MINIMIZING WIND VARIABILITY WITHIN A POWER PORTOLIO

by

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ABSTRACT

Many utilities would like to increase the percentage of renewable energy within their power portfolios. This study focused on how that might be achieved with wind power and in particular the problem of variability. Recent articles have suggested that aggregating the output of multiple wind farms could smooth the output and lower the variability. The purpose of this study was to investigate the effect of aggregating wind farms in the New England region. We analyzed three years of output from a diverse group of wind farms and found that smoothing does occur in aggregation to some degree. Furthermore, the analysis showed that New England utilities can increase the percentage of wind power within their portfolios without increasing their exposure to variability.

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INTRODUCTION

An issue facing many utilities today is the desire to increase the percentage of renewable energy within their power portfolio. The problem lies in the fact that renewables have drawbacks. This study focuses on wind power and addresses its downside which is variability. The bottom line is that too much variability increases costs. When the power level from wind is low, that deficiency must be covered by purchasing power from the spot market. When the level is too high the overage must be sold in the spot market. Given the timing characteristics of wind this often means that we are selling overages at night when the market price is low and buying during the day when prices are highest.

So the question is: How can we manage the variability of wind power? The goal of this study is to investigate possible answers to that question.

We have seen articles, such as the report “Grid Impacts of Wind Power: A Summary of Recent Studies in the United States” presented by the National Renewable Energy Laboratory, in which they assert that, “large-scale geographic diversity (results) in smoothing of aggregate power output.” Presented with this idea we began looking for studies on this issue. We discovered a study that investigated this very issue [2] whose results support the assertion. However, neither report described a methodology for aggregation and how to quantify the benefit.

With this information we set out to investigate;

1) Would aggregated smoothing result within New England?
2) If so, to what degree, and
3) If so, can we determine a process that will enable us to use this to our advantage?

The report will be demonstrated below as follows:

Section 1 describes the wind farms under study and the data collected, as well as how that data was configured for analysis.

Section 2 discusses the methodology used for the analysis as well as preliminary information obtained from the data.

Section 3 examines the core of the analysis; optimization and the OptQuest® [4] software, what it does, how we apply it to our data, and the results.

DATA

The initial data set consists of measured wind speed and power output, in ten minute intervals over three years, from thirteen locations throughout New England as seen in figure 1 and listed in table 1. To the best of our knowledge this list includes all the wind farms delivering power to the electric grid during the time covered by the data-set. The data was provided through the National Renewable Energy Laboratory (NREL). The ten minute resolution was condensed to reflect hourly averages in an effort to have a more manageable data set. (Reducing 2,211,398 data points to 368,634)

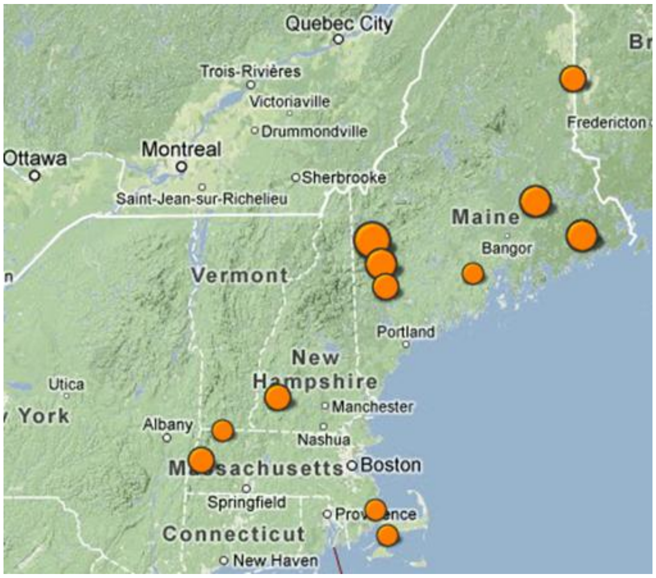

Figure 1: Wind Farm Locations [8]

Table 1: Wind Farms in Study

Plant	Mean Historical Hourly Output (kW)	Historical Standard Deviation	Min	Max
Beaulieu Wind ME	15.0	13.4	0.0	50.0
Beaver Ridge ME	1,861.5	1,475.2	0.0	4,500.0
Berkshire 1 and 2	12,241.5	9,220.6	0.0	30,000.0
Hull MA	935.8	765.4	0.0	2,460.0
Lempster Wind NH	10,115.3	7,732.7	0.0	24,000.0
Mars Hill ME	16,385.3	12,357.6	0.0	42,000.0
Oakfield Wind ME	45,190.9	33,074.0	0.0	107,090.0
Portsmouth RI	465.0	391.5	0.0	1,500.0
Princeton MA	1,071.9	878.0	0.0	3,000.0
Record Hill ME	17,349.0	15,556.0	0.0	50,600.0
Searsburg VT	2,829.7	2,165.2	0.0	6,600.0
Spruce Mnt ME	7,541.7	6,100.1	0.0	20,000.0
Stetson Ridge ME	20,015.5	16,713.4	0.0	57,000.0
All Plants Combined	136,018.2	84,242.7	140.7	340,556.1

Summary: Data was collected from the National Renewable Energy Laboratory for thirteen wind farms dispersed across New England covering a thirty-six month period. Extensive analysis was performed to better understand the nature of wind power in the region.

ANALYSIS

The data was imported into an Excel workbook to be analyzed for correlation coefficients, seasonal and hourly differences, and the frequency of high and low levels of output. The minimum, maximum, mean, and standard deviation for each location were determined as well. This preliminary analysis was required for the optimization but also provided an overview of the relational aspects of the data.

As shown in the correlation matrix below, there are no negative correlations between wind farms. A negative correlation would mean that as wind and power output is rising at one location it would be falling at another. If two farms outputs were exactly opposite with respect to time we would see a correlation of -1. A positive correlation means that the output of the farms are moving in the same direction. Having all positive correlations implies that it is not possible to create a wind farm combination that results in zero power variability. However, there are a number of farms with positive but low correlation, implying that there are wind farm combinations that will result in lower power variability than a single farm.

Table 2: Correlation Matrix

	Beaulieu Wind ME	Beaver Ridge ME	Berkshire 1 and 2	Hull MA	Lempster Wind NH	Mars Hill ME	Oakfield Wind ME	Portsmouth RI	Princeton MA	Record Hill ME	Searsburg VT	Spruce Mnt ME	Stetson Ridge ME
Beaulieu Wind ME	1.00												
Beaver Ridge ME	0.53	1.00											
Berkshire 1 and 2	0.38	0.50	1.00										
Hull MA	0.46	0.47	0.58	1.00									
Lempster Wind NH	0.45	0.56	0.79	0.62	1.00								
Mars Hill ME	0.77	0.56	0.38	0.39	0.46	1.00							
Oakfield Wind ME	0.84	0.57	0.42	0.46	0.51	0.81	1.00						
Portsmouth RI	0.33	0.41	0.56	0.64	0.54	0.32	0.35	1.00					
Princeton MA	0.41	0.55	0.71	0.67	0.73	0.42	0.45	0.72	1.00				
Record Hill ME	0.56	0.82	0.47	0.51	0.53	0.56	0.58	0.43	0.54	1.00			
Searsburg VT	0.40	0.57	0.70	0.53	0.68	0.43	0.45	0.58	0.79	0.51	1.00		
Spruce Mnt ME	0.58	0.78	0.50	0.55	0.57	0.56	0.61	0.46	0.57	0.85	0.55	1.00	
Stetson Ridge ME	0.60	0.39	0.35	0.53	0.42	0.50	0.56	0.42	0.44	0.48	0.39	0.49	1.00

As shown in the graph below, this is borne out by a simple combination of all the wind farms output which results in a higher output per unit of standard deviation (referred to as average-to-variability). The combined output for all farms results in 1.61 units of power per unit of standard deviation, whereas no single farm is above 1.40.

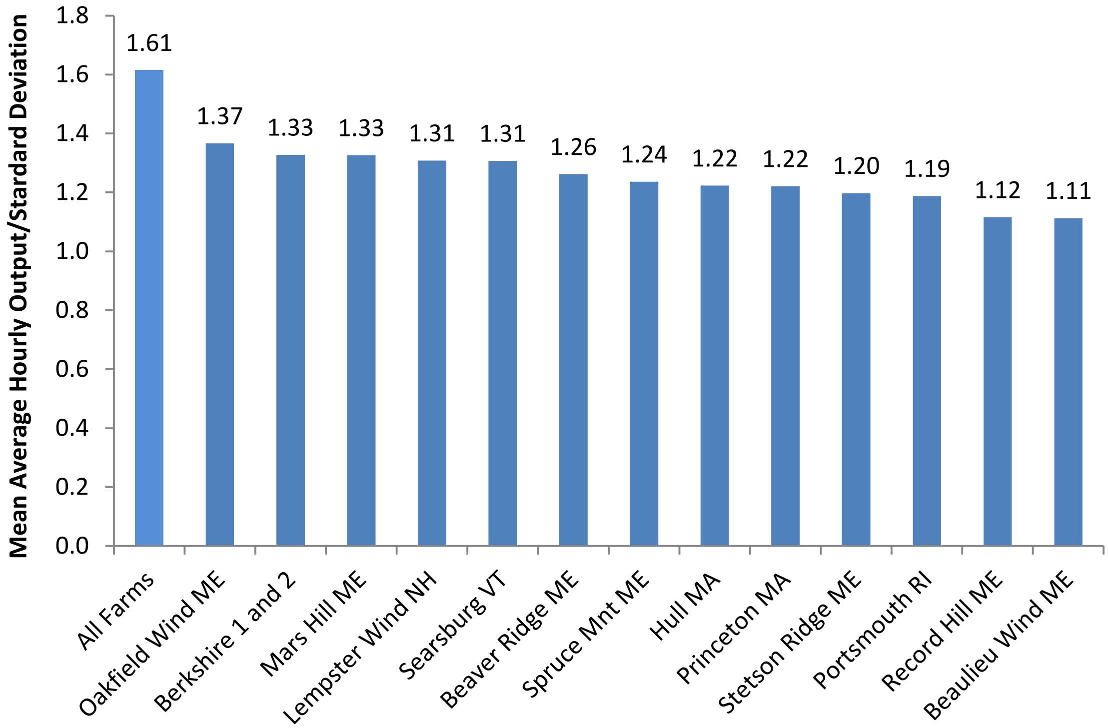

Figure 2: Unit of Output per Unit of Standard Deviation

The average-to-variability ratio is an important measure which allows us to compare standard deviations across different levels of output.

The average-to-variability ratio is the core of this report. By taking the total power produced by a given plant or combination of plants and dividing by the standard deviation we can make comparisons on an equal scale. This ratio tells us how much variability exists for each unit of power produced. Indirectly, it suggests how much conventional power is needed to cover the periods of low output.

Before the most serious analysis began, it was important to understand the characteristics of the data. We began by looking at the analysis of output across seasons which shows power output is much higher in colder months than in warmer months. The median total output (for all the farms combined) in January is nearly two and a half times that of July.

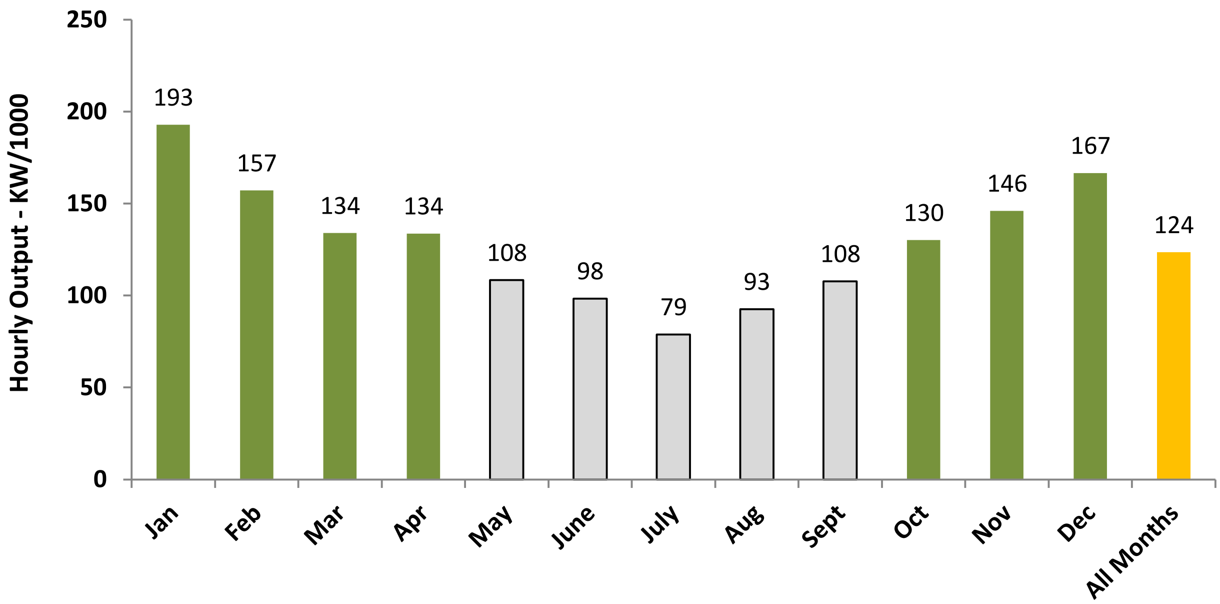

Figure 3: Median Total Output of All Farms by Month

The analysis of output (for all the farms combined) over each hour shows a similar pattern of higher output when it is cooler at night and lower output when it is warmer during the day. However, there is less difference between the highest and lowest output hours than there is between months (1.8 times versus 2.4 times).

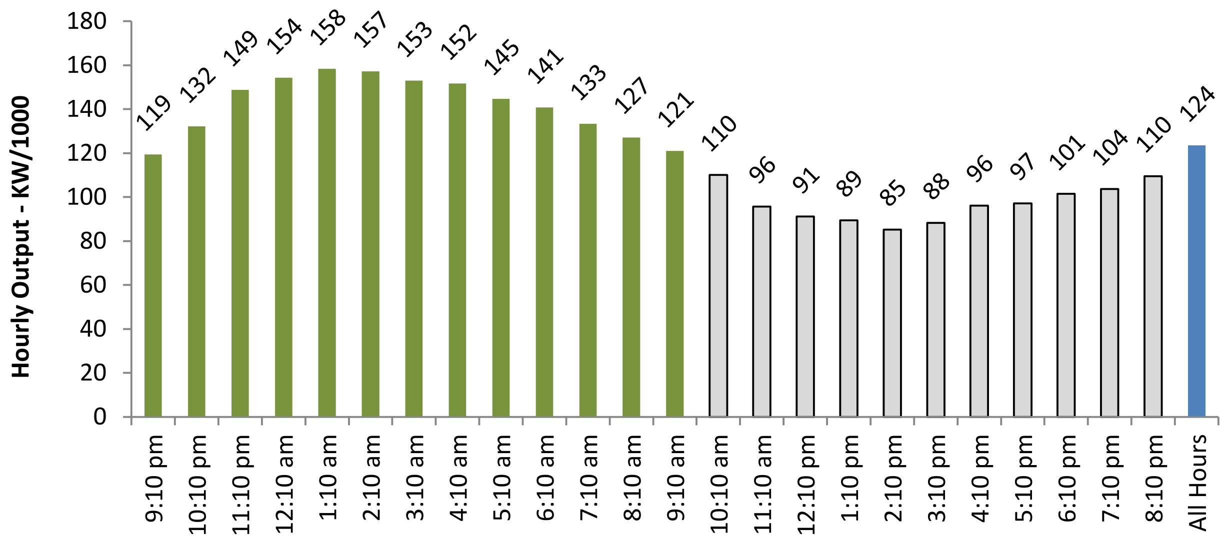

Figure 4: Median Total Output of All Farms by Hour

Figure 4 represents the 3 year average output for each hour of the day. This does not hold true for any particular hour of any particular day.

Summary; We have organized the data and defined our metric as average–to-variability. The preliminary analysis suggests that there are combinations of farms that will lower the variability. In the next section we examine different scenarios to minimize the variability.

OPTIMIZATION

To determine the combination of wind farms that would result in the minimal amount of variability for a given level of output, OptQuest multi-variable optimization software was used. OptQuest is part of the Crystal Ball software by Oracle and is self-described as [4];

> *OptQuest incorporates metaheuristics to guide its search algorithm toward better solutions. This approach uses a form of adaptive memory to remember which solutions worked well before and recombines them into new, better solutions. Since this technique doesn't use the hill-climbing approach of ordinary solvers, it does not get trapped in local solutions, and it does not get thrown off course by noisy (uncertain) model data.*

A flow-chart of the process is shown in the Appendix, figure 29 with a description of how the software achieves results.

To begin we conducted optimizations to find the percentage of power from each wind farm that would result in the minimum standard deviation of average hourly output for a mean output level of at least 1,000 kilowatts. That power level was chosen because currently Concord, MA derives approximately 3% of its total power needs from wind power with a contract with the Spruce Mountain plant for 10% of its power. Targeting 1,000 kilowatts would move wind power to approximately 5% of the total.

The optimizations were run using the historical power-output data series described above with a maximum of 25,000 simulations as their termination criteria. The first optimization used the first two years of the data set to find the optimal percentage of power from each wind farm. The results were then tested against the data set from the third year to determine if the mean output and standard deviation were significantly different. If they were not different this would support the use of optimization over historical power output series to determine future contracted power for a wind farm portfolio.

The only constraint in the optimization was that each wind farm's output could range from 0% to 25%. The percentage of each farm's output was tested in increments of 0.01%.

The first optimization results delivered a mean total hourly output of 1,000 kilowatts with a standard deviation of 593 kilowatts from the percentage of each plants output shown below in figure 5.

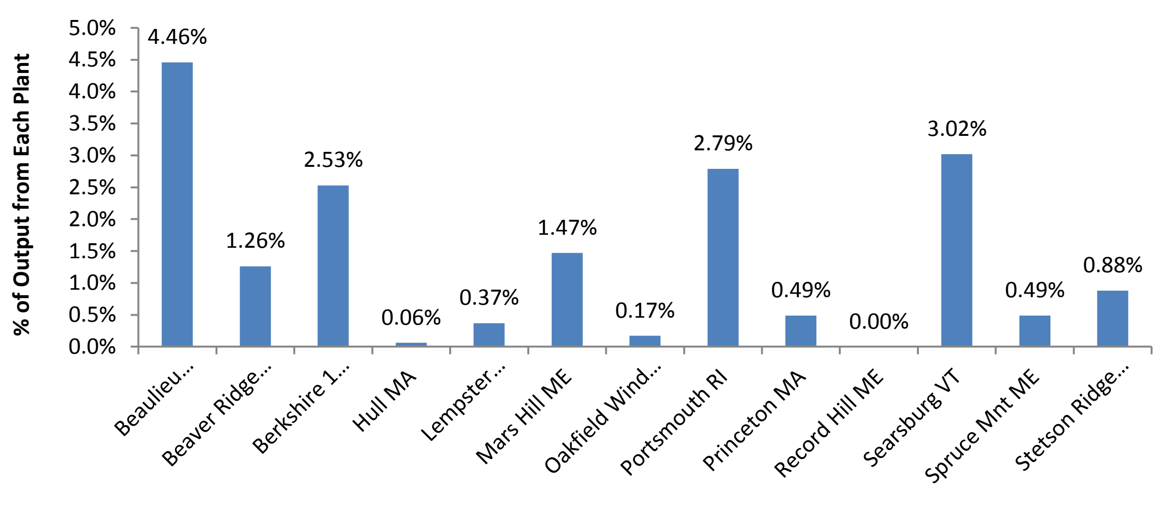

Figure 5: Optimization Percentages for 1,000 k

Testing those percentages against the out-of-sample data from the third year gives a mean total hourly output of 1,019 kilowatts with a standard deviation of 595.

The in-sample periods also have nearly the same distribution of total output as the out-of sample year illustrated in figure 6.

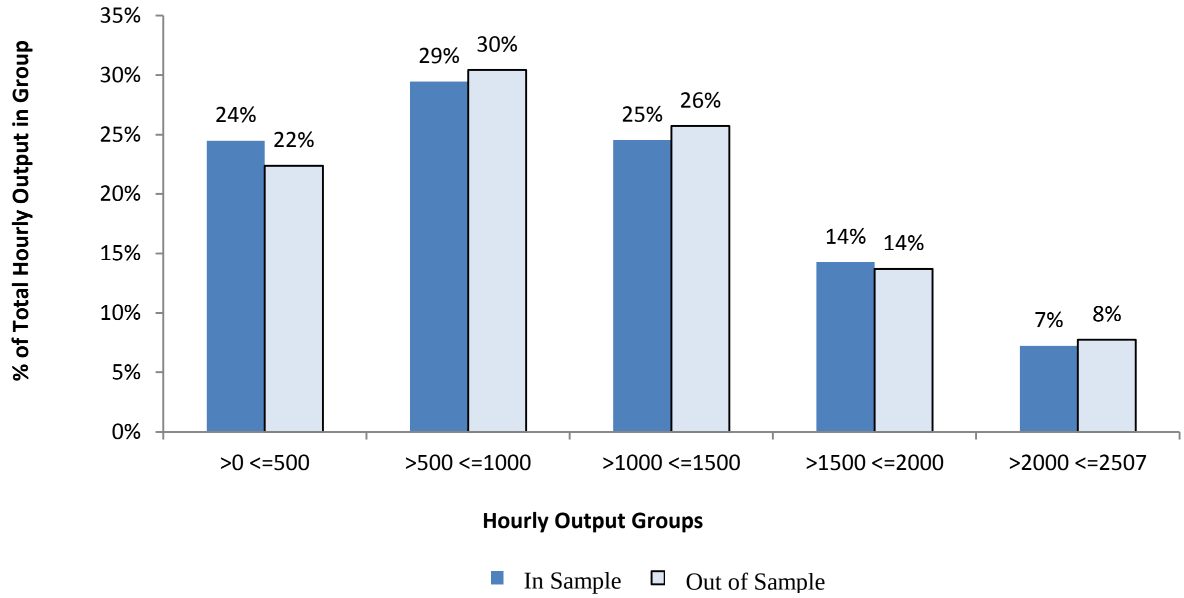

Figure 6: Distribution Comparison of Samples

Because the distributions of output levels are so similar for the out of sample data, the use of deterministic modeling using the historical data is supported.

The graphs below show the total hourly output stream that would have resulted from the optimized percentages of plant output from figure 5 for all 3 years.

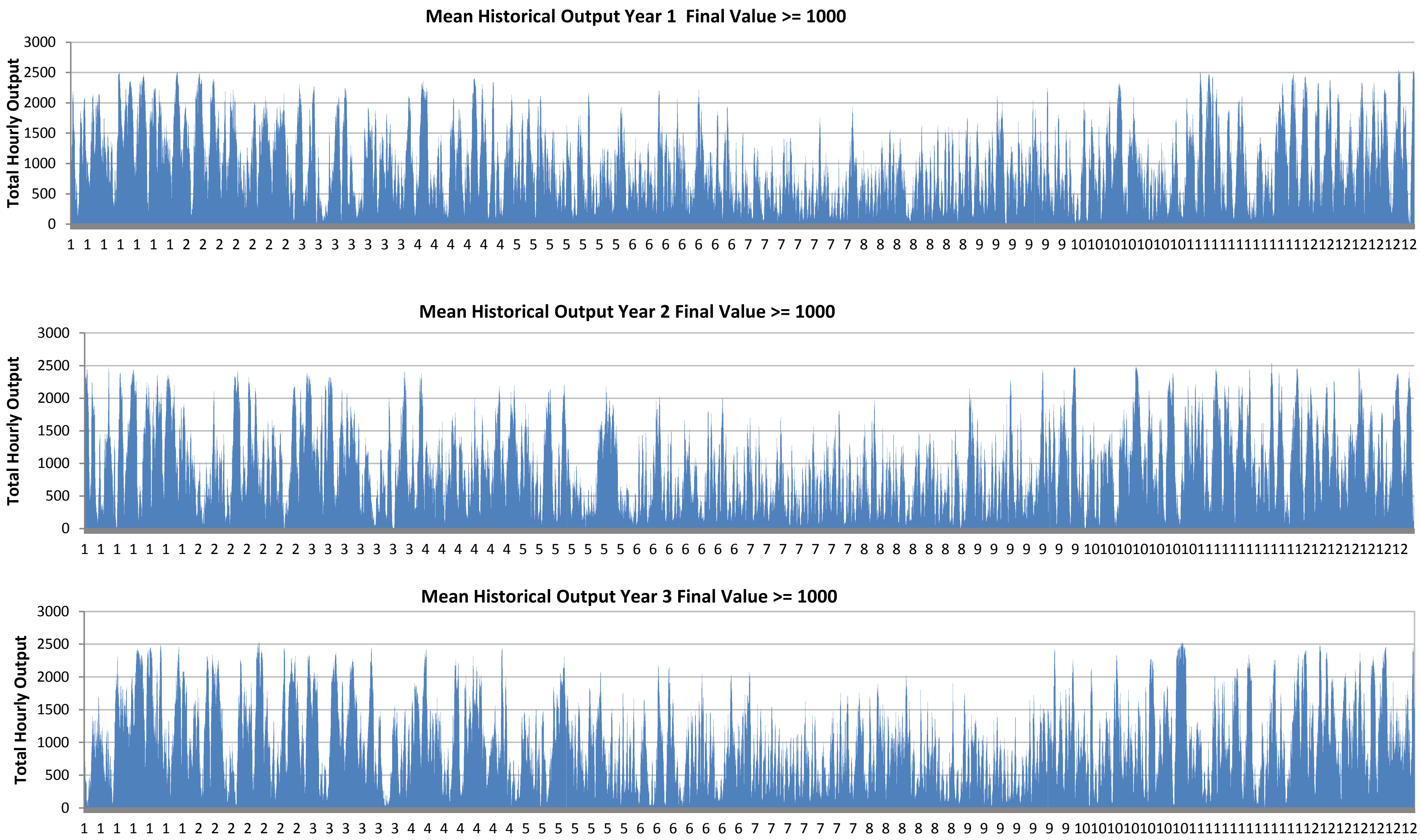

Figure 7: Hourly Output Levels of Optimized Portfolio for 1,000 kW

The relatively large level of variability remaining after optimization is due to two main factors:

1) The extreme variability of wind power levels with respect to time (figures 5-7)
2) The positive correlations between all of the wind farms (table 2).

In order to show the value of the optimization process in reducing variability we can compare the output from Concord's current contract with Spruce Mountain to an optimized portfolio of wind farms. As stated above, Concord Massachusetts is currently receiving ≈ 3% of its power requirements from the Spruce Mountain wind farm in Maine. Our research indicates that this equates to an average output of 754kW with a standard deviation of 610kW resulting in an average-to-variability ratio of 1.24. Optimization of the same level of output from multiple farms improves this ratio to 1.69. Optimized standard deviation is 27% lower. This means that the variability has been dramatically reduced. The improvement in variability can also be seen by comparing the two graphs below (figures 8-9) of the output from Spruce Mountain alone and the output of an optimized portfolio of wind farms. Each graph is zoomed in to 1 month resolution.

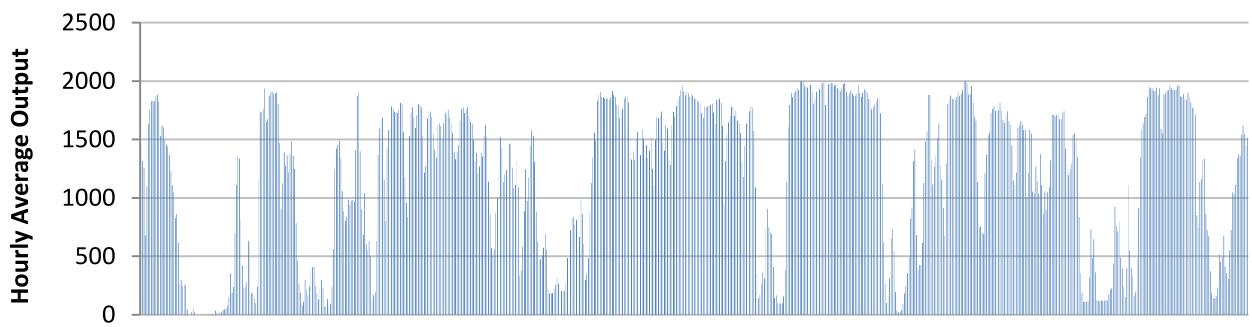

Figure 8: Current Contract of 10% Spruce Mtn. ME. Hourly Average Output for 1 Month

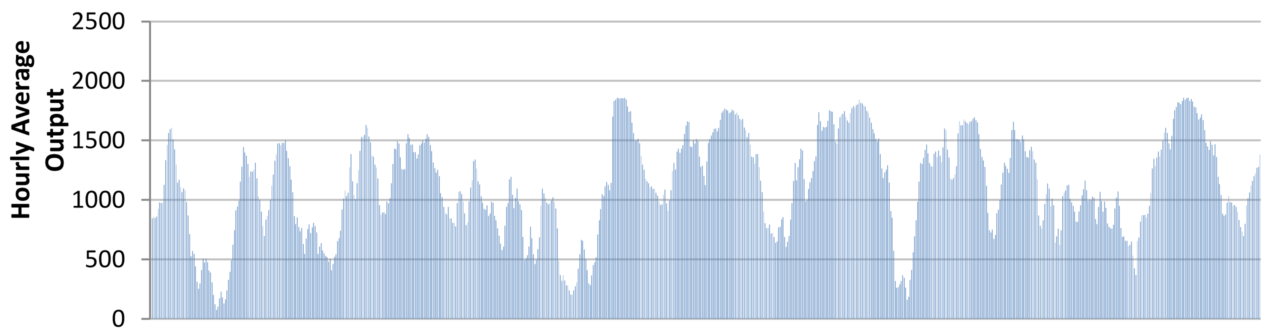

Figure 9: (Current Power Level) Optimized Hourly Average Output for 1 Month

Similar smoothing is seen for each time interval within the data-set.

Rather than receiving 10% of Spruce Mountain's power, the optimized portfolio for 754 kW is shown below.

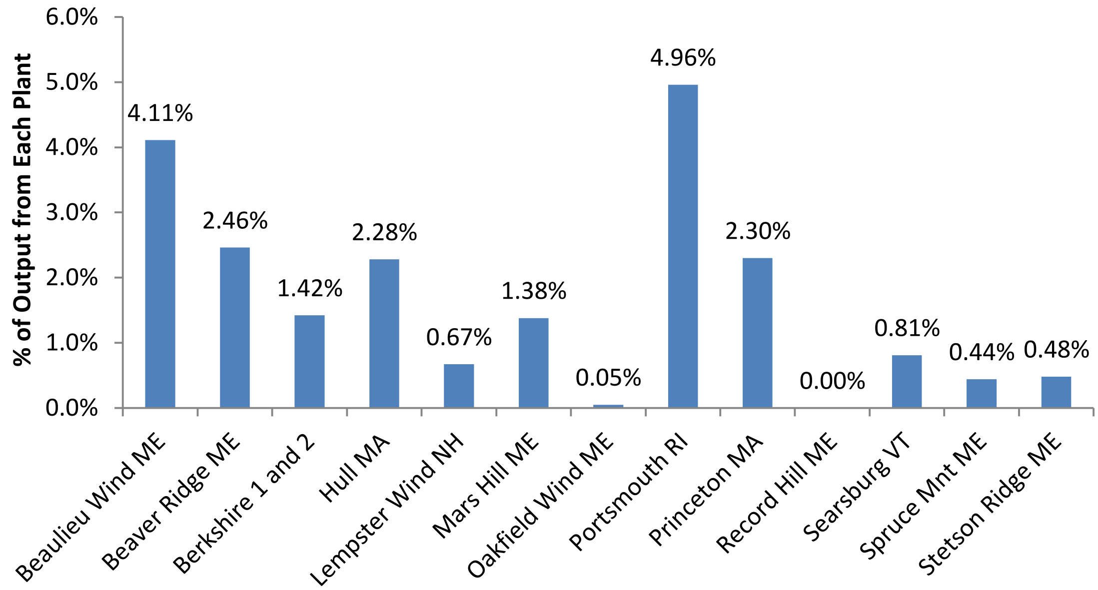

Figure 10: Optimized 754 kW

Given the high variability across seasons shown in Figure 3, other optimizations were explored to determine if variability could be lowered by using only cooler months or by optimizing cooler months separately from warmer months. The first optimization used power from September through May, removing June, July, and August which have the lowest median output. In order to achieve the same level of annual output with three fewer months, the average hourly output objective was increased from 1,000 to 1,350 kW. This optimization results in a higher average-to variability ratio than using all months (1.80 versus 1.69). This higher ratio tells us that for each kilowatt of power there is less variability.

The second optimization also removed May and September to use power from October through April. In order to achieve the same level of annual output with five fewer months, the average hourly output objective was increased from 1,000 to 1,714 kW. This optimization results in an even higher average-to variability ratio than using all months (1.88 versus 1.80 and 1.69). Once again, for each kilowatt of power there is even less variability.

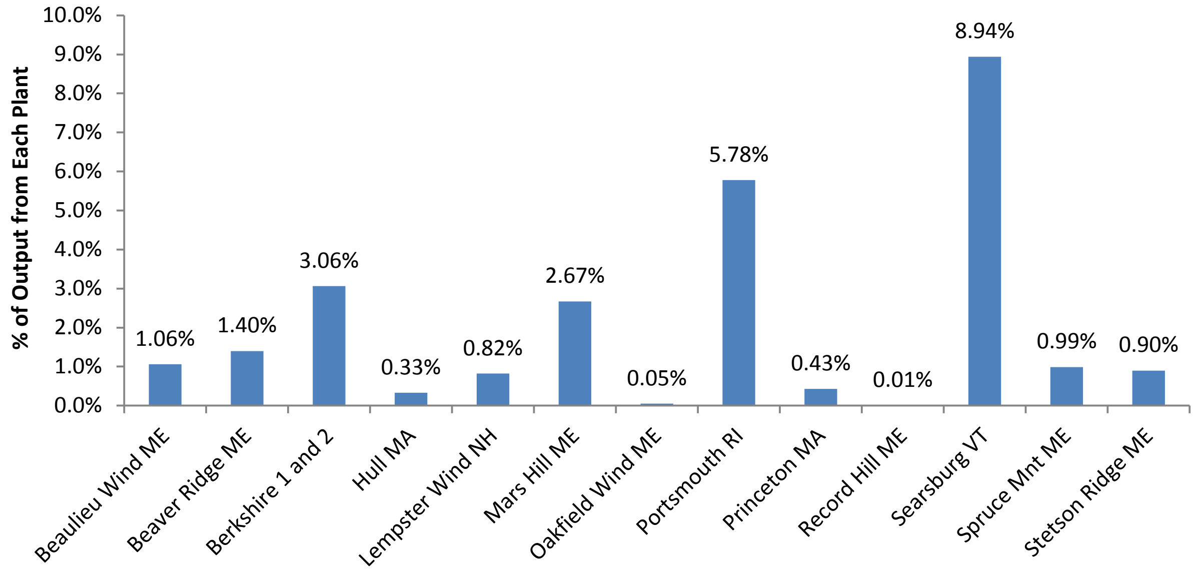

Figure 11: Optimal Contract Oct-Apr Contract. Mean Output = 1,754 kW

The third optimization was done in two parts to investigate if utilizing separate contracts in cooler and warmer months could also lower variability. The first part optimized from October through April for an output level of 1,161 kWh. The second part optimized from May through September for an output level of 774kWh, for a combined power level of 1,000 kWh over the year. The average-to-variability ratio of the October through April is 1.85, nearly 50% higher than the ratio of the current contract with Spruce Mountain at 1.24. The average-to-variability ratio of the May through September is 1.65 – very close to the optimization of all months for an output level of 1,000 at 1.69. Therefore, there is little increase in relative variability over the summer months but a decrease in variability over the winter months by utilizing separate contracts. The weighted average-to-variability of the two contracts is 1.77. The contract values for each of the optimizations are shown below.

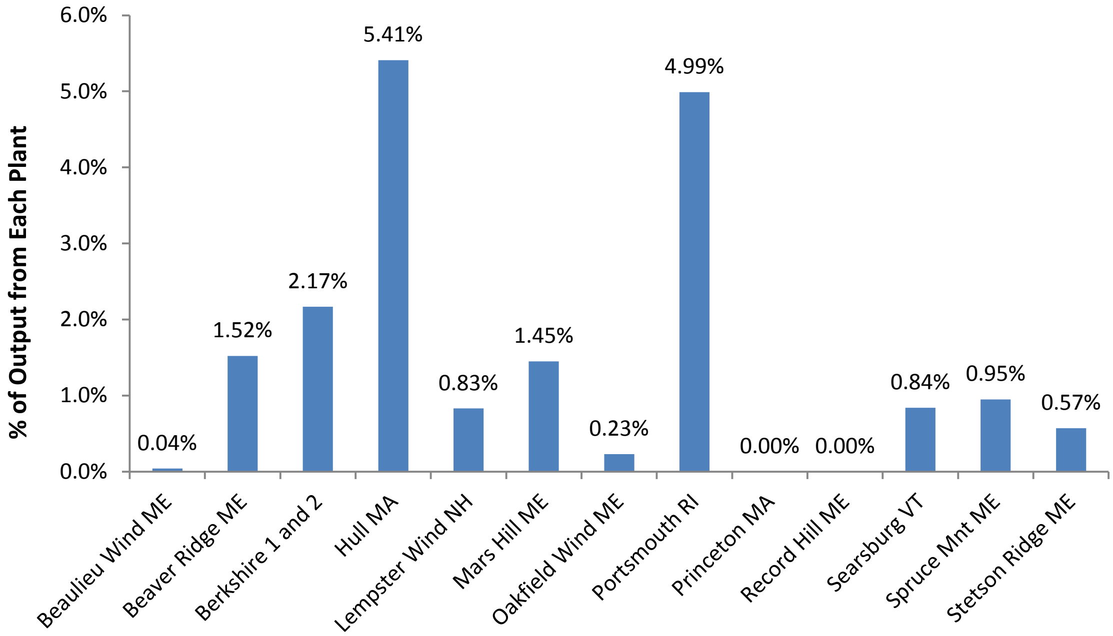

Figure 12: Optimal Contract Oct-Apr Contract. Mean Output = 1,161 kW

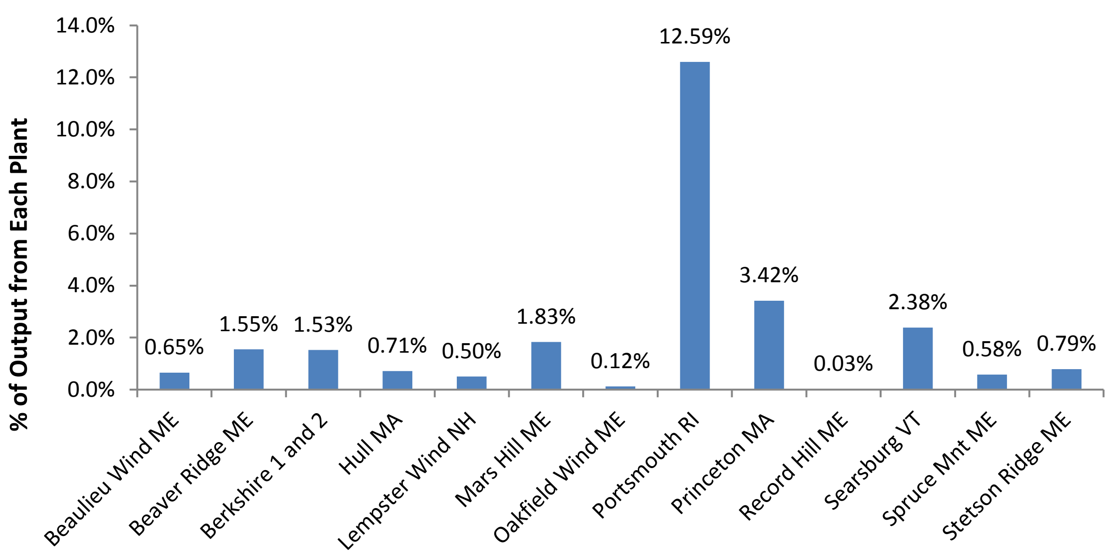

Figure 13: Optimal Contract May-Sept Contract. Mean Output = 754 kW

The figures below show the average-to-variability ratios for all optimizations and a scatter plot of mean hourly output versus standard deviation. Both of these figures show how accounting for the seasonality of wind output decreases the variability leading to more efficient levels of output per unit of variability.

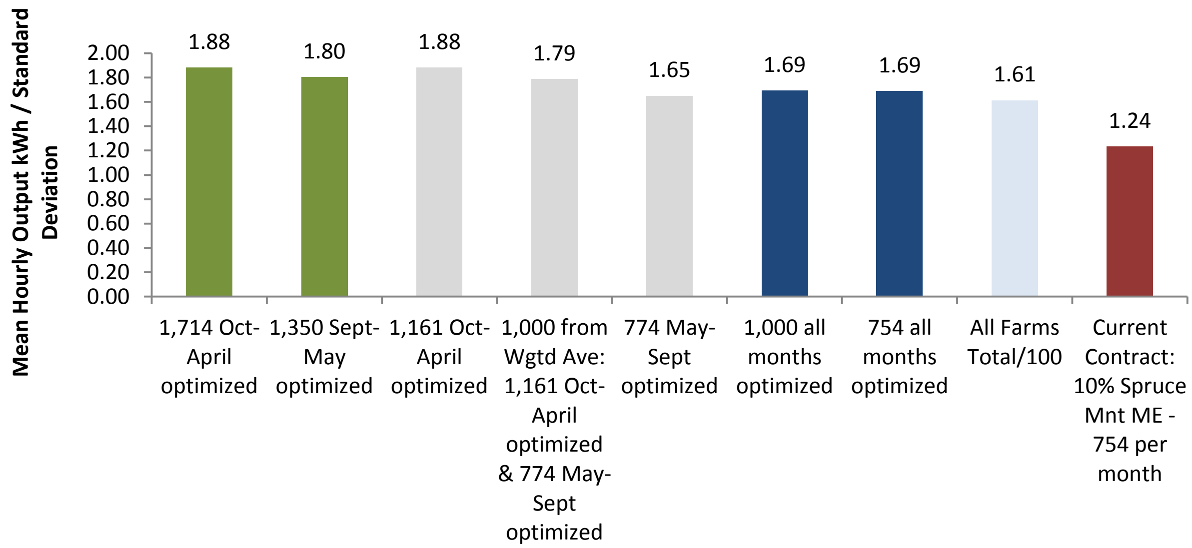

Figure 14: Average-to-Variability Ratios: Unit of Output per Unit of Standard Deviation

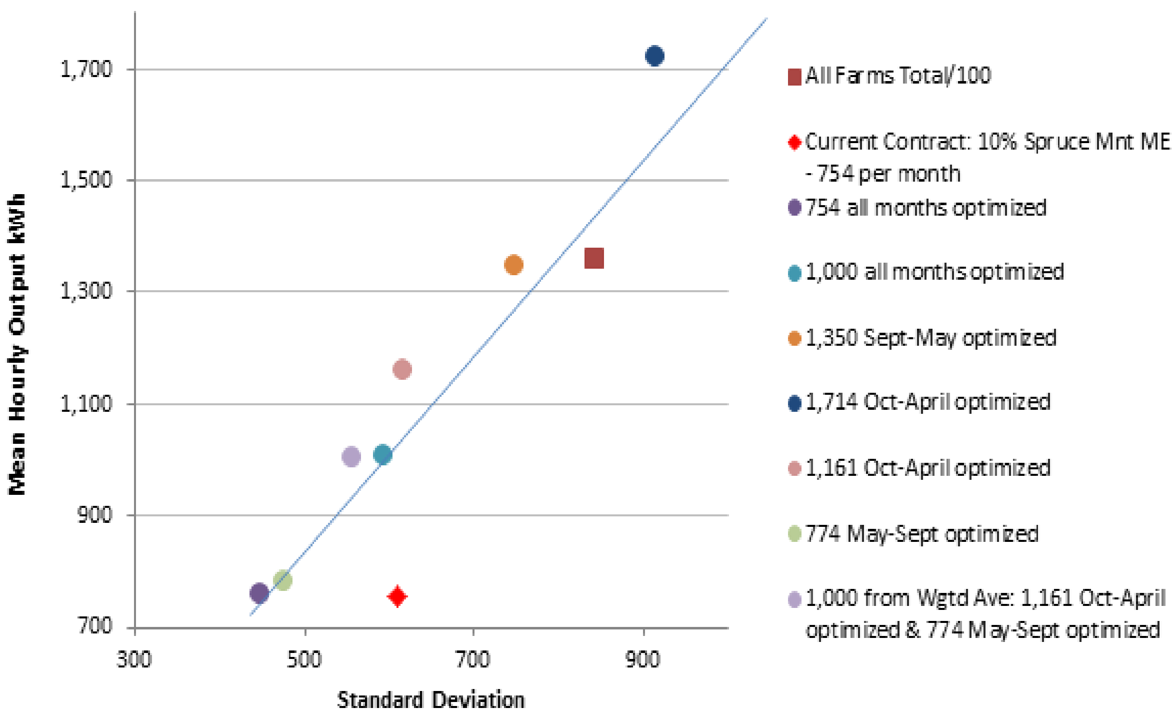

Figure15: Mean Hourly Output verses Standard Deviation

Even without specifically accounting for seasonality, the optimization process improves the total power without increasing the standard deviation. This can be seen in Figure 16 where the optimized 1,000 kW full-year contract has a slightly lower standard deviation as the current contract with Spruce Mountain but with 33% more output.

REOPTIMIZATION

The optimization results above show clear benefit in combining the output of a wind farm portfolio to lower variability for a given level of power output. However, it may not be practical to negotiate and maintain contracts with as many as 13 wind farms. Furthermore, after converting the percentages of output from each wind farm into a mean power level, many of the wind farms are not contributing a meaningful level of power. Therefore, we also investigated the benefits of combining a smaller number of wind farms – namely the six wind farms contributing the highest level of power. These wind farms are: Beaver Ridge ME, Berkshire 1 and 2, Lempster Wind NH, Mars Hill ME, Spruce Mountain ME, and Stetson Ridge ME.

The results show the same benefit as optimizing over the entire portfolio of wind farms with identical average-to-variability ratios for most.

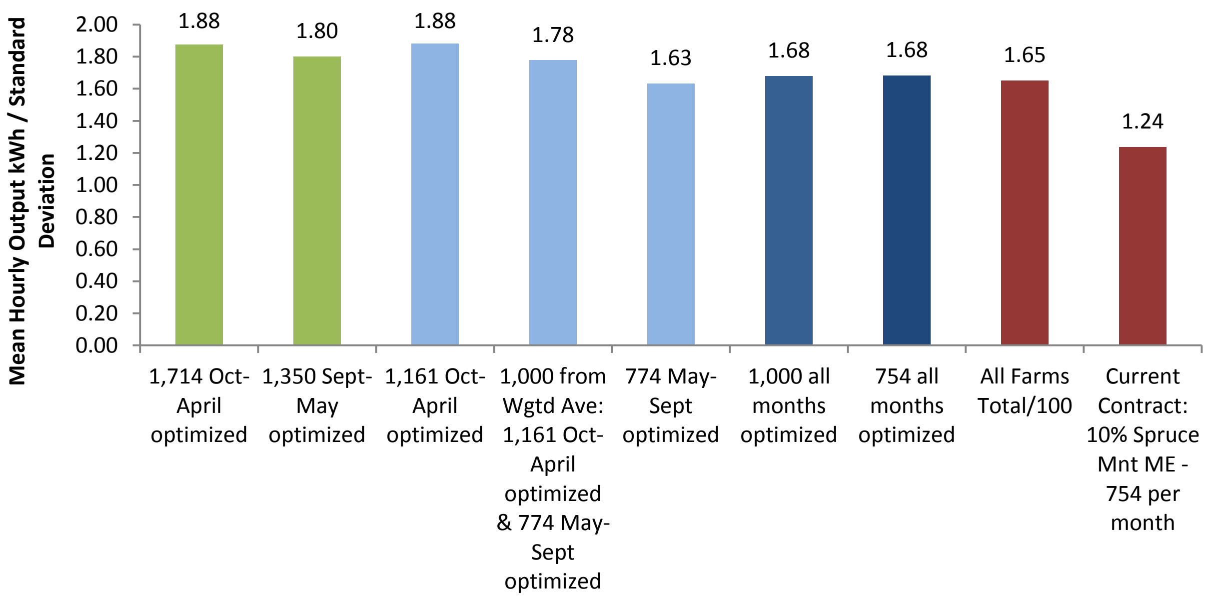

Figure16: Optimization of Top 6 Plants. Average-to Variability Ratios.

The scatter plot of mean hourly output of re-optimized combinations versus standard deviation continues to demonstrate the same relationships between output and standard deviation as the optimizations using all plants.

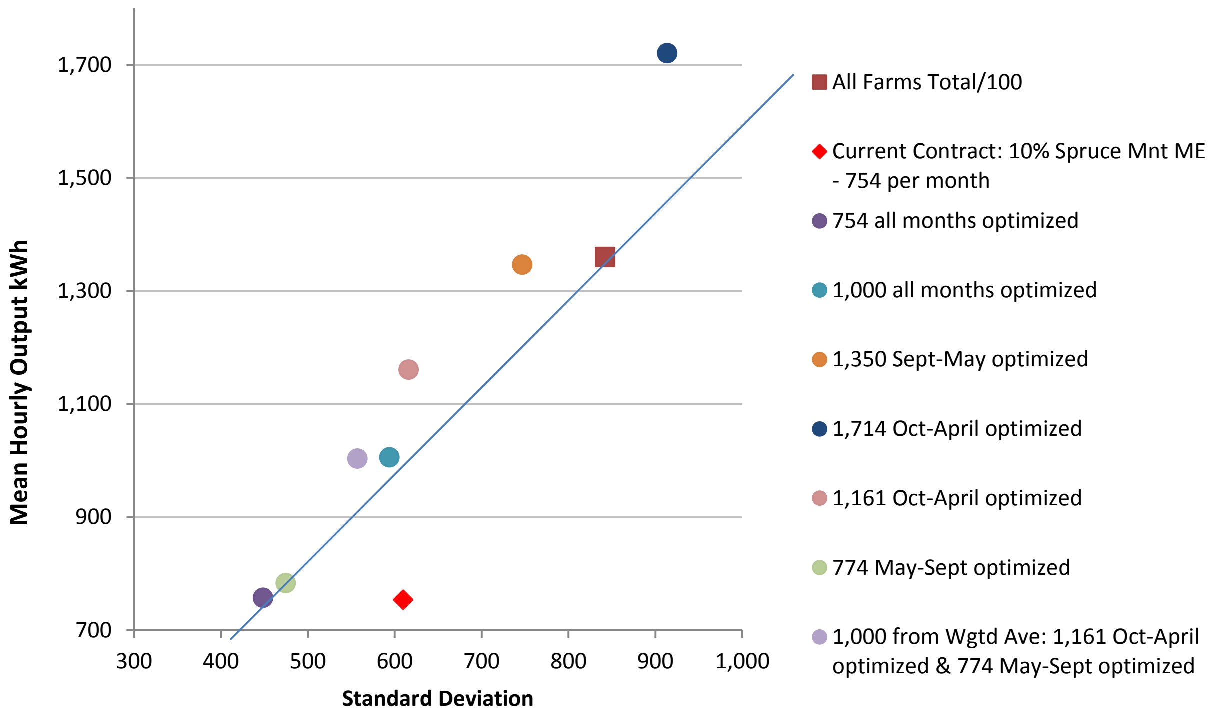

Figure 17: Mean Output of Re-optimized Top 6 Plants versus Standard Deviation.

A comparison of the results for the optimizations for all plants and the top six plants with a mean output of 1,000 kW is shown below, along with a translation of the percentage of plant output into a mean power level. Comparisons of the other optimizations show similar behavior and are included in the Appendix.

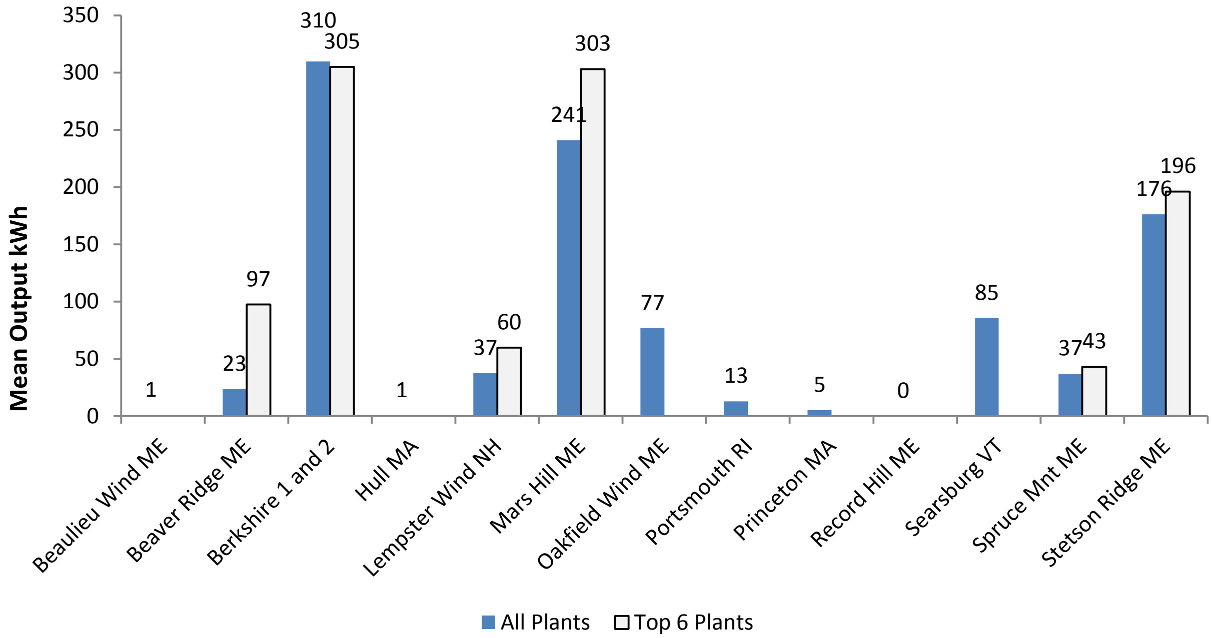

Figure 18: Mean Output from Each Plant for Optimal Contracts. Mean Output = 1000 kW.

CONCLUSION

The data confirms that the aggregate of multiple wind farms smooths the variability. However, with the relatively small area and limited topographical diversity within the New England region the amount of smoothing is somewhat limited.

The report concerning aggregate smoothing referred to in this paper [2] considered sixty wind farms in Germany which covers 137,800 square miles of diverse terrain. New England is less than half the size with a total area of 66,507 square miles and less than one quarter the number of wind farms. This is likely why New England doesn't see the same level of smoothing.

The analysis shows that New England utilities can increase the amount of wind power within their portfolios without increasing their exposure to variability. For the utility manager, this means that they can fulfill the desire to increase the percentage of wind power purchased without increasing the amount of conventional power required to cover the overages and shortages associated with wind's variability. Furthermore, this can be achieved without using the ideal optimizations which include purchasing some very small percentages. In fact, after running an initial optimization we may have results that include purchasing 0.032% of “Farm A” output. These kinds of purchases do not seem realistic. However, by taking the initial results and removing the lowest level contributors, then re-optimizing, we can achieve nearly identical amounts of power without increasing the variability. This step enables us achieve results that more closely match real world application. Decreasing the optimization resolution to match contract requirements (i.e. rounding to whole number or other percentage) should have minimal impact on the minimized variability.

The amount of variability is proportional to the amount of power purchased. However, given a utility’s tolerance for variability, the amount of wind power within their portfolio can be increased significantly.

Though beyond the scope of this report which focused solely on managing variability, this optimization methodology could be extended to include optimizing with respect to cost and balanced with managing variability. This would enable a utility to minimize two of its most significant issues.

Wind Farms in Development

The large-scale use of wind power is becoming a norm in many parts of the world. Within the next five years, a number of wind farms will be added to the New England power grid. Currently there are about fourteen large scale wind farms that are feeding into the power grid. The table blow shows the major wind farms in the development stage. The list also shows the output and the total of how much power could be added to the power grid.

Table 3: Location of wind farms in development

Location	Size (kW)		Online Date		Project Type
Number 9, ME	350,000		Unknown		Wind Farm
Deep Water Phase II, RI	450,000		2013-2014		Offshore
North Country Wind, NH	180,000		Unknown		Wind Farm
Casella Coventry Wind Project, VT	2,200		Unknown		Customer Site
Jericho Mountain Wind, NH	3,000		2014-2015		Wind Farm
Eco-Industrial Park, RI	24,000		Unknown		Wind Farm
Grandpa's Knob Wind Park, VT	45,000		2013-2014		Wind Farm
Tuttle Hill, NH	30,000		Unknown		Wind Farm
Cape Wind, MA	468,000		Unknown		Offshore
Total	1,552,200				

In 2010, a study was completed by GE about the growth of wind power in New England based on the geographical diversity that is found in this region of the United States [3]. Currently there is approximately 340 megawatts (MW) of wind generation connected to the ISO New England power grid system. If the totally power output from all the farms (commercial, privately owned, and in development/permitting) were summed, it would conclude the study done by GE. The report says that New England has the "…potential to develop more than 215 gigawatts (GW) of onshore and offshore wind generation." [3] due to the geographical diversity.

If New England were to develop all the possible wind farms the amount of power would represent a major shift in the sources of energy and characteristics of resources operating in the region. Such a large-scale penetration of wind resources would affect prices in New England's wholesale electric market and total regional emissions from other types of generation sources. New England has an abundant potential for developing renewable sources of energy from onshore and offshore wind power generation. The challenge for the region is that a significant portion of the renewable resource potential is remote from the major population centers, so transmission would be needed to transport these supplies to the electric power grid for delivery to consumers. Offshore wind resources tend to have higher capacity factors and generate more electricity overall, than onshore resources.

It is important to understand how changes in the resource mix, such as adding wind generation, would affect the dispatch of the power system across all hours. The value of wind generation is a function of many factors, including wind generation profiles for specific wind plants, system load profiles, and the penetration level of wind generation on the system." The ISO currently estimates capacity values using an approximate methodology based on the plant capacity factor during peak load hours."[3]. At higher levels of wind penetration, the ISO will need accurate intra-day and day-ahead wind power forecasts in order to ensure efficient unit commitment and market operation. In addition, as wind penetration increases, the ISO will need tools to forecast wind ramping so that system operators can prepare for volatile wind situations by obtaining additional reserves or making other system adjustments. [3]

"In 2006, President Bush emphasized the nation's need for greater energy efficiency and a more diversified energy portfolio" [7]. The effect of President Bush's emphases on renewable energy cause an effort in order to create an energy scenario that enhanced the United States energy portfolio with wind energy that would provide a total of 20% of the entire U.S. electricity production by 2030. As of 2011 wind power provides approximately 3% of total U.S. electricity generation. "In order for the United States to achieve the 20% Wind Scenario, new wind power installations would have to increase to more than 16,000 MW per year by 2018, and continue at that rate through 2030"[7]. From the 20% wind scenario, at least 46 states would experience significant wind power development based off of their geographical diversity. The "…U.S. Energy Information Administration (EIA) estimates that U.S. electricity demand will grow by 39% from 2005 to 2030…" [7]. It is estimated that the growth will be approximately 5.8 billion MW by 2030. If we were to meet the 20% Wind Scenario of that demand, the total U.S. wind power capacity would have to reach more than 300 gigwatts. Furthermore, reaching the 20% Wind Scenario energy would require a number of improvements to the current system that we rely on including; enhanced transmission infrastructure, streamlined siting and permitting, improved reliability and operability of wind systems, and increased U.S. wind manufacturing capacity. These essential changes in the power generation and delivery process would involve supporting changes and capabilities in manufacturing, policy development, and environmental regulation. [7]

Conclusion

As a result to both of the studies done by GE and the U.S. Department of Energy the theory of wind penetration is a plausible. The 20% Wind Scenario is not a prediction of the future but, in order for the idea of wind penetration at that level to be realistic there are many advancements that need to be added to the current operation system. The enhancement of our transmission infrastructure is one of the more important factors that would need to be upgraded. The technology for upgrading the transmission lines already exists and all it needs in order to be implemented is the money and the political will.

The siting and permitting process is the next important element to large-scale wind penetration in the U.S.. We have the technology for determining the best locations for constructing wind farms but the difficult portion of sitting wind farms is being permitted to build in these locations. Permitting is where the political will comes into play because the final say were the location of wind farms are is up to the environment and planning board in each community. Some areas in the United States may be easier for permits being approved because of their location.

The likelihood of large-scale wind penetration is not very feasible because of these reasons but the overall effectiveness would have a great impact on the U.S. power portfolio in a positive way. To successfully address energy security and environmental issues, the nation needs to pursue a portfolio of energy options. None of these options by itself can fully address these issues; there is no “silver bullet”.

APPENDIX

Table 4: Optimal Percentage Output from Each Plant

Optimization of All Plants							
% of Plant's Output	Current Contract	754 all months optimized	1,000 all months optimized	774 May-Sept optimized	1,350 Sept-May optimized	1,161 Oct-April optimized	1,714 Oct-April optimized
Beaulieu Wind ME	-	4.11%	4.46%	0.65%	5.55%	0.04%	1.06%
Beaver Ridge ME	-	2.46%	1.26%	1.55%	2.14%	1.52%	1.40%
Berkshire 1 and 2	-	1.42%	2.53%	1.53%	2.25%	2.17%	3.06%
Hull MA	-	2.28%	0.06%	0.71%	5.84%	5.41%	0.33%
Lempster Wind NH	-	0.67%	0.37%	0.50%	1.03%	0.83%	0.82%
Mars Hill ME	-	1.38%	1.47%	1.83%	2.12%	1.45%	2.67%
Oakfield Wind ME	-	0.05%	0.17%	0.12%	0.24%	0.23%	0.05%
Portsmouth RI	-	4.96%	2.79%	12.59%	5.34%	4.99%	5.78%
Princeton MA	-	2.30%	0.49%	3.42%	0.02%	-	0.43%
Record Hill ME	-	-	-	0.03%	0.03%	-	0.01%
Searsburg VT	-	0.81%	3.02%	2.38%	1.21%	0.84%	8.94%
Spruce Mnt ME	10.00%	0.44%	0.49%	0.58%	1.05%	0.95%	0.99%
Stetson Ridge ME	-	0.48%	0.88%	0.79%	0.78%	0.57%	0.90%

Table 3: Optimal Percentage Output from Top 6 Plants

Optimization of Top Six Plants							
% of Plant's Output	Current Contract	754 all months optimized	1,000 all months optimized	774 May-Sept optimized	1,161 Oct-April optimized	1,350 Sept-May optimized	1,714 Oct-April optimized
Beaulieu Wind ME	-	-	-	-	-	-	-
Beaver Ridge ME	-	5.71%	5.23%	6.43%	10.06%	9.48%	10.20%
Berkshire 1 and 2	-	1.93%	2.49%	2.45%	2.68%	3.45%	3.75%
Hull MA	-	-	-	-	-	-	-
Lempster Wind NH	-	0.36%	0.59%	0.57%	0.37%	0.30%	1.08%
Mars Hill ME	-	1.23%	1.85%	1.71%	1.65%	2.32%	2.63%
Oakfield Wind ME	-	-	-	-	-	-	-
Portsmouth RI	-	-	-	-	-	-	-
Princeton MA	-	-	-	-	-	-	-
Record Hill ME	-	-	-	-	-	-	-
Searsburg VT	-	-	-	-	-	-	-
Spruce Mnt ME	10.00%	0.25%	0.57%	0.38%	0.26%	0.03%	0.28%
Stetson Ridge ME	-	0.79%	0.98%	1.09%	0.78%	1.08%	1.34%

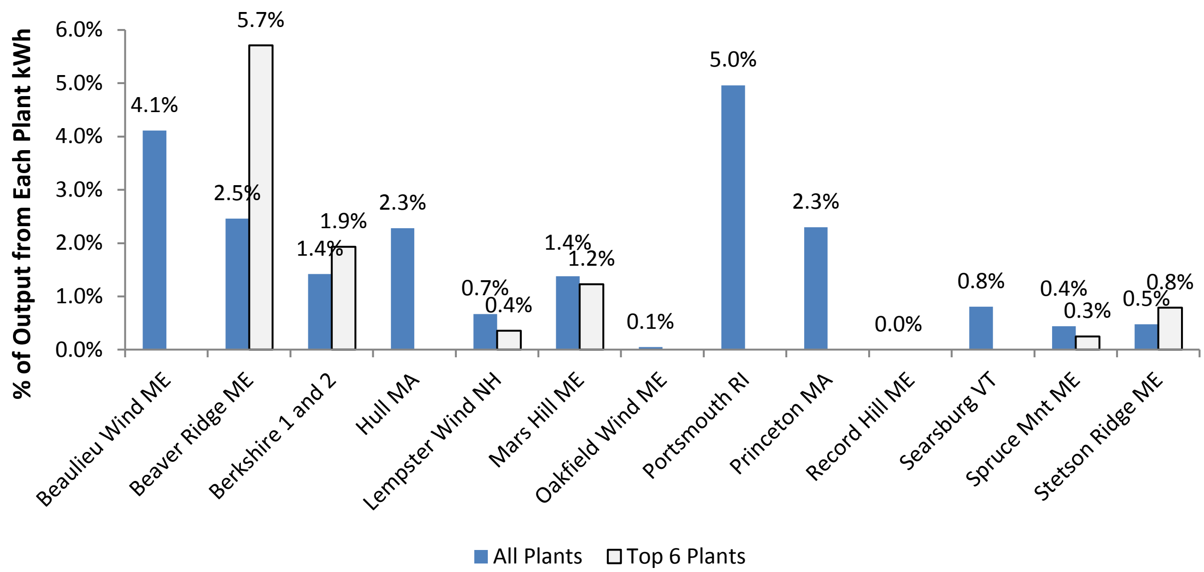

Figure 19: Optimal Contracts, Mean Output = 754 kW

Figure 19 shows the optimized contract percentages using all plants compared to the re-optimized contract percentages using only the top 6 plants for a mean output of 754 kW for an entire year.

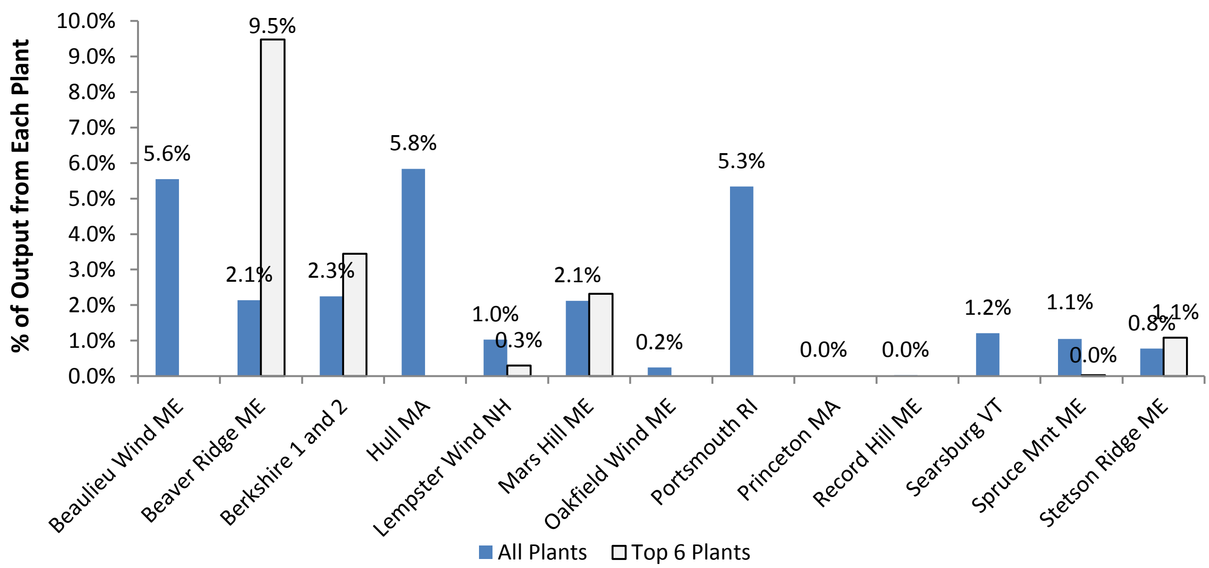

Figure 20: Optimal Sept-May Contract, Mean Output = 1,350 kW

Figure 20 shows the optimized contract percentages using all plants compared to the re-optimized contract percentages using only the top 6 plants for a mean output of 1,350 kW for a 9 month period.

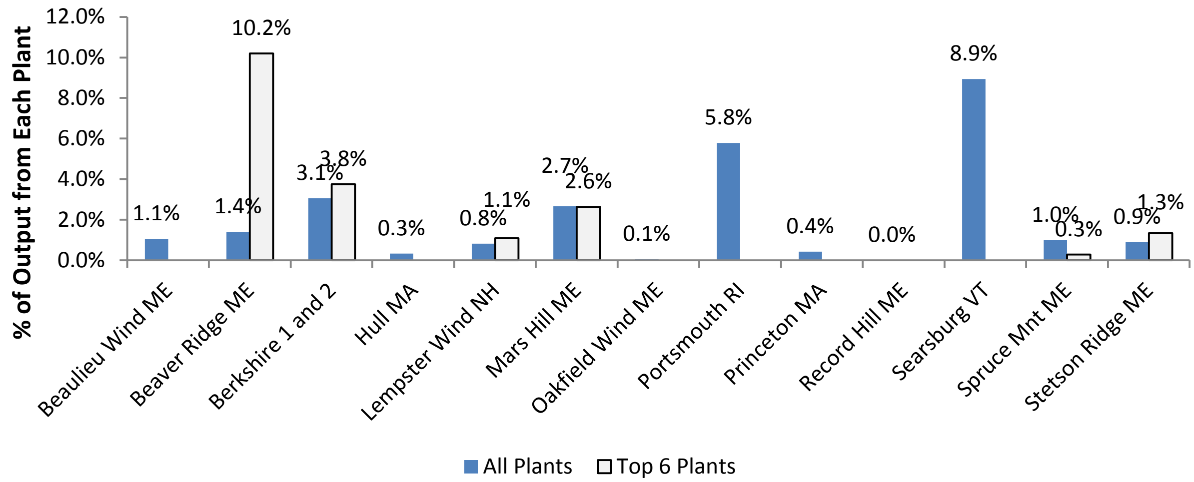

Figure 21: Optimal Oct-Apr Contract, Mean Output = 1,714 kW

Figure 21 shows the optimized contract percentages using all plants compared to the re-optimized contract percentages using only the top 6 plants for a mean output of 1,714 kW for a 7 month period.

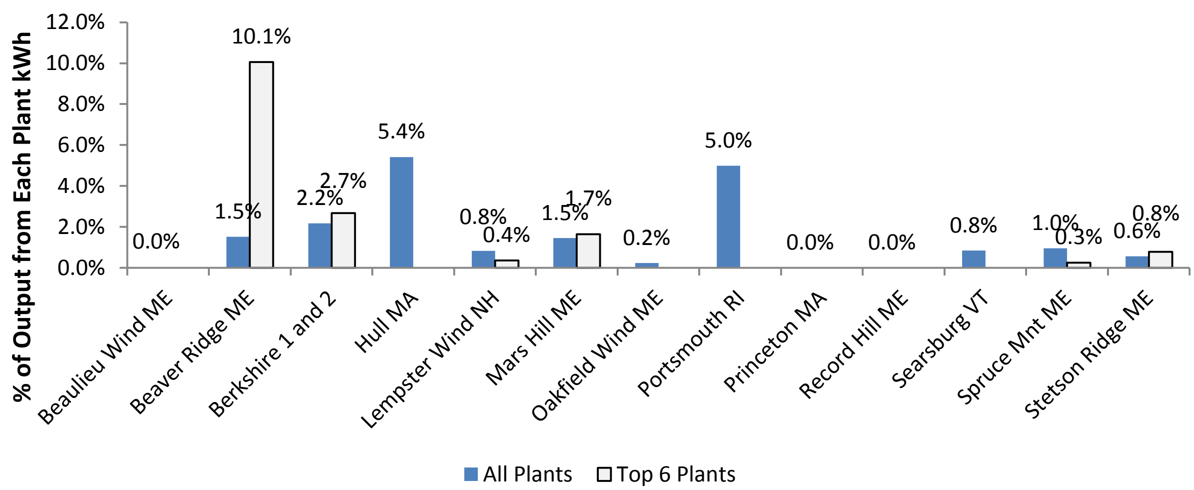

Figure 22: Optimal Oct-Apr Contracts, Mean Output = 1,161 kW

Figure 22 shows the optimized contract percentages using all plants compared to the re-optimized contract percentages using only the top 6 plants for a mean output of 1,161 kW for a 7 month period.

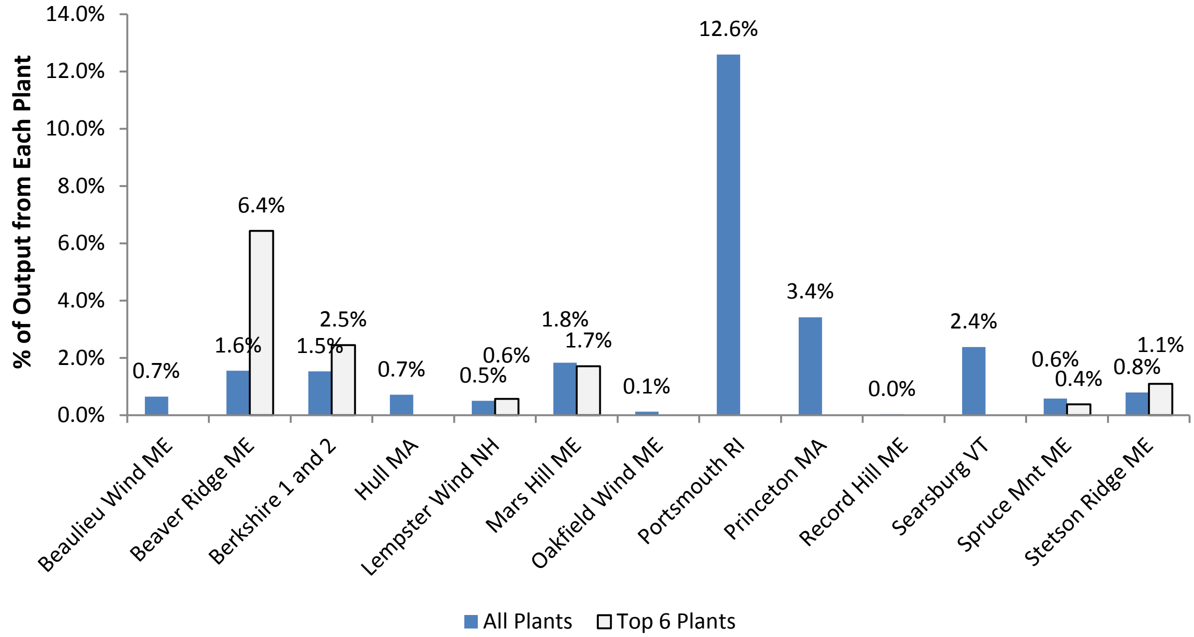

Figure 23: Optimal May-Sept Contracts, Mean Output = 774 kW

Figure 23 shows the optimized contract percentages using all plants compared to the re-optimized contract percentages using only the top 6 plants for a mean output of 774 kW for a 7 month period.

Table 4: Mean Output from Each Plant for Optimal Contract

Optimization of All Plants

Mean Output from Each Plant for Optimal Contract	Current Contract	754 all months optimized	1,000 all months optimized	774 May-Sept optimized	1,350 Sept-May optimized	1,161 Oct-April optimized	1,714 Oct-April optimized
Beaulieu Wind ME	-	1	1	0	1	0	0
Beaver Ridge ME	-	46	23	15	44	34	31
Berkshire 1 and 2	-	174	310	100	305	314	443
Hull MA	-	21	1	4	59	57	3
Lempster Wind NH	-	68	37	27	116	100	99
Mars Hill ME	-	226	241	172	378	272	502
Oakfield Wind ME	-	23	77	31	118	120	26
Portsmouth RI	-	23	13	33	27	27	31
Princeton MA	-	25	5	20	0	-	5
Record Hill ME	-	-	-	3	6	-	2
Searsburg VT	-	23	85	38	37	27	291
Spruce Mnt ME	754	33	37	24	87	84	87
Stetson Ridge ME	-	96	176	96	169	127	200

Optimization of Top Six Plants

Mean Output from Each Plant for Optimal Contract	Current Contract	754 all months optimized	1,000 all months optimized	774 May-Sept optimized	1,161 Oct-April optimized	1,350 Sept-May optimized	1,714 Oct-April optimized
Beaulieu Wind ME	-	-	-	-	-	-	-
Beaver Ridge ME	-	106	97	63	223	196	226
Berkshire 1 and 2	-	236	305	161	388	468	543
Hull MA	-	-	-	-	-	-	-

Lempster Wind NH	-	36	60	31	45	34	130
Mars Hill ME	-	202	303	161	310	414	494
Oakfield Wind ME	-	-	-	-	-	-	-
Portsmouth RI	-	-	-	-	-	-	-
Princeton MA	-	-	-	-	-	-	-
Record Hill ME	-	-	-	-	-	-	-
Searsburg VT	-	-	-	-	-	-	-
Spruce Mnt ME	754	19	43	16	23	2	25
Stetson Ridge ME	-	158	196	133	173	233	297

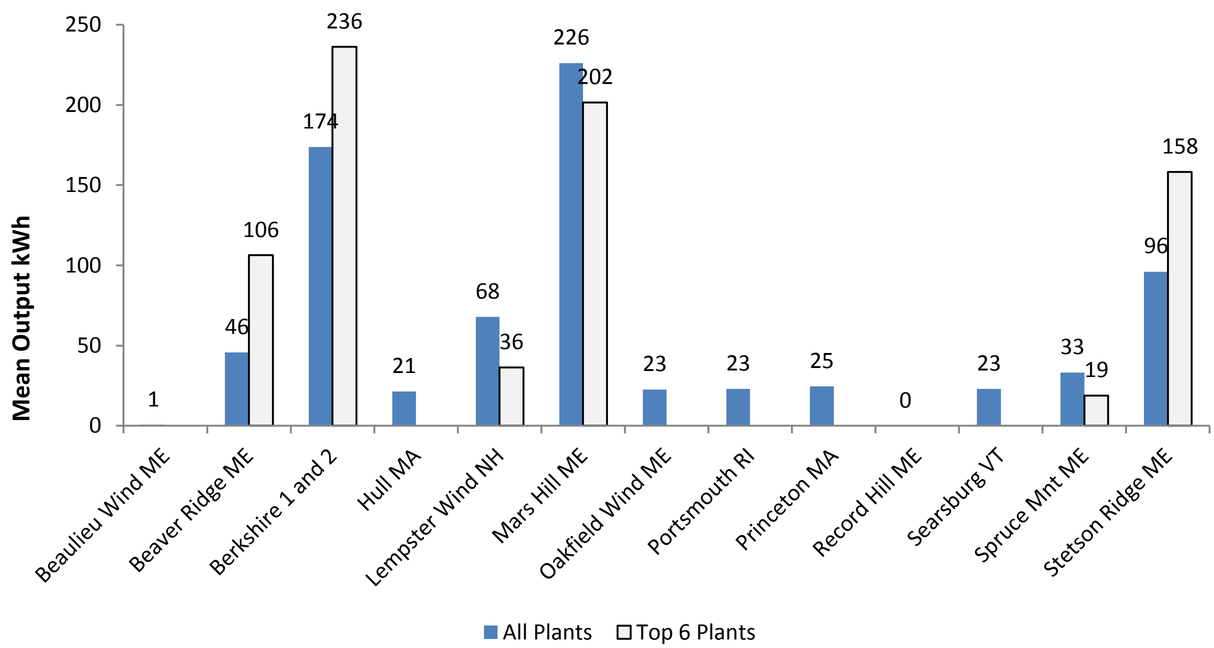

Figure 24: Mean Output from Each Plant for Optimal Contracts, Mean Output = 754 kW

Figure 24 shows the optimized contract percentages using all plants compared to the re-optimized contract percentages using all plants for a mean output of 754 kW for an entire year.

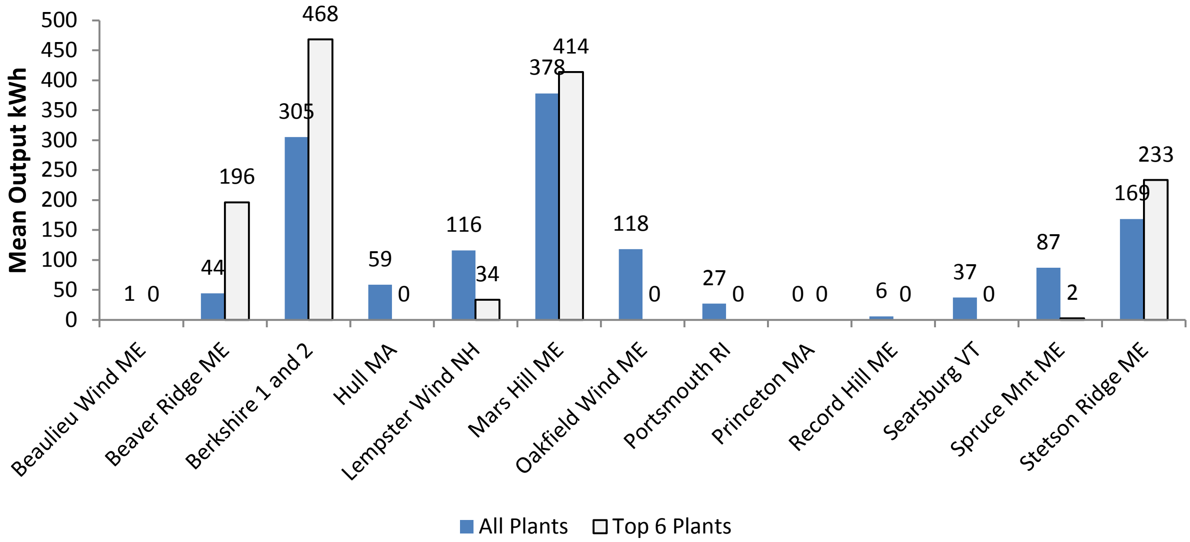

Figure 25: Mean Output from Each Plant for Optimal Sept-May Contracts, Mean Total Output = 1,350 kW

Figure 25 shows the optimized contract percentages using all plants compared to the re-optimized contract percentages using only the top 6 plants for a mean output of 1,350 kW for a 9 month period.

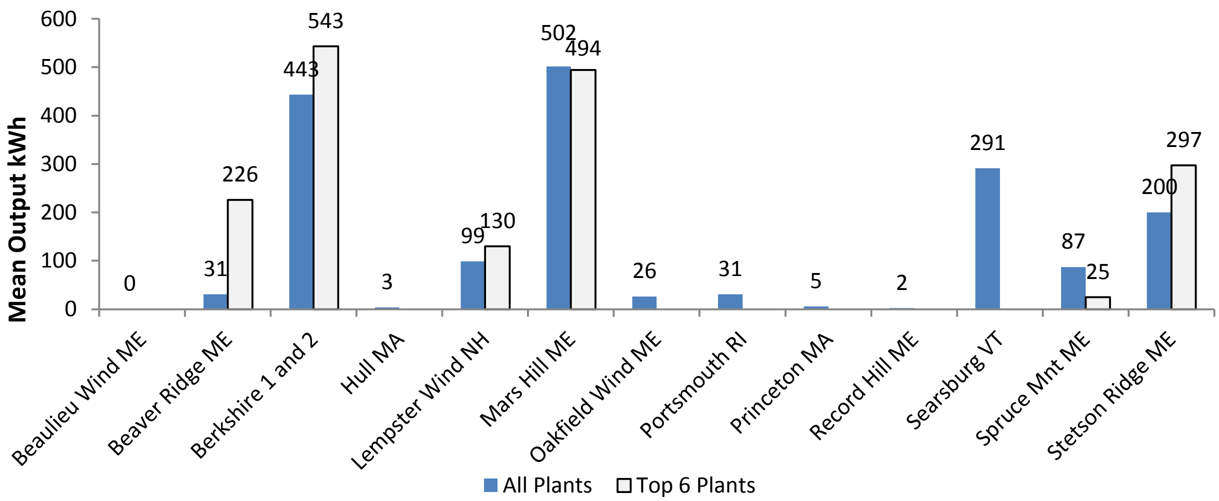

Figure 26: Mean Output from Each Plant for Optimal Oct-Apr Contracts, Mean Total Output = 1,714 kW

Figure 26 shows the optimized contract percentages using all plants compared to the re-optimized contract percentages using only the top 6 plants for a mean output of 1,714 kW for a 7 month period.

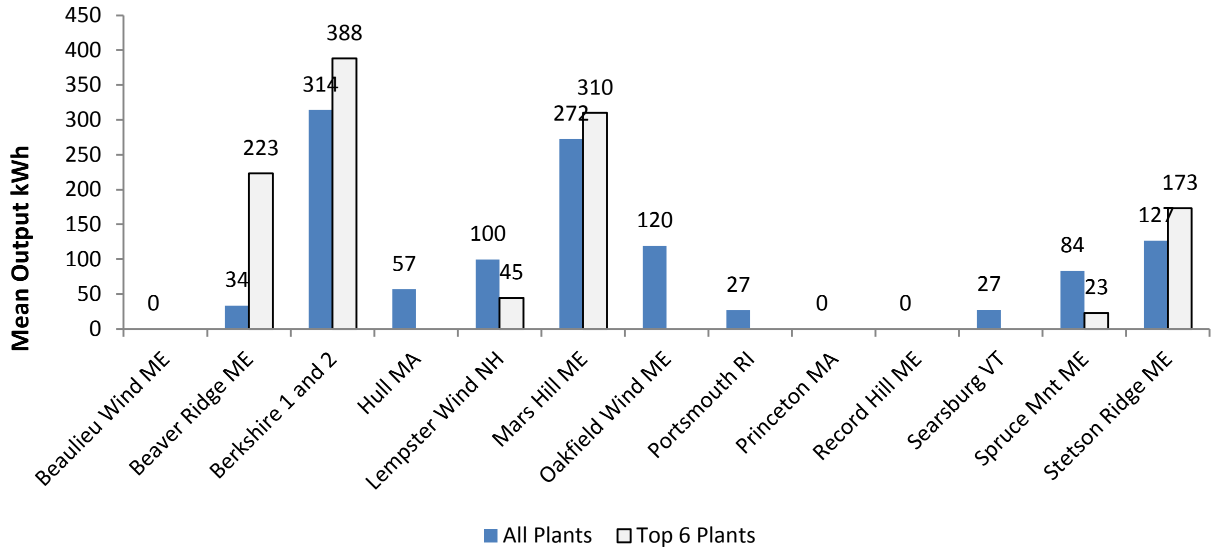

Figure 27: Mean Output from Each Plant for Optimal Oct-Apr Contracts, Mean Total Output = 1,161 kW

Figure 27 shows the optimized contract percentages using all plants compared to the re-optimized contract percentages using only the top 6 plants for a mean output of 1,161 kW for a 7 month period.

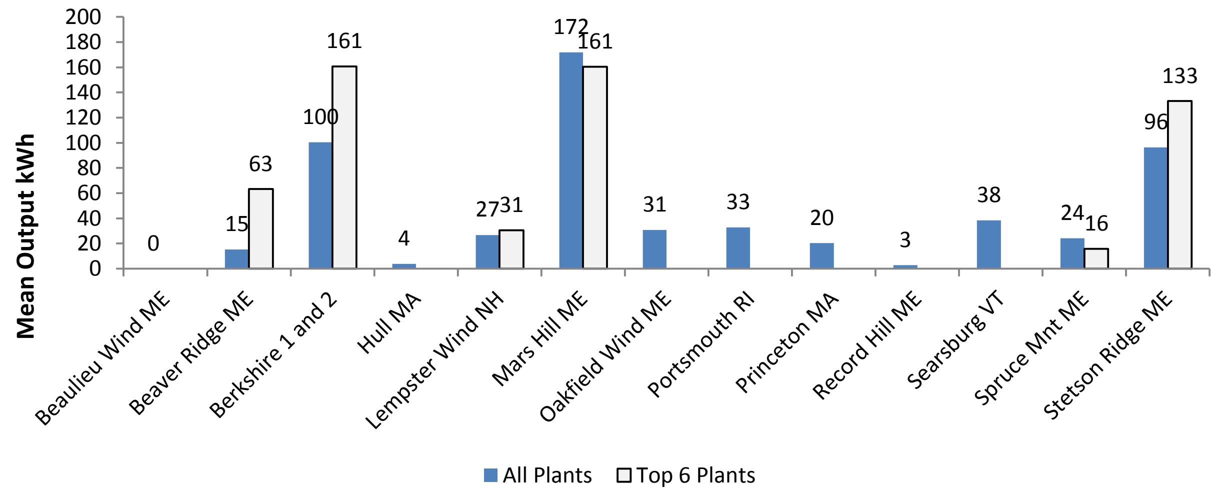

Figure 28: Mean Output from Each Plant for Optimal May-Sept Contracts, Mean Total Output = 774 kW

Figure 28 shows the optimized contract percentages using all plants compared to the re-optimized contract percentages using only the top 6 plants for a mean output of 774 kW for a 5 month period.

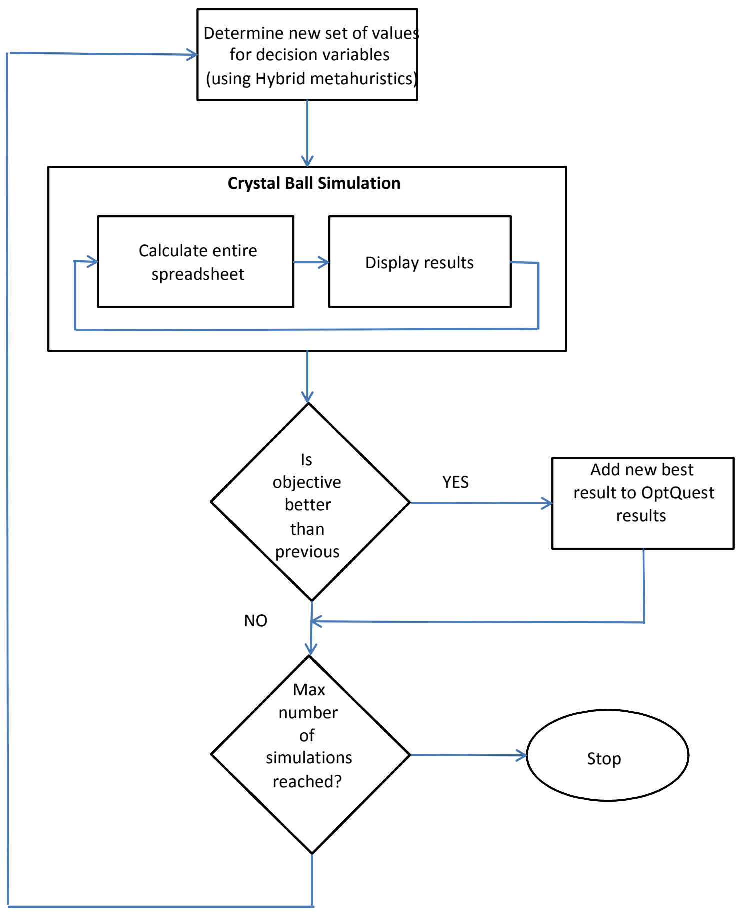

Figure 29: Crystal Ball Flow Chart

Software Description

The OptQuest multi-variable optimizer tool in Oracle's Crystal Ball ® begins by taking user defined objectives and constraints, then, within those bounds, the program chooses random variables to apply to the data-set to define solution 1. The values are changed and compared to the original solution. If this is better solution 1 is replaced. If this is worse the values are changed in an opposing manner until a best result is found. This group of results defines "neighborhood 1". The program is designed to break out of this cycle so as to not get stuck in localized results. New random numbers are applied and more neighborhoods are constructed. The software then works to compare neighborhoods of results rather than iterating through large data-sets. This allows the software to get to the best result in a dramatically shorter time-frame than conventional methods.

Glossary

Capacity Factor	The ratio of the electrical energy produced by a generating unit for a given period of time to the electrical energy that could have been produced at continuous full power operation during the same period.
ISO	Independent System Operator
Hz	(hertz) is the SI unit (International System of Units) of frequency which is the number of cycles per second.
Energy	The ability to do work.
Power	The rate at which work is done.
Average-to Variability	The ratio of variability per unit of power.

References

1 Connecticut Valley Electric Exchange

2 Quintero, Cèsar.(et al.) “Characterization and modeling of the variability of the power output of aggregated wind farms”. Web. 16 November 2012. <*http://renknownet2.iwes.fraunhofer.de/pages/wind_energy/data/Characterization_and_modeling_of_the_variability_of_the_power_output_of_aggregated_wind_farms.pdf*>

3 “Grid Impacts of Wind Power: A Summary of Recent Studies in the United States”. National Renewable Energy Laboratory. *U.S. Department of Energy*

4 Oracle Business Solutions
< *http://oracle.com*>

5 US Department of Energy. “2011 Renewable Energy Data Book”.

6 National Renewable Energy Laboratory

7 U.S. Department of Energy. “20% Wind Energy by 2030 Increasing Wind Energy’s Contribution to U.S. Electricity Supply”. Oak Ridge, Tennessee: , 2008. Web. <*http://www.20percentwind.org/20percent_wind_energy_report_revOct08.pdf*>.

8 New England Wind Forum. Web
<*http://www.windpoweringamerica.gov/newengland/projects.asp*>