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Closer Monitoring of Wind Power Generation Could Better Optimize the Charging of Electric Vehicles

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Abstract

Wind turbines are used to inexhaustibly generate electricity in an environmentally responsible manner. However, a challenge with using wind turbines is that the electricity produced depends on the speed of the wind. In many places it is windier late at night, when the demand and price for electricity are lowest, and calmer during the day, when the demand and price for electricity are highest. At times, there are such powerful winds at night that there is more electricity being generated than can be used, forcing the wind turbines to be shut down. This reduces the revenue of the wind farms which dissuades further investment. Electric vehicles, however, have a complementary profile: they tend to be recharged during the evening with little recharging done during the daytime. Electric vehicles are potential customers for the electricity wind turbines produce at night. Matching supply and demand in this manner could increase investment in wind turbines and the number of emission-free electric vehicles. This research investigates the potential synergy between wind turbines and electric vehicles. At a glance, this scheme appears to be sensible, but additional analyses must be performed. This research investigates the correlation of electric vehicle charging and wind power generation in the Pacific Northwest using data from 2011-2012. The wind data comes from the Bonneville Power Administration, who has over 3000 MW of installed wind power across the Northwest. The electric vehicle data comes from the EV Project who has over 1000 charging stations in Washington that are collecting data. The data sets were quality-controlled and then divided into both 15 minute and 1-hour intervals. To investigate the influence of seasonal trends on the correlation, the data sets were partitioned into monthly subsets. Pearson, Kendall and Spearman correlation coefficients were calculated for each month as well as other statistical measures of association. Preliminary results show that there is indeed a correlation between the two green technologies, but it is lower than anticipated. However, it was discovered the correlation is dependent on the time of year. During the summer months, from April to August, the correlation values are at their greatest, around 0.3.

Keywords: Wind Power, Electric Vehicles, Correlation

1. Introduction

Petroleum is the dominant energy source for powering transportation. In the United States alone there are approximately eight vehicles for every 10 people[1]. However, our society cannot continue to use petroleum at our current rate of consumption indefinitely. It is necessary to reduce our petroleum consumption for several reasons: there is a limited amount of petroleum and various harmful consequences to our health and environment have been found from its combustion. The world uses 32.72 billion barrels of petroleum a year, and the United States alone accounts for approximately 6.77 billion barrels per year of that consumption[2]. It is estimated that about 1.5 trillion barrels of petroleum are left in reserves throughout the world that is extractable with current technology[3]. At the current rate of consumption, there will be no more petroleum in less than 50 years. Burning petroleum releases many harmful gases, such as carbon dioxide, sulfur oxides and nitrogen oxides[4]. The large amounts of CO_2 being released into the air from burning petroleum contributes to global climate change. Sulfur dioxide and nitrogen dioxide cause acid rain, which damages plants, poisons water supplies and deteriorates respiratory health[5, 6].

Clean renewable energy options are attractive alternatives to petroleum. Many environmentally-benign renewable energy choices exist: solar, wind, geothermal, hydro, tidal, biomass and wave. Of these, wind power has seen the largest growth in the past decade. The installed wind capacity in the United States has increased from 17,400 MW in 2000 to 283,126 MW in 2012[7].

Despite many positive advantages to wind power, challenges still exist. Wind power is often hard to predict and can be largely inconsistent. For a large portion of the time there is little to no wind power, but at certain times there is a substantial amount of wind power. With no inexpensive or practical way to store the large amount of energy generated from these spikes in wind, wind power becomes a less attractive option. Sometimes there is so much wind power generated late at night and not enough load, that wind farm owners are forced to either turn off their turbines– a process known as curtailing—or sell their energy at low or even negative values (profit is still earned from government subsidies and Renewable Energy Credits)[8]. In order for wind power to be a suitable replacement for petroleum, an increase in load during non-peak hours is needed. Electric vehicles are a promising solution.

Electric vehicles (EVs) use a system of internal batteries to store electrical energy, which then is used to power the vehicle. EVs are also a green technology; they do not directly release any greenhouse gases since petroleum is not used in the vehicles. Electric vehicles are also more efficient than internal combustion engine vehicles, making them an increasingly viable option[9].

The pairing of wind power and EVs may be a solution to reducing dependence on petroleum. Wind power needs more load at night and electric vehicles need a cheap source of energy. EVs can provide demand for wind power at night which would be profitable for wind farms and good for the environment; in return EVs receive a cheaper source of electricity. The pairing of supply and demand increases the viability of EVs and wind farms in their separate markets bringing an almost carbon neutral form of transportation closer to existence.

The goal of this research is to determine the correlation between the generation of wind power and the charging of electric vehicles. It is expected that weather and peoples' driving habits will exhibit seasonal variations, so monthly variability of the correlations is also investigated. The resulting correlation coefficients are then checked for statistical significance. Lastly a claim about the viability of the pairing of the two renewable technologies will be made.

2. Data Set Description

The two data sets used for this research come from the Pacific Northwest during the years 2011 and 2012. By choosing two data sets that come from the same geographic area, the results become more meaningful.

The wind power data comes from the Bonneville Power Administration[10] (BPA) a federal nonprofit agency that is a part of the U.S. Department of Energy. BPA provides a third of the electricity that is used in the Pacific Northwest. The wind data set used contains instantaneous power generation from all of the wind farms in BPA's territory, sampled at 5 minute intervals. For 2011 this was 105,120 data points and for 2012 it was 105,408. The difference in number of data points between the years is caused by a leap year. Over the time span the wind data covers, the installed capacity of BPA wind turbine farms increased from 3200 MW to over 4500 MW.

The EV charging data comes from EV Project, a study done by ECOtality[11]. The EV Project is an infrastructure study about the effects of charging stations and electric vehicles. EV data was collected from over 100 charging stations located at various residences, public lots and workplaces. The EV data set measured the instantaneous power consumption, which was used in this research. The EV charging data was sampled every 15 minutes. This gave 35,040 data points for 2011 and 35,136 data points for 2012.

3. Methodology

The initial step was to quality control the wind power and EV data sets. Both data sets had missing values, possibly due to equipment malfunctions or other factors. Linear interpolation was used to fill the missing data points.

After data preparation, correlation coefficients were computed. Correlation coefficients measure the relationship of two separate sets of data using a value range from -1 to 1. A correlation coefficient of 0 indicates there is no correlation between the two sets of data while a coefficient of 1 indicates the two data sets are completely correlated. A coefficient of -1 indicates that the two data sets are anti-correlated. When two data sets are correlated, their data points increase and decrease at the same time, when they are anti-correlated, data points move in opposite directions. There are three correlation coefficients that are commonly used: Pearson's correlation (r), Kendall's ranked correlation (τ) and Spearman's ranked correlation (ρ). Spearman's ranked correlation allows for a straightforward and simpler approach to determining statistical significance. Spearman's ranked correlation is defined as

$$\rho = 1 - \frac{6\sum_{i=1}^{n} d^2}{n^3 - n} \tag{1}$$

where $\sum d^2$ is the sum of all the ranked differences and n is the sample size[12]. The correlation coefficients of the 2011 and 2012 data sets were found separately first, and then the correlation of the set as a whole were computed. The Pearson and Kendall correlation coefficients were computed later, but they yielded similar results.

Since seasonal variations are suspected to affect the correlation coefficients, the data were partitioned by month and the correlation coefficients of each month were computed.

Once the correlation coefficients are determined, the next step is to check if they are statistically significant. Two data sets can be correlated, but that does not mean they are statistically significant. With small data sets there is a larger chance that two data sets exhibit large non-zero correlation without being statistically significant. The t-value is a test statistic used to measure the statistical significance of a correlation coefficient, it is defined as

$$t = \rho \sqrt{\frac{n-2}{1-\rho^2}} \tag{2}$$

where n is the sample size and is ρ the correlation coefficient. The statistical significance is greatly affected by population size as can be seen from (2), therefore in a set as large as those considered in this paper even a small correlation coefficient can be deemed statistically significant.

To test the statistical significance of a correlation value a hypothesis test is conducted. In a hypothesis test a null hypothesis is chosen and then attempted to be disproven. To disprove a null hypothesis first the critical t-value is determined. To calculate a critical t-value a confidence interval is chosen, then using the degrees of freedom (which is two smaller than the sample size) and a t-curve, the critical t-value is found. Next to find the t-values of the correlation coefficients, (2) is used and then they are compared to the critical t-value. If the magnitude of a t-value is larger than the data set's critical t-value, the correlation coefficient is deemed statistically significant.

4. Results

The initial correlations were small. For 2011 all three correlation coefficients were between 0.01 and 0.02. For 2012 the Spearman correlation coefficient was 0.08 correlation and the Pearson and Kendall coefficients were 0.05. The next step was to combine the two years, but this proved to have little effect on the outcome. The correlation coefficients of the entire data sets for Spearman and Pearson were approximately 0.06 and the Kendall correlation was about 0.03.

Next the correlation coefficients were computed on a monthly basis. Figures 1-3 show the monthly correlations in 2011 for the Spearman, Pearson and Kendall correlation coefficients. The original prediction of a seasonal trend to the correlation coefficients was validated. In Figures 1-3, the summer and spring month correlation coefficients are larger and during the winter and fall months they are smaller. This seasonal trend was apparent in all three correlation coefficients for both years.

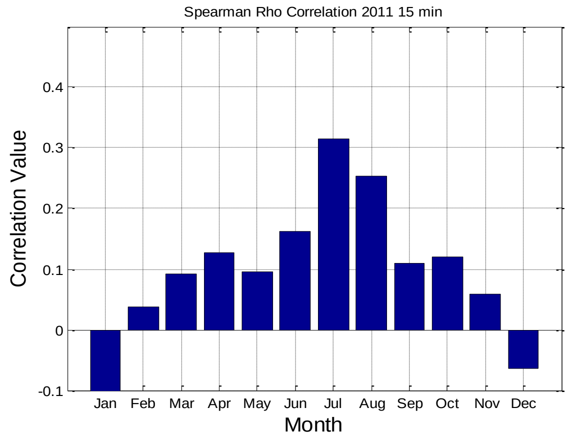

Figure 1: Monthly Spearman correlation coefficients for 2011

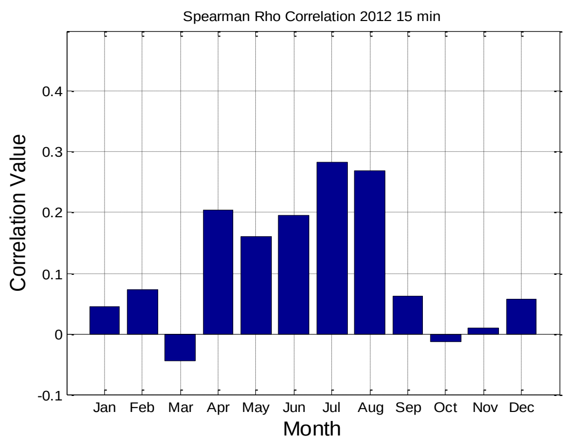

Figure 2: Monthly Spearman correlation coefficients for 2012

The average correlation coefficient values of all three types of correlation were approximately 0.1. These values are larger than the initial calculated coefficients. With the potential relationship of the two renewable technologies stemming from people charging their vehicles late at night, the correlations are quite small. The only correlation coefficient to exceed 0.3 occurred in July for 2011 and it never exceeded 0.3 in 2012.

Scatter plots for two of the months are shown in Figures 3 and 4. The diagram plots a single point that quantifies the electric power generated by wind farms and the electricity used by EVs for each point in time. A correlation of 1 would plot an angled line that increases from left to right. In July 2011 the correlation coefficient is 0.32. Figure 3 has a positive correlation, this means when there is an increase in power produced by wind, there tends to be an increase in electric vehicle charging. In December 2011 the correlation coefficient is -0.06. Figure 4 shows that there is little relation between the two data sets. This may be due to the fact that less wind power is produced in December than in July.

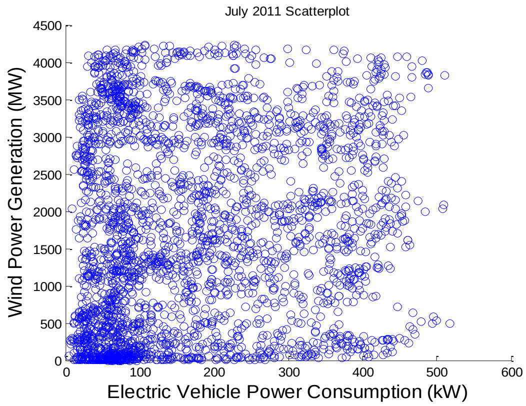

Figure 3: July 2011 Scatterplot; ρ =0 .32

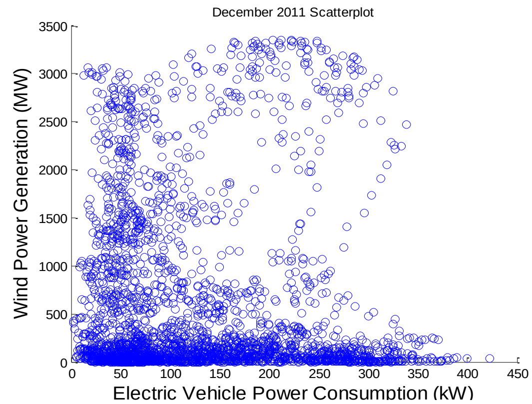

Figure 4: December 2011 Scatterplot; ρ = -0.06

With such a large sample size a critical t-value of 1.645 is obtained which is quite smaller in magnitude than the calculated t-values shown in Table 1.

Table 1: t-values for the Spearman correlation coefficient values of 2011

Month	t-value
Jan	-21.28
Feb	6.97
Mar	17.16
Apr	23.77
May	18.04
Jun	30.22
Jul	59.09
Aug	47.50
Sept	20.42
Oct	22.46
Nov	11.02
Dec	-11.93

At a 95% confidence interval the magnitudes of all the correlation coefficient t-values are much greater than the critical t-value. This shows that the correlation coefficients determined in at the beginning are indeed statistically significant, yet still small.

The small correlation coefficient values were not foreseen, the profiles of the two technologies seemed to match so well. To check this similarity the 15-minute averages for the generation of wind power and charging of EVs were computed and graphed. In other words, samples corresponding to time 0:00—regardless of which day—were averaged. Then, the samples corresponding to 0:15 were averaged, and so on until 96 averages—each associated with a 15 minute interval of the day— was computed. Figures 5 and 6 show the average value of each 15 minutely interval in a day of the data set.

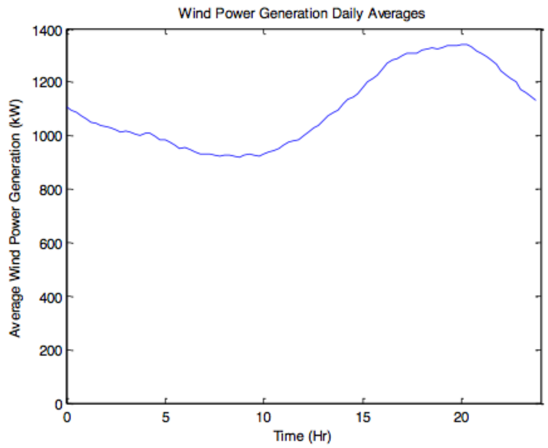

Figure 5: Wind Power Generation Daily Average

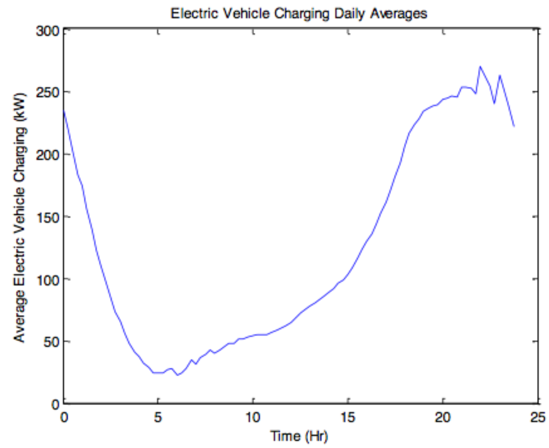

Figure 6: EV Charging Daily Average

Figures 5 and 6 both exhibit a sinusoidal shape, and are almost in phase. The correlation coefficients for the average day values were calculated and the correlation coefficients were much larger than their predecessors. The Spearman and Pearson correlations were approximately 0.85 and the Kendall correlation was about 0.67. The averages of the two data sets were quite correlated, but the non-averaged values were not. While this may seem unusual, this phenomenon is known as "ecological correlation"[13], and often occurs when samples are averaged.

5. Conclusion

There indeed is a statistically significant correlation between the generation of wind power and the charging of electric vehicles. However, the correlation coefficients overall were very low, the average of the monthly correlation coefficients was approximately 0.1. The correlation coefficients for the average day were large, but this discovery does not improve their viability, averages hide variation and inflate the correlation. The correlation coefficients for the non-averaged samples are small and suggest that simply charging electric vehicles at night may not be the only method to optimize the use of available wind energy, it may be better to monitor wind power production to determine the best time to charge electric vehicles. While we cannot control the production of wind power we can control when electric vehicles are charged.

Further research could shed light on how to improve the correlation between the generation of wind power and the charging of EVs. Finding what variables cause the seasonal trend in the data could lead to the improvements the correlation. The economic implications of an improved correlation should also be researched; by using low cost wind power to charge EVs, these vehicles could become cheaper to operate and more appealing to consumers.

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7. References

1. The World Bank, "Motor vehicles (per 1000 people)",
http://data.worldbank.org/ indicator/IS.VEH.NVEH.P3

2. US. Energy Information Administration, “International Energy Statistics/Petroleum/ Consumption”, http://www.eia.gov/cfapps/ipdbproject/IEDIndex3.cfm?tid=5&pid=5&aid=2
3. US. Energy Information Administration, “International Energy Statistics/Petroleum/ Reserves”, http://www.eia.gov/cfapps/ipdbproject/IEDIndex3.cfm?tid=5&pid=57&aid=6
4. US. Environmental Protection Agency, “Air Emissions”, http://www.epa.gov/cleanenergy/energy-and-you/affect/air-emissions.html
5. US. Environmental Protection Agency, “Nitrogen Dioxide (NO_2)”, http://www.epa.gov/airtrends/aqtrnd95/no2.html
6. US. Environmental Protection Agency, “Sulfur Dioxide (SO_2)”, http://www.epa.gov/airtrends/aqtrnd95/so2.html
7. Global Wind Energy Council, “Global Wind Report/ Annual Market Update 2013” http://www.gwec.net/wp-content/uploads/2014/04/GWEC-Global-Wind-Report_9-April-2014.pdf
8. US Department of Energy, “Federal Incentives for Wind Power Deployment” http://www1.eere.energy.gov/wind/pdfs/51452.pdf
9. E. Ungar and K. Fell, “Plug In, Turn On, and Load Up,” IEEE Power & Energy Mag., vol.8, no.3, pp. 30-35, May/June 2010.
10. Bonneville Power Administration, http://www.bpa.gov
11. EV Project, http://www.theevproject.com
12. Maurice Kendall and Jean Dickinson Gibbons: Ranked Correlation Methods (New York: Oxford University Press, 1990), 8
13. Int. J. Epidemiol. (2009) 38 (2): 337-341. doi: 10.1093/ije/dyn357 First published online: January 28, 2009, http://ije.oxfordjournals.org/content/38/2/337.full