega) - C(G|\omega)$, where G is the set of resources used in generation, ω is the observed wind speed, P is price, $Y(G|\omega)$ represents the production function and $C(G|\omega)$ is the cost function. Profits are determined from revenues $P^{*}Y(G|\omega)$ and the cost function $C(G|\omega)$. It is assumed that G is predetermined so that marginal profits can be measured relative to ω alone. Under this specification, $\Pi(G|\omega)$ is determined by the input set, but the ultimate measure of profits is conditional on the specific wind.

We assume that $Y(\cdot)$ is concave in ω while $C(\cdot)$ is convex in ω which implies that as wind increases $\frac{dY}{d\omega} > 0$ up to some point at which ω^* is optimal, $\frac{dY}{d\omega} = 0$, and then $\frac{dY}{d\omega} < 0$. 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 ω^* such that $\frac{dC}{d\omega} = 0$. For $\omega < \omega^*$ costs will be increasing as the costs associated with low wind increase and for $\omega > \omega^*$ costs associated with excess wind are incurred. Marginal profits are then equal to equation 1.

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

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

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

$$V_{put} = \int_0^{\omega_{lower}} \Pi'(\omega)(\omega_{lower} - \omega) f(\omega) d\omega \qquad for\ \omega < \omega_{lower} \tag{2}$$

and

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

The values of V_{put} and V_{call} depend on the parameters in Equations 2 and 3, namely $f(\omega)$ which represents the probability distribution function of the wind speed, the lower and upper wind strike levels ω_{lower} and ω_{upper} and the absolute value $\Pi'(\omega)$ which increases as wind speeds move away from ω.

2.1. Insurance contract

We assume the insurance contract has a few particularities. First, it is modeled as a zero-cost collar contract, i.e., no premium is paid. Second, due to strong seasonality, the one year contract is divided intro four independent quarters, where at the end of each all financial tradings are liquidated. Third, we consider that the this insurance contract can be modeled as a bundle of daily European type real options with expiration time t (t = 1,2,...90).

2.2. Risk measure

Manage risk is an important issue for many areas of knowledge. In this paper we adopt the Conditional Value-at-Risk (CVaR) as a risk measure to determine the wind strike levels for the producer, while assuming that the insurance firm is sufficiently diversified and thus risk neutral toward wind and energy risk. CVaR is based on Value-at-Risk (VaR) (Jorion, 2007), thus it is important to understand VaR.

VaR is a quantile commonly used to measure losses in a portfolio for various scenarios of it, i.e., VaR summarizes the expected maximum loss over a target horizon within a given confidence interval. Therefore, VaR_α is a reference and indicates that the $\alpha\%$ of the generated sets will be greater than this value. If a probability distribution is created for these scenarios it will be possible to represent VaR_α as shown in Figure 2.

Therefore, let X be a discrete random variable, the VaR at a confident level $0 \leq \alpha \leq 1$ is the minimum profit value such that the probability of achieving a lower profit is higher than or equal to $1 - \alpha$, i.e.,

$$VaR_\alpha(X) = min\,\{x : p(X < x) \geq 1 - \alpha\} \tag{4}$$

The risk measure CVaR was first described by Heath et al. (1999) with a set of properties that, according to the authors, would be desirable for a measure of risk and that the VaR measure did not have. CVaR overcomes at least one of VaR's limitations: measuring the potential losses exceeding VaR. By calculating the mean of the loss exceeding the VaR value, CVaR provides a better indication of the potential losses exceeding the assumed confidence level. Based on VaR, the CVaR (Rockafellar and Uryasev, 2000) is known as the mean excess loss of $1-\alpha\%$ worst scenarios of the previous portfolio returns, i.e., it is the expected

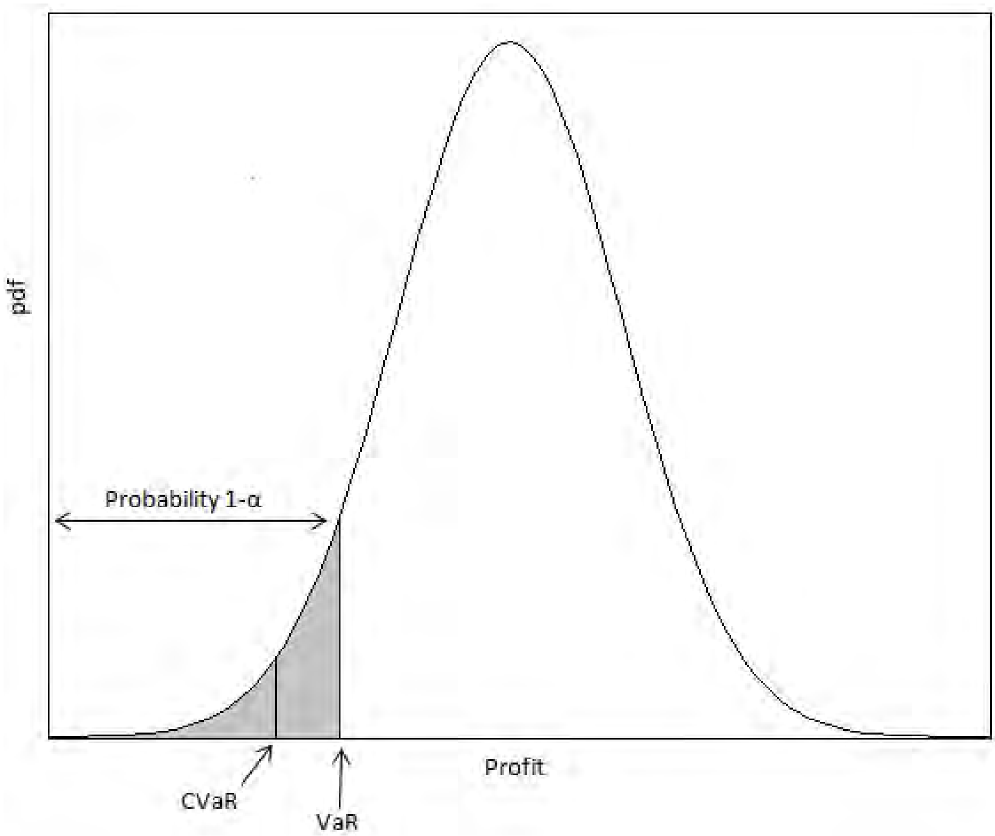

Figure 2: Profit distribution.

value of those profit lower than the VaR (shadow area of Figure 2). The CVaR expression is presented below:

$$CVaR_{\alpha}(X) = E[x : x \leq VaR_{\alpha}(X)] \tag{5}$$

An important contribution was given by Rockafellar and Uryasev (2000) that developed a linear optimization formulation to express CVaR_{α}. This formulation is very suitable for problems that work with scenarios. If scenarios are used the CVaR of a probability distribution can be calculated by solving the following optimization problem:

$$CVaR_{\alpha} = \max_{z,\delta(i)\geq 0} z - \frac{1}{\alpha}\sum_{i\in N} p_i \delta(i) \tag{6}$$

subject to

$$R_i \geq z - \delta(i), \forall i \in N \tag{7}$$

where p_i is the probability of achieving a profit equal to R_i, and z is an auxiliary variable whose optimal value is equal to VaR. Once the optimization problem is solved, for those scenarios with a profit lower than the VaR, the value of the variable $\delta(i)$ represents the difference between the VaR and the value of profit in scenario i; for other scenarios, $\delta(i)$ is zero.

A valuable function based on CVaR_α is developed in Street (2010) for risk averse decision makers. Once the decision maker decides to use the CVaR_α as a measure to express his satisfaction, it can serve as his certainty equivalent. According to this measure, risk is the difference between the potential loss and what is expected (see equation 8). In the following equation α is a risk aversion parameter.

$$Risk(\tilde{R}) = E(\tilde{R}) - CVaR_\alpha(\tilde{R}) \tag{8}$$

where μ is the value measure, and $E(\tilde{R})$ is the expected value of an uncertain profit $\tilde{R}$. This value measure based on CVaR can be associated with the expected value "adjusted" (or penalized by risk), i.e:

$$\mu(\tilde{R}) = (1 - \lambda)E(\tilde{R}) - \lambda CVaR_\alpha(\tilde{R}) \tag{9}$$

This function allows the risk-averse decision maker to adjust his degree of risk aversion using the λ value, where λ is a second risk aversion parameter. In this paper, the different risk aversion levels of the producer are simulated by increasing the value of lambda (λ) from 0 (risk neutral case) to 1 (high risk aversion case). The farther CVaR is from the expected value, the greater the risk aversion. Then, the risk metric is a convex combination of the expected value (risk neutral) and the CVaR (risk averse):

$$\mu(\tilde{R}) = E(\tilde{R}) - \lambda \left[E(\tilde{R}) - CVaR_\alpha(\tilde{R})\right] \tag{10}$$

$$\mu(\tilde{R}) = E(\tilde{R}) - \lambda Risk(\tilde{R}) \tag{11}$$

As a robustness check for this assumption, in section 6.1 we use another performance measure.

3. Model

We run the stochastic model at the beginning of the time period covered by the insurance in order to define those points which leads to good results for both companies. We separate our model in three stages: in the first stage we generate the results for the producer; in the second stage we calculate the wind strike levels for the insurer and in the third stage we consider the intersection of those points obtained in the first two stages. All stages require the data on spot prices and wind forecast.

3.1. Stage 1 - The producer's choices

The producer's points are calculated taking into account all forward contracts in the period covering the insurance contract. In this kind of contract the producer assumes the risk of providing an energy amount at a fixed price for the consumer and when the production is below the contract the producer must buy the energy deficit in the pool at prevailing prices. The producer revenue, without the insurance contract, is shown in equation 12.

$$\tilde{R}_t = P^c Q + (\tilde{Y}_t - Q)\tilde{P}_t \tag{12}$$

Where $\tilde{R}_t$ is the producer revenue in the time t, P^c is the fixed price of the forward contract, Q is the energy demand, $\tilde{Y}_t$ is the production in period t, $\tilde{P}$ represents the market prices. The part $P^c Q$ is always positive. On the other hand, when the production is below the demand Q, the part $(\tilde{Y}_t - Q)\tilde{P}_t$ is negative. If it happens at times of high market prices, the losses accumulated by the producer can be significant.

We calculate the revenue and value measure with and without the insurance contract. The producer's strikes choice is made by taking into account the equation 13. We stored all minimal and maximum power combinations that increase the producer's value measure.

$$\mu(\tilde{R}(\omega)|\ \omega > \omega_{lower}; \omega < \omega_{upper}) > \mu(\tilde{R}(\omega)) \tag{13}$$

These stored values are then converted to wind speed strikes, which are the boundaries that reduce the producer's risks.

3.2. Stage 2 - The insurer's choices

In each quarter the wind speed (m/s) is converted to power (MWh) using the conversion table provided by the turbine manufacturer. From this data our model test all minimum and maximum power combinations that generate a positive expected value for the insurer according to the equation 14.

$$E[\tilde{R}(\omega)|\ \omega < \omega_{lower}] + E[\tilde{R}(\omega)|\ \omega > \omega_{upper}] \geq 0 \tag{14}$$

Whenever a positive average is found, the power values are stored and at the end of the process these values are converted into wind speed, which results in a set of minimum and maximum wind speed combination that is profitable to the insurer.

3.3. Stage 3 - The intersection

Finally, all values stored in the stages 1 and 2 are compared. Those values that are equal in both phases form the contract region, i.e., it refers to those wind strikes (lower wind, wind upper) that form the collar boundaries of a zero-cost insurance contract.

3.4. Decision framework

Consider a contract that insures the company for losses: if profits are negative the insurer covers the loss, but if profits are large, the producer loses the excess. Since the producer is risk averse, it will choose the distribution with the higher value measure (μ), i.e., it will accept the contract if μ increases to μ'. On the other hand, if there is no contract, the insurance firm's profit is zero. Since it is risk neutral, it will accept any contract with positive expected values. There is no payment of premium, since part of the production goes to the insurer.

Moreover, the decisions made by the producer and the insurer depend both on non-negotiable and negotiable variables (Jiang et al., 2006; Pineda et al., 2010). In our case, 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 in order to celebrate an insurance contract.

4. Application

We apply the model to the case of a wind farm in the northeast of Brazil. The wind farm has a long term energy contract, 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.

4.1. Price data

We assume that the proxy for spot market energy price is the "Preço de Liquidação de Diferenças" (PLD) determined by the Electrical Energy 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 producer in the Brazilian northeast, only the corresponding time-series for that submarket was used.

Descriptive statistics of spot prices are presented in Table 1, where the minimum and maximum values of PLD are US\$5.21 and US\$274.3, respectively.

This table shows that the prices are higher in the first and third quarters, but the coefficient of variation (standard deviation divided by the average), which is respectively 0.71, 0.83, 0.80 and 0.93, is higher in the second and fourth quarters. These values report the fact the price risk is higher during the change of dry season to rainy, and vice-versa, as there is much uncertainty about reservoir levels at the end of the rainy season.

Table 1: Descriptive statistics of prices.

	Prices Simulations *(US$)			
Quarters	mean	median	standard	deviation
First	105.66	83.25	74.91	
Second	78.44	60.6	65.35	
Third	85.22	64.17	68.44	
Fourth	72.3	51.35	67.32	

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

4.2. Wind data

We use examine the monthly database of the wind series for the period running from January 1990 to July 2014. 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.

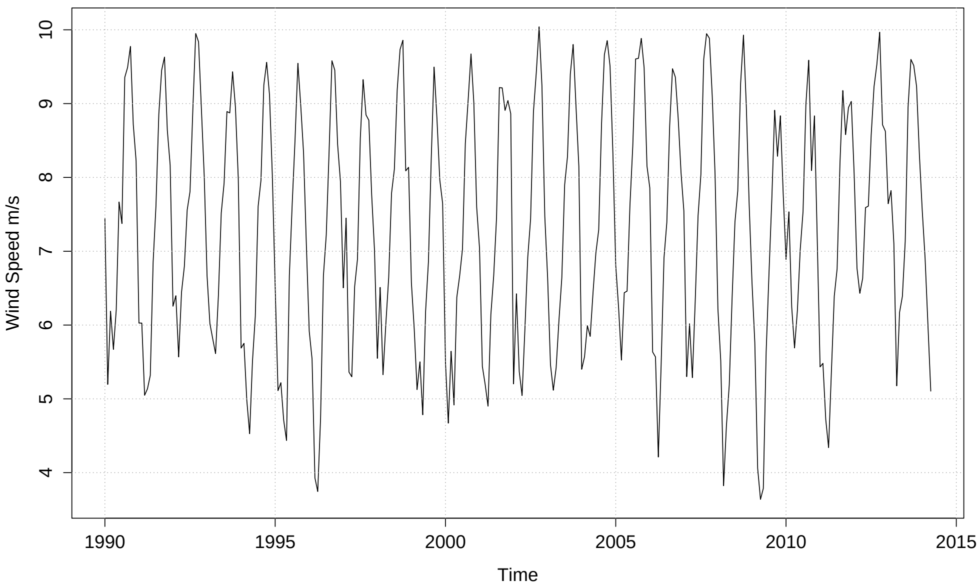

Figure 3: Historical wind series.

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 (Peterson and Hennessey Jr, 1978), according to equation 15.

$$\overline{U}_{h_1} = \left(\frac{h_1}{h_2}\right)^{\alpha} \overline{U}_{h_2} \tag{15}$$

where, $\overline{U}_{h_i}$ is the wind speed, h_i is the height of each measure of wind speed and α is the wind speed vertical profile exponent, also known as the Hellmann exponent. Following Kaltschmitt et al. (2007), we adopted an alpha of 0.27 for unstable air and inhabited environments.

The descriptive statistics of the monthly wind data is presented in Table 2. The wind speed series is skewed to the left, platykurtic, and can be shown to follow a Weibul distribution. It 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 (1991). The null hypothesis of a unit root 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. In general, the ARMA(p,q) models can be described as follows:

$$y_t = \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + c + \epsilon_t \tag{16}$$

where y_t is the wind speed at time t, ϕ_i is the autoregressive coefficient and θ_j is the moving average coefficient. ϵ_t is a random error term and c is a constant.

Table 2: Descriptive statistics.

Sample Statistic	Full Sample
Mean	7.297
Median	7.447
Minimum	3.639
Maximum	10.04
Standard deviation	1.61
Skewness	-0.119
Kurtosis	-1.058
Jarque-Bera	0
ADF	0.01
PP	0.01
KPSS	0.1

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). For each model we used a rolling window of 240 observations and we estimated the monthly prediction errors. The results showed that the ARMAX 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 corroborates this choice.

We use monthly dummies as exogenous variables to capture the seasonality of wind speed. The wind stochastic process is represented by the equation 17, considering the ARMAX model, i.e:

$$V_t = 2.802 + 0.367 * (V_{t-1} - d_{t-1}) + 0.281 * (V_{t-2} - d_{t-2}) + d_t + \epsilon_t \tag{17}$$

Using the forecast data, we draw the wind distribution and descriptive statistics through the insured period. These results are presented in Figure 4 and Table 3 respectively. This table shows the third and fourth quarters the periods with the strongest winds, i.e., in these quarters the wind can reach higher speeds. The first two quarters, on the other hand, are characterized by low wind speed. In addition, the coefficient of variation is 0.13, 0.16, 0.11 and 0.10, respectively, which means that wind uncertainty is greater in the first quarters.

Table 3: Descriptive statistics of wind.

	Wind Simulations (m/s)				
Quarters	mean	median	standard deviation	minimum	maximum
First	5.97	5.98	0.78	3.04	8.24
Second	5.96	5.94	0.95	2.86	9.01
Third	8.58	8.64	0.99	5.57	11.53
Fourth	8.71	8.72	0.86	5.81	11.35

Figure 4 corroborates these results by presenting a regular wind distribution throughout the year 2015, but with some seasonal adjustments. Furthermore, this distribution clarifies the negative correlation of wind with the hydro power cycle since the strongest winds occur in dry seasons periods, i.e., at the moment that the hydrological affluence in hydroelectric reservoirs is reduced.

Considering these results, the producer has higher gain expectations over the periods in which the winds are stronger, which indicates that long term contracts are made considering the high energy production in these quarters. If wind speeds decreases in these periods, it can lead to serious financial losses since the pool price is uncertain throughout the year. Therefore, it could be in the interest of the producer to obtain insurance for the wind farm.

5. Results

For each quarter of the year 2015 we found all wind speed combinations (lower and upper wind) that both parties would be willing to accept. Table 4 reports the number of combinations in each quarter that is negotiable, considering a variation to the producer's risk aversion. The higher λ, the greater the risk aversion.

In all scenarios there are more contract possibilities in the fourth quarter. Considering a variation in λ, for values below 0.5 the third quarter exhibits the second amount with more contract; to values between 0.6 and 0.7, is the third quarter; finally, for values above 0.8, the first quarter has the second number with more contract possibilities. We assume the producer has an average, or $\lambda = 0.5$.

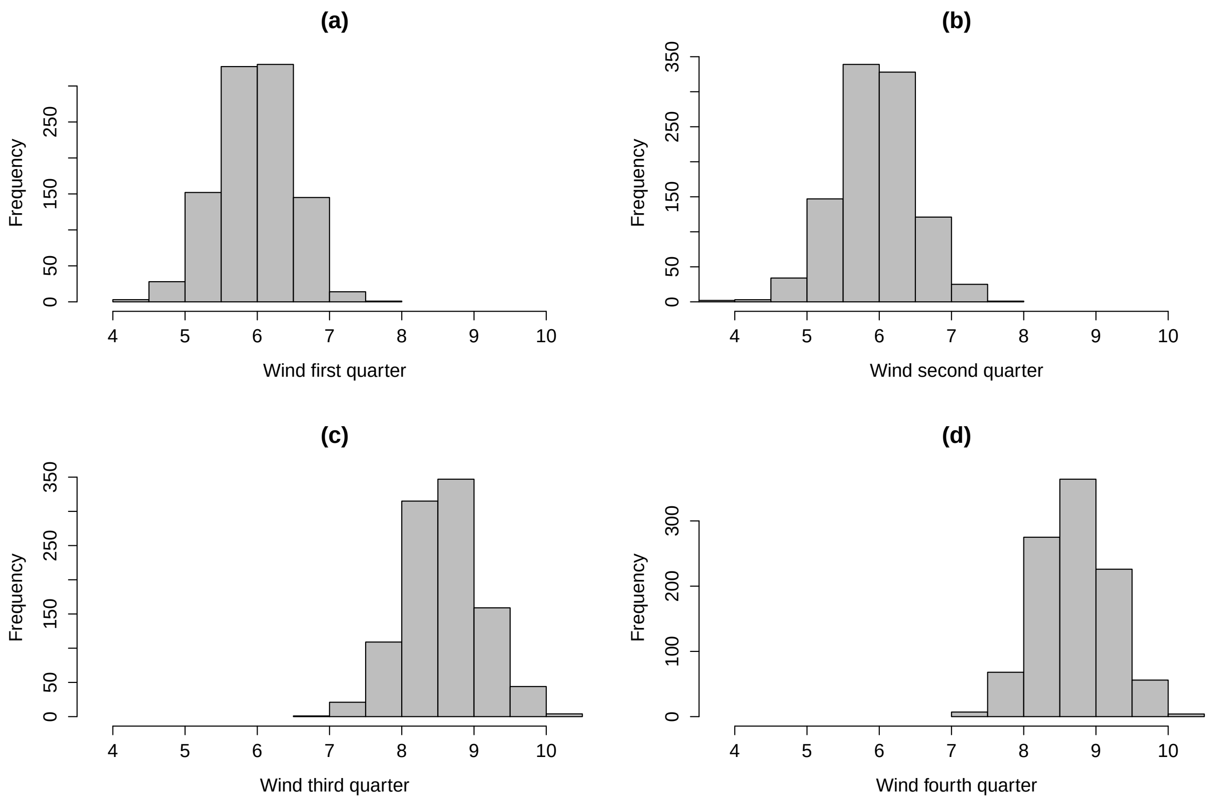

Figure 4: Wind distributions.

Figure 6 shows all points that both companies be willing to accept, considering a feasible contract in the first quarter [1]. The points in the contract region are the intersection of those points that generate a positive expected value for the insurer and a higher value measure (μ) for the producer.

The region in light grey, i.e., the crosses bellow the black points, refers to all wind

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

Table 4: Results of contract opportunities throughout the year.

	Lambda (λ)									
Quarters	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
First	403	417	435	460	486	517	580	655	782	994
Second	564	568	571	572	582	591	602	620	648	715
Third	486	495	506	521	539	569	611	661	746	937
Four	708	717	737	755	783	819	863	933	1065	1328

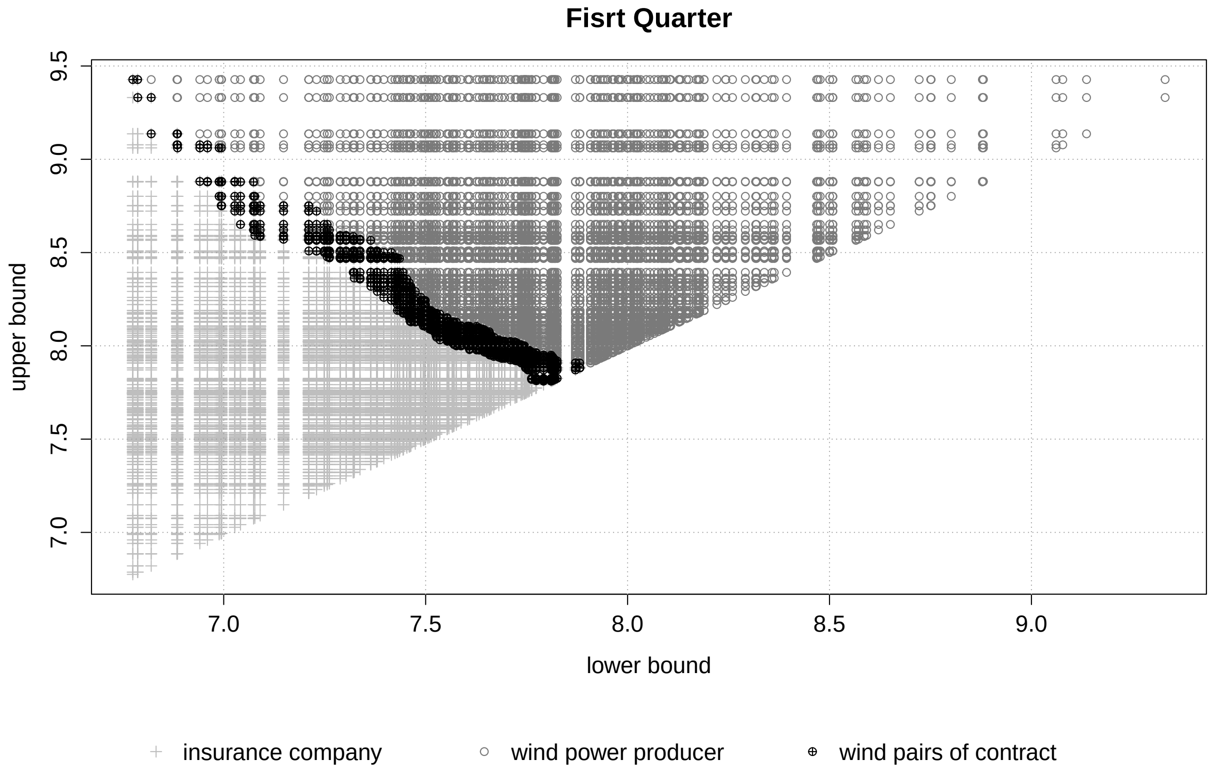

Figure 5: Contract region.

combinations that the insurer is willing to accept. The region in dark grey, i.e., the circles above the black points represents all wind combinations that the wind power producer is willing to accept. The part highlighted in black is the intersection of these points, i.e., the combinations of wind speed that are simultaneously good for both companies. The gaps in the decision region are because the simulations are discreet. The contract region for all quarters of 2015 is displayed in Figure 6, which follows the same logic of Figure 5.

We note in all quarters there are strikes points that would lead companies to close a deal. In particular, there are more opportunities for agreement on the second and fourth quarters. The second period is characterized by light winds, but with high wind uncertainty and energy price risk. The fourth quarter is characterized by strong winds, but with high price uncertainty, which could lead to financial losses. In all cases, the shortest distance between the strikes, i.e., the collar range, is zero, which means that the minimum strike is equal the

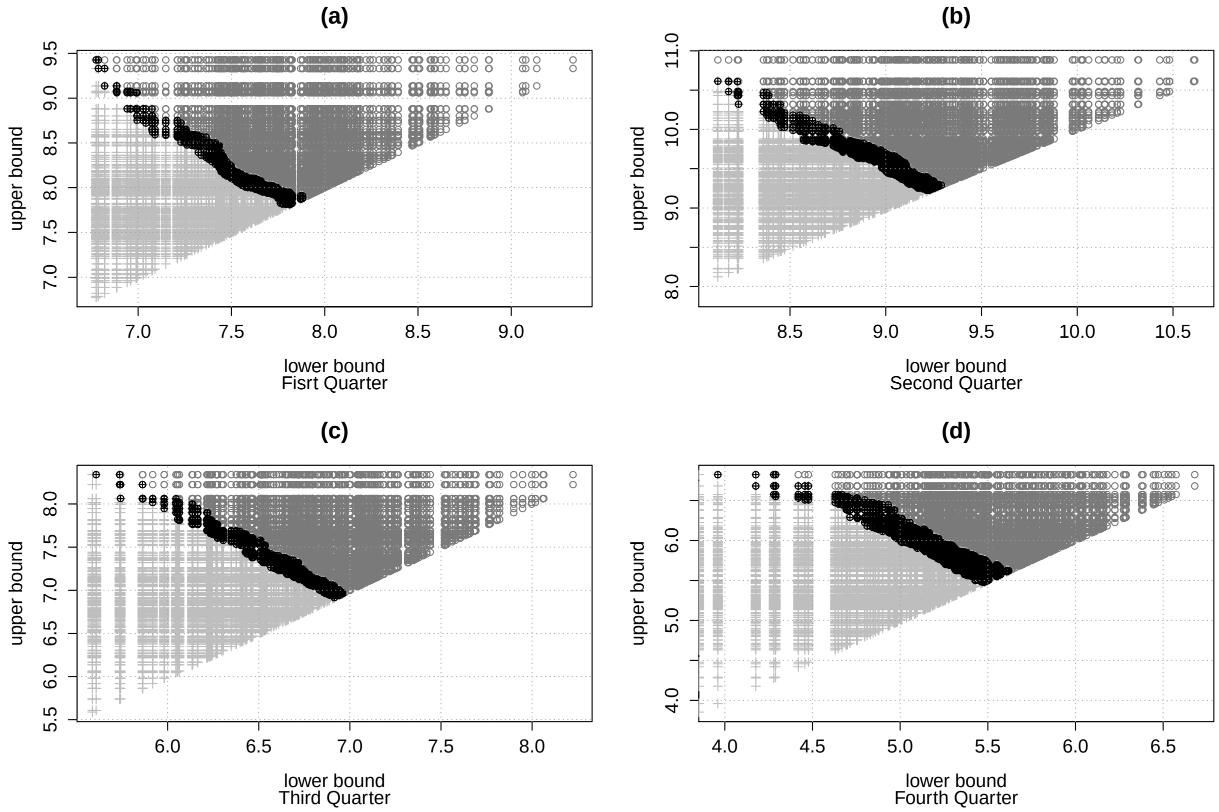

Figure 6: Contract region of all quarters.

maximum strike. The largest distance in each quarter is respectively 2.65, 2.49, 2.73 and 2.86. The third and fourth quarters are those periods with larger distances between the lower wind and the upper wind. In the other quarters these intervals are smaller. Furthermore, in the first and second quarters most of wind combinations have lower bound above the mean and upper bound below it. In the last two quarters, only in some scenarios wind points are simultaneously below or above the wind mean.

The insurance contract benefits for both companies is presented in Figure 7. The points in the contract region have a descending spiral shape, which means that for wind combinations very favorable for the producer, the insurer has expected value close to zero; otherwise, the opposite occurs. In the middle both companies are good, but could be better. Moreover, we note that the first and second quarters are those periods in which the producer earns higher value with the insurance contract. The expected value of insurer is higher in first

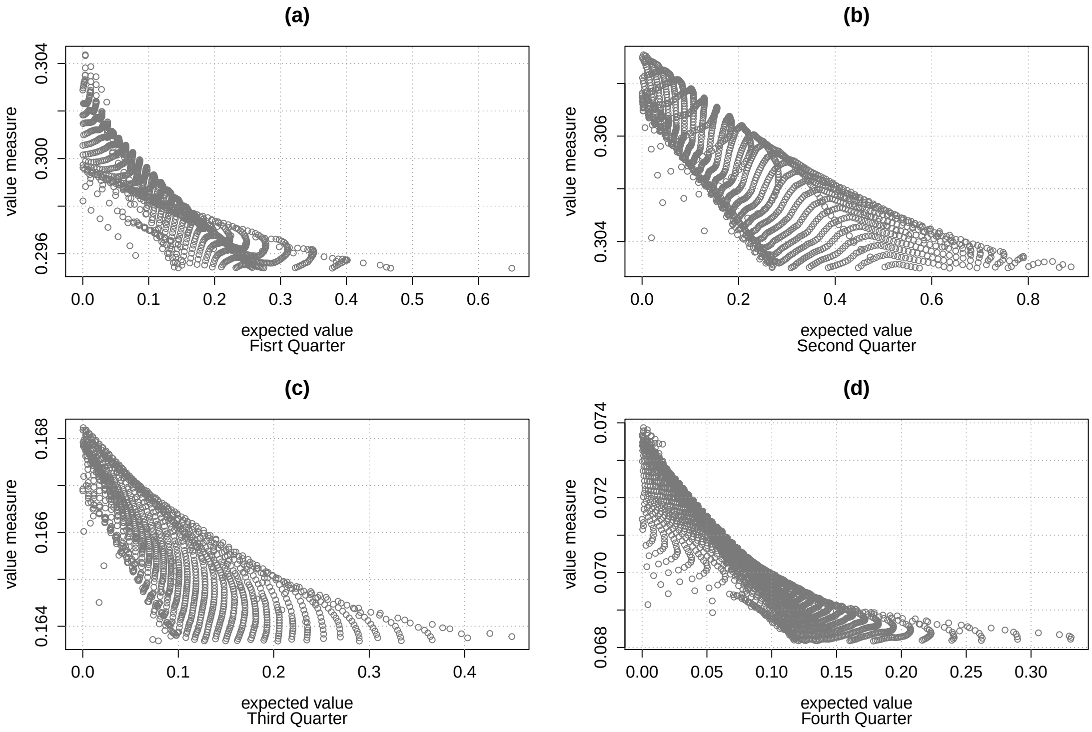

Figure 7: Comparison of gains in the contract region.

and second quarters too.

Finally, we show that when the energy producer has long term contract obligations, there are pairs of upper and lower wind strike levels that make a zero cost collar wind insurance contract valuable for both the producer and the insurer. Within this set, the particular set of strike levels that will be chosen will depend largely on the bargain power of each of the firms, but optimally the negotiation should focus on the range of strike wind indicated.

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. According to Inderst (2002) this may be reasonable if there is competition and sufficiently homogeneity among the various agents. Lien and Moosa (2004) studies the relationship between bargaining approaches and operational hedging techniques for currency collars and found that as long as one of the firms is more risk averse than the other, both firms gain from a collar.

6. Robustness test

In this section we will present two robustness tests. Firstly, we analyze the previous results under a different performance measure, and then we consider the case of a risk-averse insurer.

6.1. The Omega measure

The Omega measure is a performance measure introduced by Keating and Shadwick (2002) and defined as a ratio of potential gains over possible losses (Eling and Schuhmacher (2007); Bertrand and Prigent (2011); Kapsos et al. (2014)). The Omega measure makes no assumptions regarding the distribution of the 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. However, as stated by Keating and Shadwick (2002), when the returns are normally distributed or when higher moments are insignificant, Omega tends to agree with traditional measures such as the Sharpe ratio.

The measure is a function of the return level and requires no parametric assumption on the distribution. Returns below its specific exogenous threshold point (L) are considered as losses and returns above as gains, as is shown in Figure 8.

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:

$$\Omega(L) = \frac{\int_L^b [1 - F(x)]dx}{\int_a^L F(x)dx} \tag{18}$$

Where F is the cumulative distribution function of X. Note that the gain area in Figure 8 represents the numerator of equation (18) and the loss area is the denominator.

There is an alternative representation of the Omega measure that is equivalent to equation (18), which can be represented by the ratio between two expectations (Kazemi et al., 2004) as:

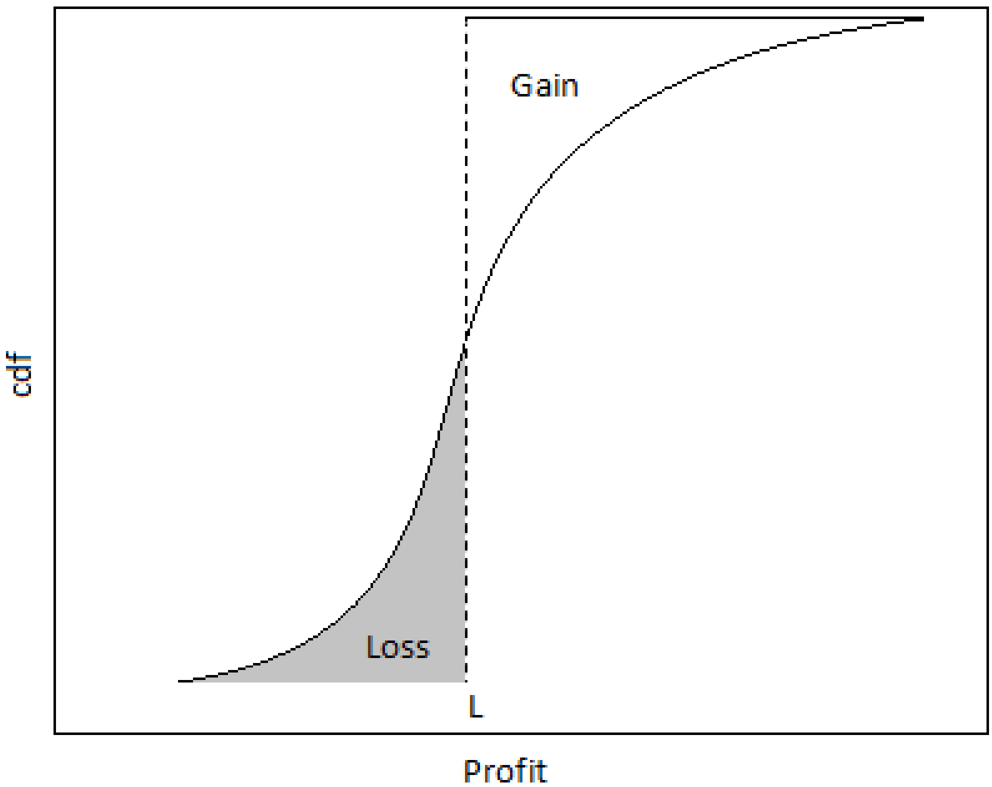

Figure 8: The omega performance measure.

$$\Omega(L) = \frac{\int_L^b (x-L) f_x(x) dx}{\int_a^L (L-x) f_x(x) dx} = \frac{E[max(X-L;0)]}{E[max(L-X;0)]} \tag{19}$$

Equation (19) can be interpreted as the ratio between an undiscounted call option and an undiscounted put option, both with strike price L (Eling and Schuhmacher (2007) and Kaplan and Knowles (2004)).

6.1.1. Results

The Omega measure is determined by the choice of the thresholds (L). The results of the thresholds values are presented in Table 5 for each quarter of the contract period [2]. These results are on scale of a single turbine, but the wind farm has 28 turbines [3].

[2]The Omega measure is calculated on the distribution of profits and both the L and the distribution are in millions of USD.

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

Table 5: Descriptive statistics of thresholds.

	Thresholds (L)		
Quarters	1 Turbine	28 Turbines	Contract
First	0.13	3.59	289
Second	0.10	2.80	633
Third	0.11	3.00	506
Fourth	0.09	2.59	298
Total	0.43	11.98	1726

The thresholds (L) is the percentile of 15% of the producer profit distribution without the insurance contract. Assuming these thresholds values to the Omega measure, the second and third quarter are the periods with higher intersection between the points of interest of the insurer and the producer. Despite the contract region have been higher in these quarters, we observe a considerable number of intersections in all periods, i.e., there are wind strikes combinations in all quarters of 2015.

Finally, Figure 9 shows the benefits of the insurance contract for both companies. As before, the strike points have a descending spiral shape. For high values for the producer, the insurer earns little, and vice-versa. This figure also presents the relationship between the Omega measure of the producer and the expected value of the insurer under a different point of view. We note that, as in Figure 7, the first and second quarters are the periods with the high Omega measure, while the second and third quarters, on the other hand, are the periods with the high expected value.

6.2. Risk averse insurer

A common assumption in finance is that firms are risk-neutral towards non systematic risk, as this risk can be eliminated through a well diversified portfolio of assets, either by the firm itself or by its shareholders. However, wind power generation in Brazil is concentrated in the northeast region of the country, and thus the insurance firm may not be able to fully diversify its wind volume risk.

In order to analyze the impact of this assumption, we test the case where the insurer is risk-averse and its impact on our results. For this purpose, we use equation 10 where the

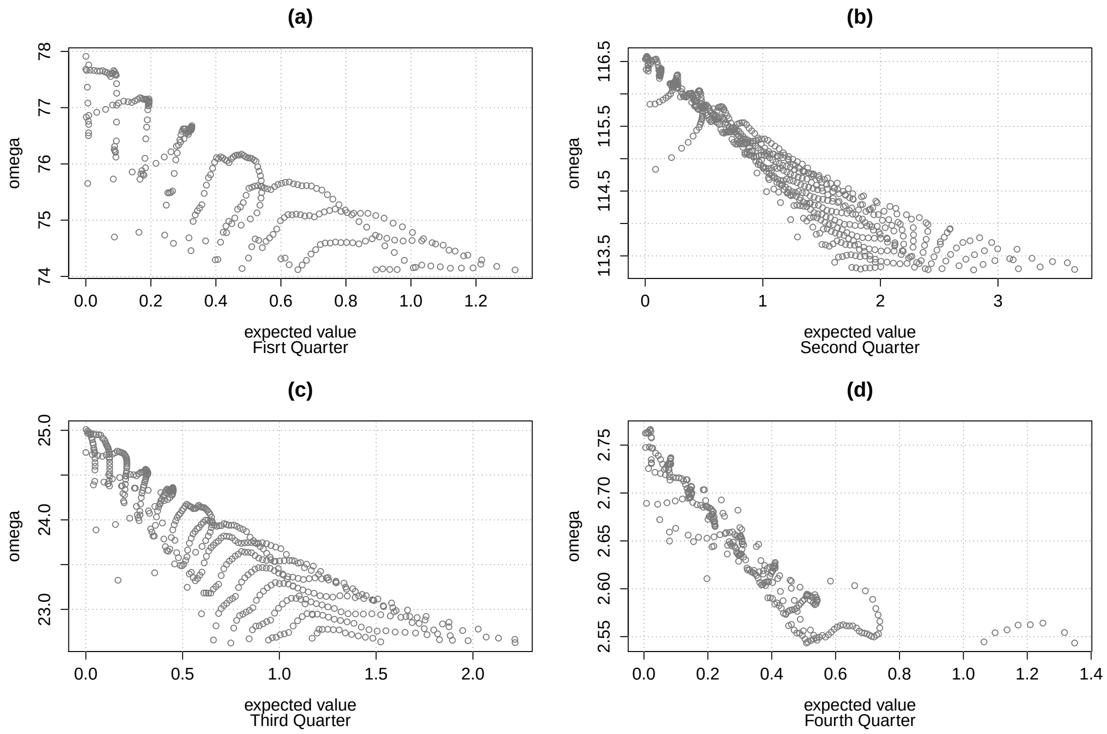

Figure 9: Omega measure.

only change is the inclusion of the risk aversion of the insurer, considering a variation of $\lambda \in [0, 1]$ for the insurer:

$$\mu(\tilde{R})_{insurer} = E(\tilde{R}) - \lambda_{insurer} \left[E(\tilde{R}) - CVaR_{\alpha}(\tilde{R}) \right] \tag{20}$$

$$\mu(\tilde{R})_{producer} = E(\tilde{R}) - \lambda_{producer} \left[E(\tilde{R}) - CVaR_{\alpha}(\tilde{R}) \right] \tag{21}$$

6.2.1. Results

The results of the sensitivity analysis for the insurer and the producer in the first quarter are shown in Table 6. We observe that as the insurer increases its risk aversion, the number of strike combinations is reduced, i.e., it reduces the possibility of both firms agreeing on an insurance contract. On the other hand, an increase in the risk aversion of the producer results in a greater number of acceptable strike combinations. This can be explained by the fact that a more risk averse producer is more likely to see value in insuring his wind volume.

Table 6: Number of strikes combinations.

First Quarter										
	$\lambda_{producer}$									
$\lambda_{insurer}$	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0	403	417	435	460	486	517	580	655	782	994
0.1	151	162	178	200	226	256	319	394	521	733
0.2	15	17	25	30	43	51	79	113	203	415
0.3	0	0	0	0	0	0	0	7	32	112
0.4	0	0	0	0	0	0	0	0	0	4
0.5	0	0	0	0	0	0	0	0	0	0

Similar results are obtained for the other quarters and are presented in the Appendix (see Table A.7). Most importantly, from a certain level onward of risk aversion of the insurer there are no more possibilities for agreement between the parties.

7. Conclusions

In this article we propose a stochastic model to determine a set of parameters for a zero-cost insurance collar for a wind power producer to reduce the financial risk associated with energy shortfall and pool prices when it has long term contracts. Due to strong wind seasonality, we chose to divide the one year contract period into four quarters and independently determine the bounds for the upper and lower strike levels for each of the quarters.

The results show that there are possible contract region in all quarters. Particularly, in the second and fourth quarters there are more opportunities for both firms to enter into the insurance contract, since there is high wind volatility in the former and high price volatility in the latter. The wind combinations (lower and upper wind) that limit the contract region are respectively (7.8 , 7.8) and (6.7 , 9.4) for the first quarter, (9.2 , 9.2) and (8.1 , 10.6) for the second quarter, (6.9 , 6.9) and (5.6 , 8.3) for the third quarter, (5.6, 5.6) and (3.9 , 6.8) for the fourth quarter. Combinations with zero range refer to the starting point of the model. We also found a negative correlation between the risk measure of the producer and the expected value for the insurer.

The results of this model may be useful for both wind energy producers and insurance firms, as it provides a range of feasible collar insurance parameters that benefits both parties, and which that can serve as a guideline for negotiation. It is worth noting that the final pair of wind strike levels that will be chosen depend on the bargaining power of the companies that are negotiating the insurance contract. Also, by reducing the overall level of risk for the firm, the decision to enter into an insurance contract has an important impact on the future choices of a energy producer. An insured power company, for example, may choose to sell more futures and forwards contracts and take on a greater amount of debt in order to increase production capacity, among others.

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Appendix A. Sensitivity Analysis of λ

Table A.7: Number of strikes combinations considering the insurance and the producer are risk-averse.

Second Quarter										
	$\lambda_{producer}$									
$\lambda_{insurer}$	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0	564	568	571	572	582	591	602	620	648	715
0.1	282	286	289	290	300	309	320	338	366	433
0.2	35	36	37	37	40	44	49	58	72	115
0.3	0	0	0	0	0	0	2	3	3	7
0.4	0	0	0	0	0	0	0	0	0	0
Third Quarter										
	$\lambda_{producer}$									
$\lambda_{insurer}$	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0	486	495	506	521	539	569	611	661	746	937
0.1	238	247	258	273	291	321	363	413	498	689
0.2	65	70	74	79	86	100	124	155	218	393
0.3	14	15	16	16	18	22	29	40	56	125
0.4	0	0	0	0	0	2	6	6	10	25
0.5	0	0	0	0	0	0	0	0	0	0
Fourth Quarter										
	$\lambda_{producer}$									
$\lambda_{insurer}$	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0	708	717	737	755	783	819	863	933	1065	1328
0.1	468	477	497	515	543	579	623	693	825	1088
0.2	197	203	220	235	262	298	342	412	544	807
0.3	59	61	65	74	83	97	117	149	233	459
0.4	15	15	16	20	20	25	30	42	76	182
0.5	5	5	5	7	7	8	10	12	19	47
0.6	0	0	0	2	2	2	2	2	3	8
0.7	0	0	0	0	0	0	0	0	0	0

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