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Time Span does Matter for Offshore Wind Plant Allocation with Modern Portfolio Theory

Lana V. L. Costa-Silva[1], Vinicio S. Almeida[2], Felipe M. Pimenta[3], Giovanna T. Segantini[4]*

[1]Federal University of Rio Grande do Norte, Brazil, [2]Federal University of Rio Grande do Norte, Graduate School of Management, UFRN-PPGA, Salgado Filho Av., 3000, Lagoa Nova, Natal-RN, 59078-900, Brazil, [3]Federal University of Santa Catarina, Brazil, [4]Federal University of Rio Grande do Norte, Brazil. *Email: giovanna.ufrn@gmail.com

ABSTRACT

Allocating wind farms across different locations may reduce the problematic intermittency of wind. The objective of this research was to analyze the optimal allocation of offshore wind farms in the U.S. East Coast through modern portfolio theory. The research was conducted with 25.934 secondary observations of offshore wind energy produced by 11 hypothetical offshore wind farms. We calculated six minimum variance portfolios, each referring to a distinct time period. Four rebalancing strategies were settled in order to assess the performance of the portfolios we estimated. The results indicate that MPT can be used to calculate the diversification of offshore wind farms locations, which may reduce the individual variability of hourly wind power changes.

Keywords: Modern Portfolio Theory, Optimal Allocation, Offshore Wind Power
JEL Classifications: C61, C53, L94, Q42, Q47

1. INTRODUCTION

Wind energy has been receiving a considerable load of attention in the past few years. Probably, this is due to the fact of being mainly dependent on a renewable source, with little environmental impact, and having comparatively low costs for implementation and operation (Chupp et al., 2012; Hansen, 2005). Most of the energy generated from wind turbines worldwide comes from onshore facilities. However, some authors have discussed the potential advantages of relying on offshore sites (Kaldellis and Kapsali, 2013; Levitt et al., 2011; Lu et al., 2013). There is also a growing concern with regards to potential environmental and social impacts of onshore wind plants, e.g. Moller (2006) and Tsoutsos et al. (2009), which also may drive resources to offshore alternatives (Bilgili et al., 2011).

The development of offshore wind energy, as other sources, has on its path both technological and financial-economic sustainability issues. On the economics side, some works have dealt with financial viability and economic support policies (e.g. Green and Vasilakos (2011); Levitt et al. (2011)). Others have discussed how wind turbines should be arranged geographically to take advantage on sets of wind incidence (Chupp et al., 2012). It is known that offshore wind sites also overcome onshore wind sites due to its higher stability. Nevertheless, offshore wind energy programs may also benefit from this rationalization. It is essential to control the energy output in order to advance steadier (Kaldellis and Kapsali, 2013) and growing energy consumption.

However, the conventional models used in the design of wind energy plans are incapable of weighting an intermittent nature of the winds, negatively affecting in the capacity to supply energy in the measured needs (Neuhoff et al., 2008). So, some authors have demonstrated the possibility of using optimization techniques to propose how real assets should be selected to maximize the performance/risk relationship. Even though we may find works relying on various optimization procedures (Milligan and Factor, 2000; Kempton et al., 2010; Lu et al., 2013), many others employed specifically the modern portfolio theory (herein MPT), as developed by Markowitz (1952) to propose portfolios of energy assets in general (Humphreys and McClain, 1998; Muoz et al., 2009; Arnesano et al., 2012) and portfolios of onshore wind energy assets (Hansen, 2005; Drake and Hubacek, 2007; Roques et al., 2010; Rombauts et al., 2011; Chupp et al., 2012).

Based on that, in this work, we propose the application of MPT to calculate steadier sets of offshore wind energy generation. This analysis is not usual to offshore wind data, although well explored for onshore data. In addition, works published have not considered the need to rebalance portfolios periodically. Portfolios of financial assets can be rebalanced with low cost (bid-ask spread and commissions). This is not the case of real assets, and specially wind farms. In our analysis we show time span may generate different suggestions for wind farms allocation.

The remainder of the paper proceed as follows. In section 2, we outline the portfolio theory main concepts and discuss the related literature. In section 3, we describe the sample selection and provide descriptive statistics. Section 4 presents our empirical results. Section 5 concludes.

2. METHODS

In our approach, we intend to show how to combine wind farms power generation from different locations by means of MPT analysis to achieve a more stable wind power production. MPT was initially proposed by Markowitz (1952) for the efficient selection of financial asset portfolio and is based on the investor's goal of maximizing future expected return for a given level of risk that he is willing to accept. The approach of investments diversification is also highlighted as an advantage. Therefore, the characteristics of a portfolio can be very different from the characteristics of the individual assets that integrate the portfolio.

According to Markowitz (1952), MPT requires two inputs: A vector containing the expected returns for each asset considered in the sample and a matrix of its covariances. The expected return for a portfolio p of n assets, E (R_p), is given by the weighted average return of each asset included, as Equation 1 shows.

$$E(Rp) = \sum_{i=1}^{n} (X_i E(R_i)) \tag{1}$$

Where E (R_i) is the asset i expected return, n is the number of assets in the portfolio p, X_i is the fraction of the asset i in the portfolio p, subject to:

$$\sum_{i=1}^{n} X_i \tag{2}$$

Portfolio risk is calculated as shown in equation 3:

$$\sigma_p = \sqrt{\sum_{i=1}^{n} Xi\sigma_i^{\,2} + \sum_{i=1}^{n}\sum_{\substack{j=1 \\ i\neq 1}}^{n} (X_i X_i \sigma_{ij})} \tag{3}$$

Where σ_p is the portfolio p standard deviation (SD), σ_i is the estimated SD for each asset i and σ_{ij} is the covariance between each pair of assets i and j. The other terms have been defined. So, the risk of the portfolio, σ_p, is not just the weighted average of each asset risk, but, it also includes the correlation coefficient between assets' returns, which means that the benefits of diversification may come from low covariance between asset returns.

Several works (e.g., Roques et al. (2010), Rombauts et al. (2011) Chupp et al. (2012), Arnesano et al. (2012) and Cunha and Ferreira (2015), to cite a few) have attempted to apply portfolio theory to develop energy planning.

Roques et al. (2010) show, by means of MPT analysis, that the optimization of wind investment complements preexisting conventional investment models. However, the authors neglect the variability of wind resources. This problematic might be overcome by geographically dispersed portfolio of wind farms (Rombauts et al., 2011; Chupp et al., 2012). Cunha and Ferreira (2015) show that the diversification helps to reduce the energy production variability, although, highest return solution is associated with higher risk and is dependent on assumed cost of each investment.

The adoption of a model based on portfolio theory may be an efficient alternative to assist the decision making related to geographic location of offshore wind farms. Based on the average energy generated in each potential site for wind turbine allocation we may find an optimal portfolio of wind power investments.

3. DATA AND DESCRIPTIVE STATISTICS

The data base is composed by 11 meteorological stations, located in a radius of 2,500 km of the East coast of the USA, which have an estimated propensity to produce offshore wind energy. See Figure 1. The wind velocity was recorded by National Data Bouy Center, through anemometers installed at each station. According to Figure 1, the stations 1, 2, 5, 6, 7, 9 and 10 have fixed platforms and their anemometers are located 40 m above the sea level. The others stations support buoys, which are located 5 m above of sea level (Kempton, et al., 2010).

The minimum amount of wind velocity to start the turbine and generate power is 3.5 m/s, and the upper limit is 30 m/s. After that, the turbine is automatically turned off for safety purposes. Based on this routine, we excluded from the sample the gaps that lasted for 4 h or more without energy production. For smaller gaps, we filled with linear interpolation. Our final sample remained with 25,934 observations for the period between 1998 and 2002.

Table 1 displays the descriptive statistics about return and risk for each station. Over the period, the highest average energy production by hour was at station P06 (2.285 MW) and the lowest level of SD was at P01 (1.542). Since the return and production variability of each meteorological station are measured, we estimated optimal portfolios considering different windows.

Figure 1: Meteorological stations location

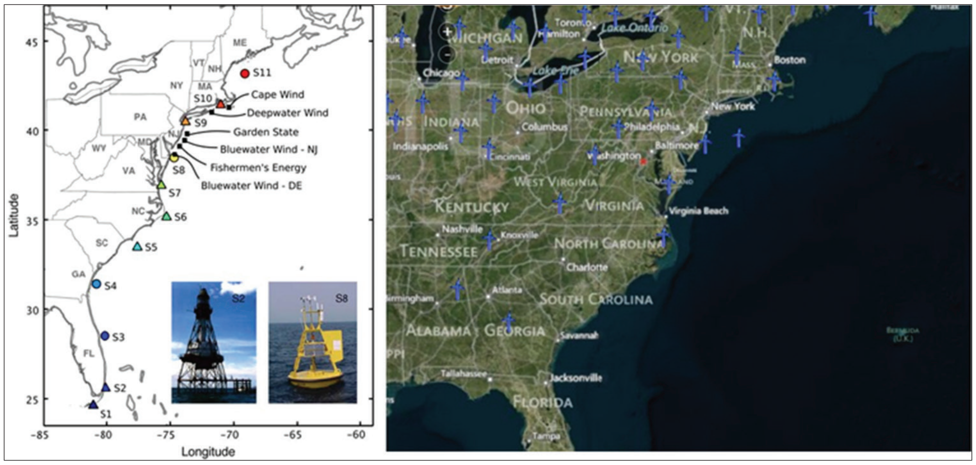

Table 1: Descriptive statistics

Site	Mean±SD					
	1998	1999	2000	2001	2002	1998-2002
P01	1.13 (1.39)	1.41 (1.57)	1.29 (1.45)	1.63 (1.69)	1.72 (1.60)	1.40 (1.54)
P02	1.36 (1.51)	1.61 (1.65)	1.40 (1.51)	1.69 (1.71)	1.61 (1.53)	1.51 (1.59)
P03	1.27 (1.46)	1.90 (1.72)	1.82 (1.68)	1.73 (1.74)	1.94 (1.67)	1.70 (1.67)
P04	1.50 (1.62)	1.66 (1.70)	1.66 (1.72)	1.45 (1.64)	1.72 (1.76)	1.59 (1.69)
P05	1.54 (1.75)	2.11 (1.92)	2.18 (1.88)	2.01 (1.86)	2.31 (1.92)	2.00 (1.88)
P06	1.84 (1.84)	2.36 (1.92)	2.39 (1.90)	2.28 (1.89)	2.81 (1.89)	2.29 (1.91)
P07	1.41 (1.56)	2.02 (1.80)	2.08 (1.89)	1.87 (1.78)	2.23 (1.86)	1.89 (1.80)
P08	1.61 (1.70)	2.03 (1.89)	2.14 (1.95)	1.87 (1.79)	2.14 (1.89)	1.94 (1.86)
P09	1.94 (1.78)	2.12 (1.87)	2.14 (1.91)	1.92 (1.80)	2.26 (1.86)	2.06 (1.85)
P10	1.93 (1.80)	2.18 (1.88)	2.27 (1.89)	2.06 (1.80)	2.26 (1.82)	2.13 (1.85)
P11	1.82 (1.89)	2.22 (2.01)	2.45 (2.00)	1.82 (1.88)	2.27 (1.89)	2.11 (1.96)

SD: Standard deviation

Table 2: Wind plants portfolios

Stations	1998 (%)	1999 (%)	2000 (%)	2001 (%)	2002 (%)	1998-2002 (%)
P01	12	3	12	9	14	9
P02	11	17	7	13	15	14
P03	2	10	15	8	4	8
P04	18	13	10	11	7	13
P05	5	6	7	5	4	5
P06	11	14	14	16	18	14
P07	6	7	2	10	8	6
P08	0	0	0	1	0	0
P09	17	10	11	8	11	12
P10	10	11	8	13	9	10
P11	7	9	15	7	10	9

4. EMPIRICAL ANALYSIS

The analysis begins by calculating the efficient frontier. Figure 2 displays yearly mean variance efficient frontiers from 1998 to 2002, yearly and for the full set of the 1998-2002 period. The efficient frontier includes a set of optimal portfolios. Any point along the way represents a combination of meteorological stations, and the minimum variance and maximum return are presented.

Table 2 displays the portfolios for 1998, 1999, 2000, 2001 and 2002, and a portfolio for the 1998-2002 period. In this initial analysis, P08 would not beever consider to receive a wind power plant, since it has 0% allocation in every estimated portfolio,

Table 3: Wind plants portfolios descriptive statistics

Site	Average (%)	SD (%)	Minimum	Maximum (%)
P01	10	3.87	3	14
P02	13	3.49	7	17
P03	8	4.58	2	15
P04	12	3.69	7	18
P05	5	1.03	4	7
P06	15	2.35	11	18
P07	7	2.66	2	10
P08	0	0.41	0	1
P09	12	3.02	8	17
P10	10	1.72	8	13
P11	10	2.95	7	15

SD: Standard deviation

except in 2001 (with only 1%). On the other hand P06, P02, P04 and P09 are serious candidates for receiving wind power plants, considering they have the highest overall allocation across years (15%, 13%, 12% and 12%, respectively). High SD s, in Table 3, might suggest sites where, under our analysis, would require the highest rebalancing efforts, as P03 and P01 (SD 4.58% and 3.87%, respectively).

Once the weights of the minimum variance portfolios (MVPs) have been calculated for each period, the next step is to analyze the performance of portfolios considering rebalancing strategies. We designed four rebalancing strategies in order to facilitate the allocation of wind power generation considering the variability of the winds of a certain period. Table 4 simplified the rebalancing strategies used in this research.

The first strategy is designed to consider the weights derived from the MVP in each period and applied to daily offshore wind for the same time. In the second one, we employed the weights from the MVP in each year and applied in the following year. For example, the weights from 1998 data were used to calculate returns and SD for 1999 portfolio. In the third and the fourth strategies, we considered fixed weights. In the third, the weights were based on 1998 data, and in the fourth we employed a naive strategy, where the weights are distributed equally, (1/11), among all the assets. Table 5 shows its main results.

Given that all portfolio are minimum-variance optimization, which present the highest stability of offshore wind energy production, we can compared the strategies focusing our attention on expected returns. Thus, the first strategy presents the best return

Figure 2: Mean-variance efficient frontiers, (a) 1998 efficient frontier, (b) 1999 efficient frontier, (c) 2000 efficient frontier, (d) 2001 efficient frontier, (e) 2002 efficient frontier, (f) 1998-2002 efficient frontier

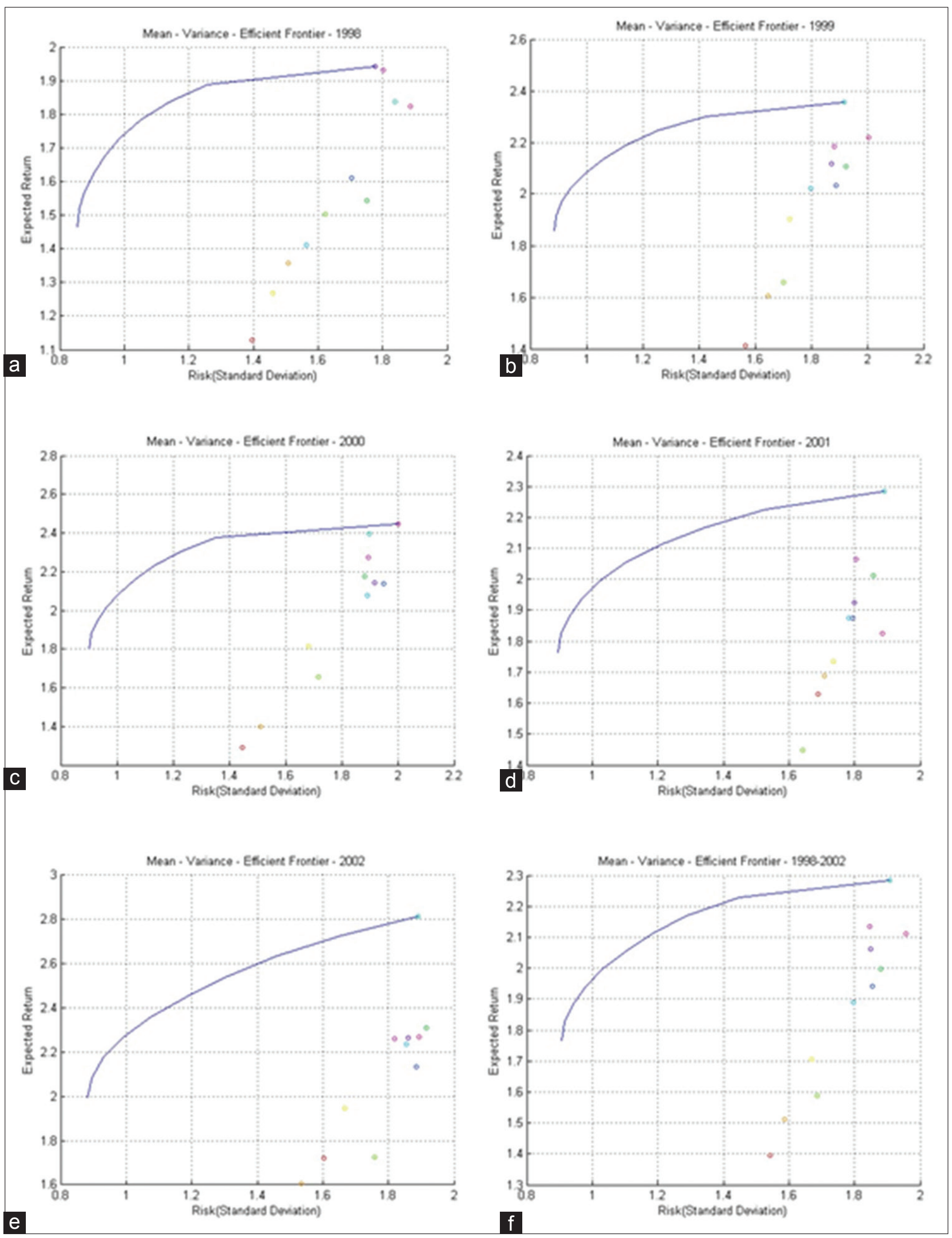

Table 4: Synthesis of rebalancing strategies

Pesos	1ª strategy						2ª strategy						3ª strategy						4ª strategy					
	98	99	2000	01	02	98-02	98	99	2000	01	02	98-02	98	99	2000	01	02	98-02	98	99	2000	01	02	98-02
C98	X						X						X		X	X	X							
C99	X						X																	
C00	X									X														
C01				X						X														
C02				X																				
C98-02						X																		
1/11																			X	X	X	X	X	X

Table 5: Rebalanced portfolios performance

Rebalancing		1998 M (MW/h) DP	1999 M (MW/h) DP	2000 M (MW/h) DP
1a	Strategy	1,5950,888	1,9710,913	2,0040,956
2a	Strategy	-	1,9030,903	1,9690,952
3a	Strategy	-	1,9030,903	1,9020,940
4a	Strategy	1,5780,904	1,9660,934	1,9820,980
		2001 M (MW/h) DP	**2002 M (MW/h) DP**	**1998-2002 M (MW/h) DP**
1a	Strategy	1,9170,945	2,1380,913	1,8640,929
2a	Strategy	1,8670,947	2,1870,947	-
3a	Strategy	1,8010,909	2,0610,910	-
4a	Strategy	1,8500,928	2,1170,942	1,8750,956

in the distribution of potential wind farm plants, considering data for the years 1998, 1999, 2000 and 2001. For the observations of 2002, the second strategy appears to be adequate. When we consider the full sample, 1998-2001, the fourth strategy is more efficient.

5. SUMMARY AND CONCLUSIONS

In this paper, a portfolio theory model for offshore wind power allocation was employed. The results show that by allocating offshore wind farms across different locations, with gains of diversification, may reduce the individual variability of hourly wind power changes from its location. This analysis shows that some sites may not be adequate to receive wind farm plants. From our sample, the site represented by P08 is not suitable to generate wind power, when we consider other potential sites. This is due because of the correlation of the winds between the meteorological stations P08 with the others. Since we are dealing with real assets, rebalancing may be of major concern since it does not come with low costs.

Rebalancing strategies need to be considered and we evaluated some strategies. The first strategy, with annual rebalancing, presented the best yearly results. However, for the full period, the fourth strategy, with naive rebalancing showed better results. This discussion may be valuable to policymakers as they decide how to incentive investment in wind power generation.

REFERENCES

Arnesano, M., Carlucci, A., Laforgia, D. (2012), Extension of portfolio theory application to energy planning problem the Italian case. Energy, 39, 112-124.

Bilgili, M., Yasar, A., Simsek, E. (2011), Offshore wind power development in Europe and its comparison with onshore counterpart. Renewable and Sustainable Energy Reviews, 15, 905-915.

Chupp, B.A., Hickey, E., Loomis, D.G. (2012), Optimal wind portfolios in Illinois. The Electricity Journal, 25, 46-56.

Cunha, J., Ferreira, P.V. (2015), Designing electricity generation portfolios using the mean-variance approach. International Journal of Sustainable Energy Planning and Management, 4, 17-30.

Drake, B., Hubacek, K. (2007), What to expect from a greater geographic dispersion of wind farms? A risk portfolio approach. Energy Policy, 35, 3999-4008.

Green, R., Vasilakos, N. (2011), The economics of offshore wind. Energy Policy, 39, 496-502.

Humphreys, H.B., McClain, K.T. (1998), Reducing the impacts of energy price volatility through dynamic portfolio selection. The Energy Journal, 19(3-6), 107-131.

Hansen, L. (2005), Can wind be a firm resource? A North Carolina case study. Duke Environmental Law and Policy Forum, 15, 341-382.

Kaldellis, J., Kapsali, M. (2013), Shifting towards offshore wind energy recent activity and future development. Energy Policy, 53, 136-148.

Kempton, W., Pimenta, F.M., Veron, D.E., Colle, B.A. (2010), Electric power from offshore wind via synoptic-scale interconnection. Proceedings of the National Academy of Sciences, 107, 7240-7245.

Levitt, A.C., Kempton, W., Smith, A.P., Musial, W., Firestone, J. (2011), Pricing offshore wind power. Energy Policy, 39, 6408-6421.

Lu, X., McElroy, M.B., Nielsen, C.P., Chen, X., Huang, J. (2013), Optimal integration of offshore wind power for a steadier, environmentally friendlier, supply of electricity in China. Energy Policy, DOI: 10.1016/j.enpol.2013.05.106. Available from: http://www.sciencedirect.com/science/article/pii/S0301421513004618.

Markowitz, H. (1952), Portfolio selection. The Journal of Finance, 7, 77-91.

Milligan, M., Factor, T. (2000), Optimizing the geographic distribution of wind plants in Iowa for maximum economic benefit and reliability. Wind Engineering, 24, 271-290.

Moller, B. (2006), Changing wind-power landscapes: Regional assessment of visual impact on land use and population in Northern Jutland, Denmark. Applied Energy, 83, 477-494.

Muoz, J.I., de la Nieta, A.A.S., Contreras, J., Bernal-Agustn, J.L. (2009), Optimal investment portfolio in renewable energy: The Spanish case. Energy Policy, 37, 5273-5284.

Neuhoff, K., Ehrenmann, A., Butler, L., Cust, J., Hoexter, H., Keats, K., Kreczko, A., Sinden, G. (2008), Space and time: Windin an investment planning model. Energy Economics, 30, 1990-2008.

Rombauts, Y., Delarue, E., Dhaeseleer, W. (2011), Optimal portfolio theory-based allocation of wind power: Taking into account cross-border transmission-capacity constraints. Renewable Energy, 36, 2374-2387.

Roques, F., Hiroux, C., Saguan, M. (2010), Optimal wind power deployment in Europe A portfolio approach. Energy Policy, 38, 3245-3256.

Tsoutsos, T., Tsouchlaraki, A., Tsiropoulos, M., Serpetsidakis, M. (2009), Visual impact evaluation of a wind park in a Greek Island. Applied Energy, 86, 546-553.