A Comparison of Methods for Sizing Energy Storage Devices in Renewable Energy Systems

by

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B.Eng, University of Victoria, 2009

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Supervisory Committee

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Abstract

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Penetration of renewable energy generators into energy systems is increasing. The intermittency and variability of these generators makes supplying energy reliably and cost effectively difficult. As a result, storage technologies are proposed as a means to increase the penetration of renewable energy, to minimize the amount of curtailed renewable energy, and to limit the amount of back-up supply. Therefore, methods for determining an energy system's storage requirements are being developed. This thesis investigates and details four existing methods, proposes and develops a fifth method, and compares the results of all five methods. The results show that methods which incorporate cost, namely the Dynamic Optimization and the Abbey method, consistently yield the most cost effective solutions. Under excellent renewable energy conditions the results show that the cost-independent methods of Korpaas, Barton, and the Modified Barton method produce solutions that are nearly as cost effective but have greater reliability of energy supply than the Dynamic Optimization and Abbey solutions. This thesis recommends a new path of research for the Modified Barton method: the incorporation of cost through the confidence level. This thesis also recommends the development of new sizing methods from various aspects of the methods presented.

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Acknowledgments

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Nomenclature

Autonomy: The relative amount of time which the wind-storage system is self sufficient.

CDF: Cumulative Density Function.

ESD: Energy Storage Device.

EV: Expected Value.

FFT: Fast Fourier Transform.

LOLP: Loss of Load Probability, the probability the wind-storage system will be unable to fully supply load.

PDF: Probability Density Function.

Periodogram: Variance as a function of frequency.

WS: Wind Speed.

Symbols

A: Amplitude

E_{Store}: Store Energy

P_{Backup}: Backup Power

P_{Charge}: Charge Power, also subscripted ‘Ch’

P_{Curt}: Dumped or Curtailed Power

$P_{Discharge}$: Discharge Power, also subscripted ‘Dch’

P_{Dump}: Dumped or Curtailed Power

P_{FP}: Firm power, constant system load

P_{Load}: System Load

P_{Net}: Net Power

P_{Wind}: Wind Power

t: Discrete time step

T: Length of time considered

u: Wind speed designation in Barton’s method

α: Efficiency correction in Barton’s method

κ: Variance of wind speed to variance of wind power conversion

γ: Confidence level

σ: Standard deviation

η: Efficiency of storage device, subscripted either charge, discharge or roundtrip

ζ: Storage Size

τ: Storage Period

ω: Frequency

ν: Wind Speed

ν_{CutIn}: Minimum wind speed at which turbine will generate power, below which it is off.

ν_{CutOut}: Maximum wind speed at which turbine will generate power, above which it will turn off.

1 Introduction

1.1 Background

There is a social, environmental, and economic push to reduce emissions from fossil fuel fired generators and to reduce dependence on fuels. As a result, use of renewable sources for energy supply is increasing. Amongst renewable energy technologies wind energy converters are relatively mature and cost effective [1] and are being installed in greater numbers. There is some unpredictability or intermittency associated with wind energy, resulting in rapid fluctuations in generation. Fluctuating generation is smoothed through fast ramping of dispatchable generators, through altering the load to fit the available generation, or through transferring energy to and from a storage device [2].

Storage devices should be utilized when an energy system has a high penetration of intermittent wind power, when there is a suitable storage technology available, and when it improves operation of the energy system. High penetration of intermittent power is necessary for viability of storage devices because low penetration variations can be absorbed through ramping of existing generation. Furthermore, intermittency of wind power is necessary for viability of storage devices. A single wind site or aggregation of wind sites with low variability will be more easily absorbed and may not require storage. In energy systems where storage is required a suitable storage technology must be available. For instance, systems requiring relatively large amounts of energy storage may be limited to site-specific technologies like pumped hydro storage. Whereas systems requiring relatively small amounts of storage have a greater number of storage options such as chemical storage in batteries or fuel cells. Whichever technology is applicable, the resulting storage device must improve system operation; which may include reduction in emissions, improved reliability, and reduced cost of energy supply [3–5].

In order to keep costs at a minimum, the size requirements for energy storage devices must be determined. Storage devices will have capital and possibly operating costs in addition to finite lives. Sizing a device too small may either reduce its operating life through over use, such as exceeding maximum depth of discharge too frequently [6], or render it ineffective at balancing load. Sizing a device too large will result in increased capital costs which will increase the cost of supplying energy; therefore, effective storage sizing is necessary.

1.2 Factors Affecting Wind and Storage Energy Systems

The size of an energy storage device is affected by the renewable energy generation, by the load to be supplied, and by the economics of the energy system [7]. As previously stated, renewable energy sources often generate energy unpredictably. The range of unpredictable generation, the rate at which generation changes, and the frequency with which generation changes will affect the amount of storage required. The storage device matches the unpredictable generation to the system load, therefore, system load can also affect store size. A flexible load or a load which is positively correlated with the renewable generation will require less storage than a load which is negatively correlated or out of phase with the naturally occurring frequencies of the renewable generation. Finally, the costs of storage relative to the costs of backup generation or loss of reliability will affect how much storage is optimal. As with renewable generation and load, the costs associated with supplying energy and installing storage systems are often site-specific.

The renewable generation characteristics affecting energy storage requirements include the average amount of renewable power, the variance, and the frequency of variance. The average amount of generation will determine how much of the load can be met directly.

Generally, a high average means the site spends more time producing energy, translating to more time the generator is directly meeting load and less time that a storage device or backup generator is utilized. However, high average generation does not always translate into smaller storage devices as the variance of a wind site also affects storage size. For instance, a wind site that spends 50% of its time at full output and the remaining time at no output would have an average of 50%. However, the large range, from full to zero, would require a storage device to smooth and balance output. Furthermore, the frequency at which this power output varies will affect storage size. Using the example of a site with 50% average generation, if this site's output varied rapidly from hour to hour the storage device would be relatively small, only needing to store a few hours worth of energy. This is shown in Figure 1-1 where plot (a) shows a simplified system where net power varies from hour to hour. Net power, P_{Net} is given in Eqn. (1.1) where P_{Wind} is wind generation and P_{Load} is system load.

$$P_{Net} = P_{Wind} - P_{Load} \tag{1.1}$$

The store cycles from full to empty to full rapidly. However, the required storage size is only 1 MWh.

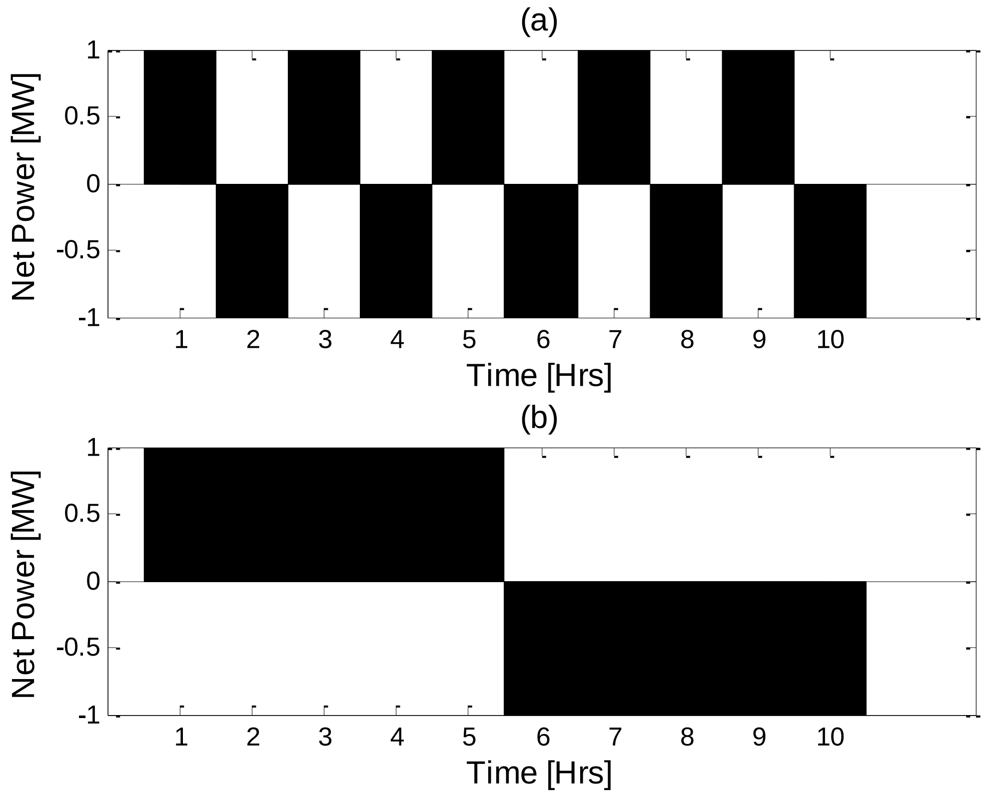

Figure 1-1: Example of store size given different net power conditions. Plot (a) shows small storage size, plot (b) shows large storage size.

In contrast, if the site spent several hours at full output and an equal amount of time at no output, the device would need to be large enough to store many hours worth of energy. Again Figure 1-1 shows this in plot (b) where the net power does not vary as rapidly and therefore the storage device must be larger, in this instance 5 MWh. In summary, the average generation, the variance, and the frequency of variance will all affect storage size requirements.

Similarly, system load can affect storage requirements; in particular from load flexibility and correlation between the load and renewable generation. Load flexibility refers to the ability to alter load as necessary to balance supply and demand; generally referred to as demand side management [8], [9]. An energy system with a large capacity for demand side management will require less storage than a system with no ability to alter load. Another factor affecting storage size is the correlation between load and generation [10], which refers to how load and generation vary together in time. A perfect positive correlation between load and generation would require no storage as there would be balance at all times. A simplified example is shown in plot (c) of Figure 1-2 where the load and generation are nearly matched and thus the net power does not change significantly.

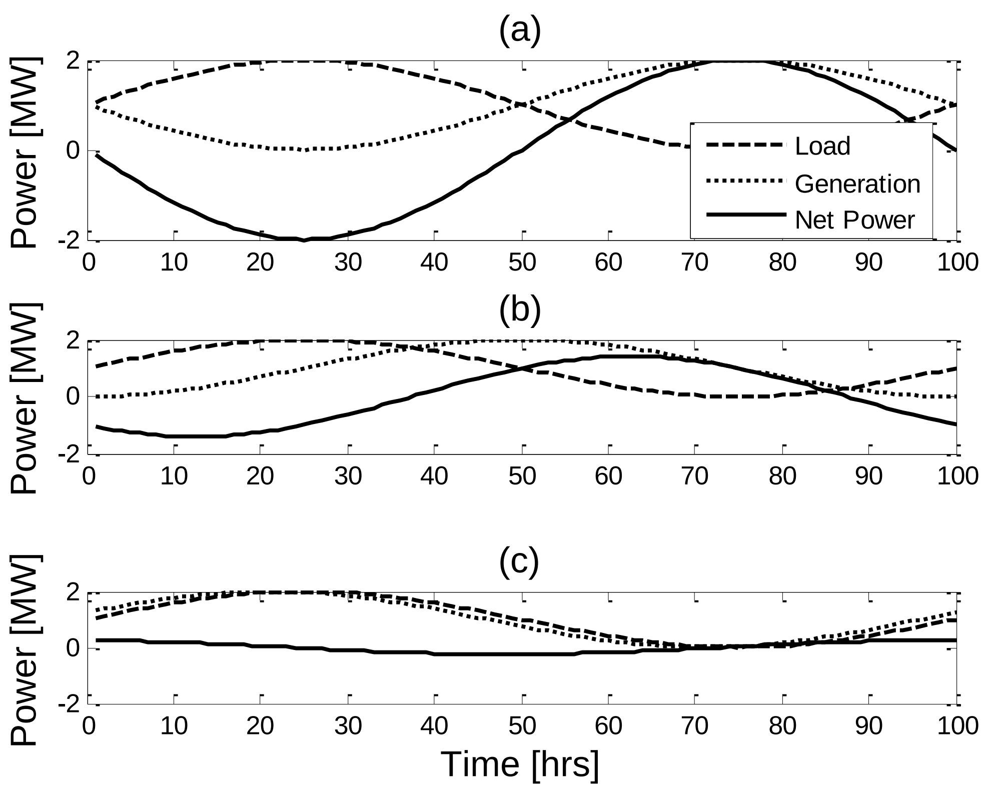

Figure 1-2: Effects of Load-Generation Correlation on Net Power. Plot (a) shows large net power resulting from load and generation totally out of phase. Plot (b) shows reduction in net power when load and generation are partially out of phase. Plot (c) shows low net power when load and generation are almost in phase.

Alternatively, a strongly negative correlation would require significant storage as load would be at a minimum while generation is at a maximum and vice versa. This is shown in plot (a) of Figure 1-2, where load and generation are perfectly out of phase and large positive and negative net powers result. In such negatively correlated systems the storage device attempts to shift load and generation together.

Another factor affecting storage requirements is the cost of supplying energy, separated into capital costs and operating costs. Energy storage devices will have a capital cost which will increase the overall energy supply cost. This increase in cost is offset as a storage device will decrease the amount of curtailed energy [2] and decrease the amount of required back-up energy or loss of load, both of which have operating costs. Therefore the capital costs relative to the operating costs can affect how much energy storage to install.

Energy storage requirements are affected by wind characteristics, load characteristics, and energy system costs. Wind sites with high variability will require energy storage to smooth out generation. Similarly, systems without demand side management capability will also require energy storage. Finally, systems which have a high cost associated with back-up energy or loss of load may financially benefit from having energy storage systems. These factors are included in determining energy storage requirements.

1.3 Defining Storage Requirements

Methods for sizing energy storage draw upon some of the previously mentioned factors as inputs. The relative importance or weight of each factor varies from method to method. This thesis presents several methods which are sensitive to energy system costs. It also shows that methods neglecting system costs are most sensitive to wind resource data.

There is no clear consensus on which method to utilize for sizing energy storage. This section introduces some of the most simple, most novel, or most cited methods for sizing energy storage.

Many methods draw on purely statistical information such as probability density functions (PDFs) and variance to determine store size. PDF and expected value methods, such as the methods proposed by Korpaas [11] and Gavanidou [12], first utilize the mean and variance of a data set to construct a PDF, for example, from a time series of wind speeds. This PDF gives the probability of a wind speed and hence a wind power occurring. Scenarios of operation can be constructed at each possible wind speed and an expected value determined. A novel and highly cited method proposed by Barton [13] draws on this scenario-based calculation but also uses variance of wind speeds as a function of frequency. In this method, a large wind speed data set is used to generate a periodogram which is then filtered to determine variance over a desired frequency range where storage will operate. This desired frequency range corresponds to the storage period, for instance 24hrs, or 1 year. Additional statistical information, like the correlation between wind power and variable load can be used to alter the store size. For instance, Barton’s method calculates a periodic variance to attempt to capture the effects of variable load on storage size. The storage sizes from the above methods are generated using only power or historical resource data and results from statistical analysis. Some basic statistical information, like PDFs of wind speeds, is readily available from sources such as the Canadian Wind Energy Atlas [14]. The speed of construction and calculation of the previously mentioned methods means sensitivity analysis of all parameters is quickly executed with the exception of sensitivity to cost.

Cost sensitivity is captured with techno-economic optimization. The attraction of optimization is that a single method can incorporate the technical constraints of a real system and the correlations between input data sets, and produce a lowest cost solution.

A common type of optimization is a dynamic optimization, where the term *dynamic* refers to the incorporation of time into the model. Detailed constraints ensure the model closely replicates real world conditions [15]. Some constraints like ramping rates can only be implemented when adequate temporal resolution of data are available. Also, to capture seasonal variations and correlations, data sets must be several years in length. The required data quality, the amount of computational memory and speed required to yield a solution, and robustness issues due to the deterministic modeling of stochastic processes are weaknesses of dynamic optimizations [16].

Alternative optimization methods exist which avoid some of the above problems. The issue of data requirements can be mitigated by simulating data. For instance, data sets can be built with Markov chains or ARMA models [17]. Another alternative is to use discrete wind speed-based scenarios built from PDFs. The scenario concept is demonstrated by Pereira [18], Abbey [19], and Brown [20]. A further benefit of using scenarios is a reduction in variables. A few representative scenarios are shorter than a time series data set and thus have fewer variables, which in turn eases memory requirements and allows for more detailed constraints. A final benefit of using scenarios and stochastic optimizations is an improvement in solution robustness. Whereas the dynamic optimization yields a specific solution for given data, stochastic optimizations yield more general solutions. The robustness comes from reducing the larger data sets into a few characteristic, or most likely to occur, scenarios.

Methods of sizing energy storage devices are largely dependent on the energy system to be modeled. The energy system design will determine which technical constraints and data inputs are relevant to the storage sizing method.

1.4 Objectives

As previously discussed, there are many existing methods for sizing storage. The number and variety of methods published indicates sizing energy storage is an evolving area. While the number of methods is increasing, there is little research available comparing methods. The objective of this thesis is to develop and detail five methods of sizing energy storage for remote and grid connected systems and investigate their sensitivity to factors which are known to influence energy system performance and hence storage requirements. The intent of these methods is for energy system design and to be used by energy system planners. One of these methods will be developed for the first time in this thesis; the other four will be derived from existing methods.

1.5 Summary of Methods

There are five methods included in this thesis, four of these methods are largely based on existing methods identified in the literature and have only minor modifications, the fifth method represents a significant modification from an existing method. The first method is proposed by Barton [21] and is partially replicated by Gassner [22]. It is both highly cited and novel in its approach to filtering by frequency. Second, is a PDF method from Korpaas [23] which is cited, relatively simple and easy to replicate, and utilizes probabilities only to size storage. The third method is a dynamic optimization developed by the author but is obvious in its complexity and design. The fourth is a cited two-stage optimization that is derived from work by Abbey [19] which was chosen because of its incorporation of probabilities and optimization. The fifth is a modification of Barton's method intended to reduce complexity without significantly affecting results. Finally, in order to test and compare these methods, a time-series function is developed.

The analyses presented in this thesis are based on the energy system shown in Figure 1-3. This system design is relatively simple and includes wind power P_{Wind}, a variable system load P_{Load}, and an energy storage device (ESD) with charging and discharging powers P_{Ch} and P_{Dch} respectively. The system is sized and intended to be wholly wind supplied with the storage device balancing wind generation and load. To allow generation and load to be balanced at times the storage device is either full or empty, two additional variables are included: backup power, P_{Backup}, and curtailed or dumped power, P_{Curt}. When required, a desired storage period of 24 hours will be assumed. This length is chosen because work by Barton [21], Gassner [22], and Abbey [19] all utilize a 24 hr storage period.

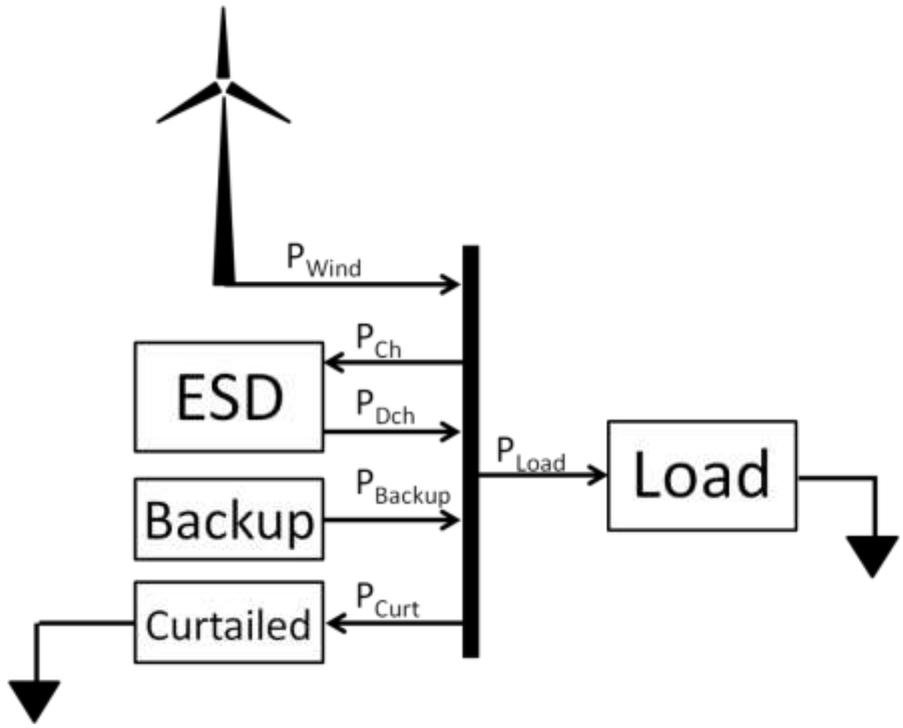

Figure 1-3: Diagram of modeled energy system.

Testing of the alternative storage sizing methods is performed under varying wind site conditions, varying system load, and varying costs. Sites tested include high and low variance locations with a large range of capacity factors. Similarly, load profiles are changed to simulate conditions from baseload, or low variance, to peaking, or high variance. Load profiles are offset from wind data to test for effects of diurnal and seasonal correlation. Finally; sensitivity to capital and operating costs are examined. The variables and testing are not exhaustive but are sufficient to demonstrate the abilities and sensitivities of the five methods.

The results are discussed and applications and recommendations presented in the conclusion. This thesis provides details on five different methods for sizing energy storage. Of these, the modification of Barton's method is presented for the first time in this report, validation of this method is achieved by comparing it to the other four methods. Furthermore, this thesis gives a comparison of the results from all these methods and discusses the strengths and weaknesses of the different approaches. Finally, recommendations are made as to how best apply and improve storage sizing algorithms.

2 Sizing Methods

This chapter details four storage sizing methods: Barton's method, Korpaas' method, the Dynamic Optimization, and Abbey's two-stage optimization. Barton's method uses wind speed variance as a function of frequency to calculate a storage size. The Korpaas method utilizes PDFs of wind speed and an iterative process to size energy storage. The Dynamic Optimization is a basic linear dynamic optimization based on the energy system of Figure 1-3. Similarly, Abbey's two-stage optimization utilizes the energy system of Figure 1-3, but generates characteristic scenarios and iteratively tries various store sizes.

2.1 Barton's Method

The performance of a wind powered energy system is affected by the magnitude and frequency of variations in wind speed. For instance, diurnal variations affect the amount of energy storage required to ensure reliability throughout a day [13]**.** In the same way, seasonal variations affect the amount of long term storage required to balance out energy over the year. Barton's method [21] filters the magnitude of variance at common frequencies, such as diurnal or seasonal cycles, and uses the magnitudes to size energy storage requirements.

2.1.1 Filtering by Frequency

Filtering wind speed variance requires a filter function and a transformation of wind speed time series data into the frequency domain. The transformation requirement is met through construction of a periodogram, which can be calculated from a Fast Fourier Transform (FFT). A periodogram, turns a time series data set of wind speeds into variance of wind speed as a function of frequency. This function is derived in Appendix A. Barton's method then filters the periodogram three times to isolate: the long term variance or store period average variance, the short term variance, and the state of charge variance. These filters are shown in Figure 2-1 and presented as equations in Appendix A.

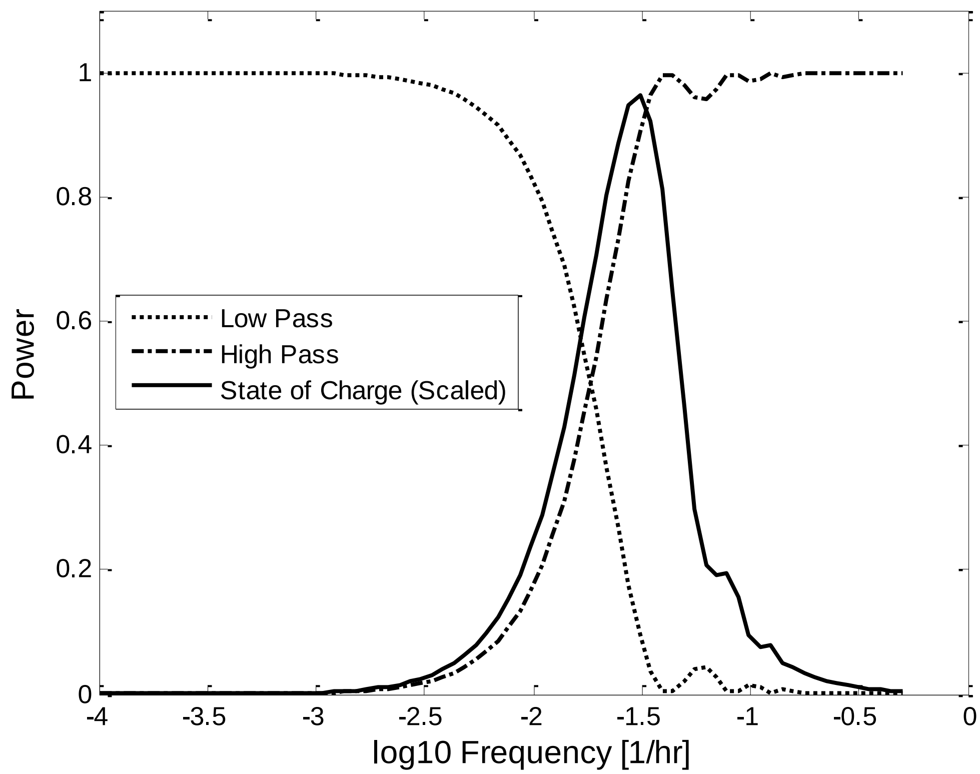

Figure 2-1: Filter Functions for 24hr Store Period. Low pass filter isolates long term variance, high pass filter isolates short term variance. State of charge filter is scaled by 20.

The filtered short and long term variances are utilized to determine probability density functions, detailed in Appendix A, while the state of charge variance is used in the calculation of storage size. This filtering process is shown in the flowchart of Figure 2-2 where wind speed data is first converted to an FFT and periodogram, and then filter functions are used to isolate variance. At this stage Barton’s method has variance of wind speeds which must be converted to variance of power.

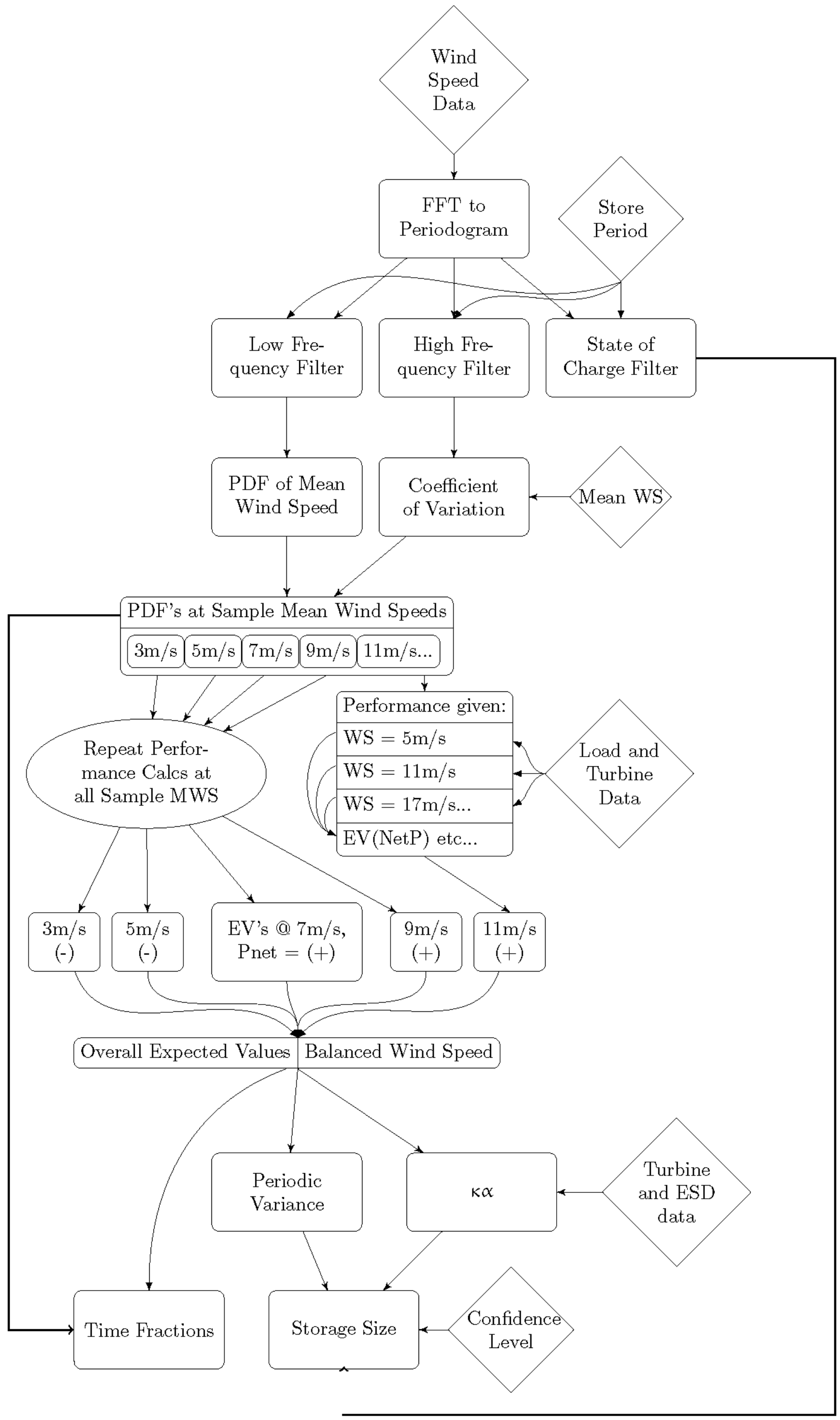

Figure 2-2: Flowchart of Barton's Method

2.1.2 Spreadsheeting Method

The conversion of wind speed variance to wind power variance is complicated by the non-linear relation between wind speed and wind power, as in a wind turbine manufacturer's power curve [24]. Barton's method must therefore determine a wind speed at which to convert speed to power. This speed is known as the balanced power wind speed. Furthermore, Barton's method accounts for inefficiencies and finite ratings of store charge and discharge powers via an adjustment factor, α. The calculation of α and the determination of a balanced speed is accomplished through a spreadsheeting method. The term *spreadsheeting* is used because it offers a convenient visualization of the method as shown in Figure 2-3.

Simplified Spreadsheet Representation of Barton's Method for a Load Power of 0.5				
Within Period / Period Average	P(mean-1 st.dev)= 0.31	P(mean)= 0.38	P(mean+1 st.dev)= 0.31	Expected Value
P(mean=4m/s)= 0.43	3m/s	4m/s	5m/s	
P(mean=8m/s)= 0.36	6m/s	8m/s	10m/s	
P(mean=12m/s)= 0.21	9.1m/s	12m/s	14.9m/s	$P_{net@12m/s} = 0.345$

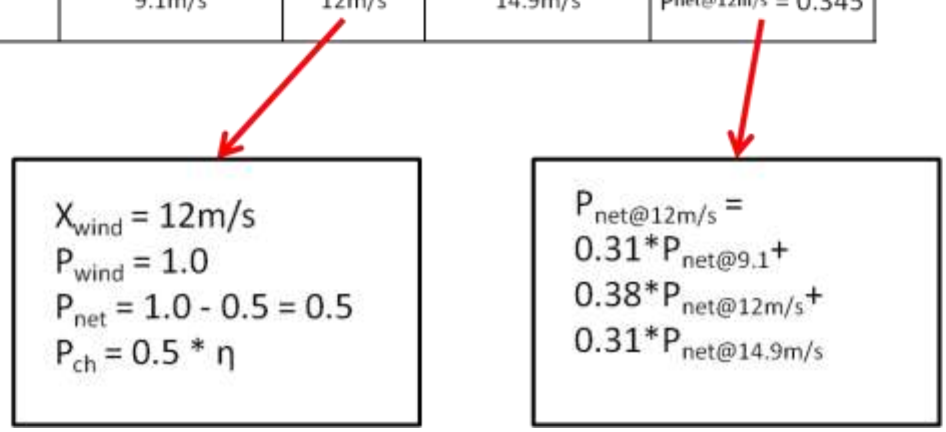

Figure 2-3: Simplified spreadsheet representation of Barton's Method. This figure shows one spreadsheet for a load of 0.5. For variable load there will be a spreadsheet for each possible load.

The rows in the spreadsheet represent storage period average wind speeds, these are shown in Figure 2-4.

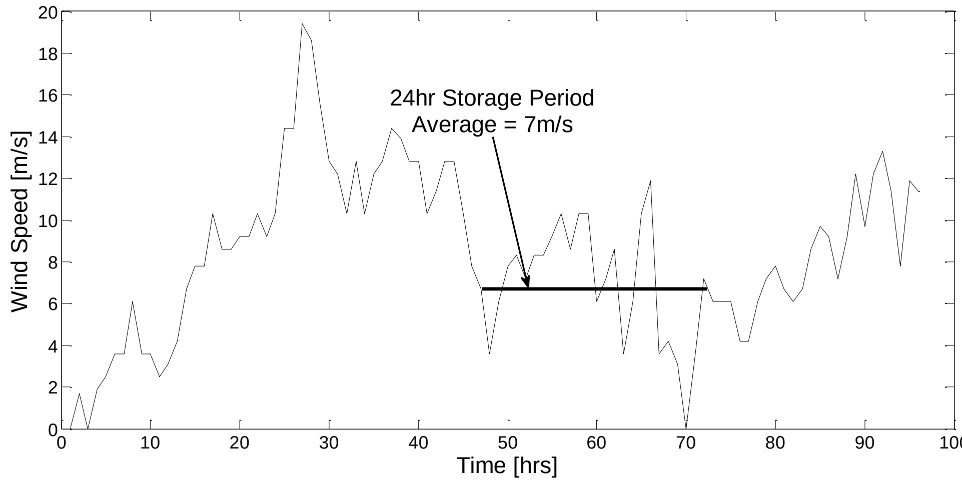

Figure 2-4: Long term average wind speeds. In this figure the long term wind speed is based on a 24 hr storage period and is shown with an arbitrarily placed 24hr window with a long term mean of 7m/s. The short term wind speeds are those which fall within the 24hr window.

Based on the storage period average wind speed PDF, a series of average speeds are each assigned a probability of occurrence, this is shown in the rows of Figure 2-3. The columns of Figure 2-3 represent short term wind speeds. Each column is assigned a probability of occurring from the short term wind speed PDF and the short term wind speed in each column is based on long term wind speed in the row, this is described in Appendix A. The result is a matrix or spreadsheet of wind speeds. At each cell the system's operating state is calculated based on the cell's wind speed. These include values for wind power, net power, charging powers, curtailed power, and backup power. The values across each row are convolved with their associated probability of occurrence to give an expected value of system performance for that mean speed. The mean speed with net power closest to zero is deemed the balanced wind speed. The spreadsheeting process begins in Figure 2-2 when the high and low frequency variance is used to construct PDFs at sample mean wind speeds. Performance is then calculated at each mean wind speed and the results combined into expected values, this is the conclusion of the spreadsheeting process, again shown in Figure 2-2. The data generated by the spreadsheet calculations can be utilized to estimate the overall system operating characteristics.

2.1.3 Storage Size

Once the balanced wind speed is determined there are three factors which are utilized to adjust the state of charge variance, $\sigma^2_{\Delta E\tau}$, into a required store size. These are κ, α, and γ. κ is the wind turbine gradient at the balanced wind speed and it converts the variance in wind speed to variance in wind power, it is given as:

$$\kappa = \left.\frac{dP_T}{du}\right|_{u=u_{balanced}} = \frac{\sigma_{P_{wind}(u_{balanced})}}{\sigma_{u(t)}} \tag{2.1}$$

α is an adjustment factor for the efficiency losses and finite power ratings of the energy store. α is calculated from the spreadsheet results for the balanced mean wind speed. It is given as:

$$\alpha^2 = \frac{\sigma^2_{Pch/dch}}{\sigma^2_{P_{net}}} \tag{2.2}$$

This is the ratio of variance in the system charge and discharge powers to the net system power variance.

The final factor, γ, is the confidence level. This term allows adjustment of storage size to account for unknowns. In a system which places a large emphasis on reliability or which has access to low cost storage the confidence level would be high. Alternately, a system with expensive storage options or a tolerance of unreliable operation would use a lower confidence level. The final calculation of storage size, ζ_τ, is therefore given as:

$$\zeta_\tau = \gamma\kappa\alpha\sigma_{\Delta E_\tau} \tag{2.3}$$

There is a further addition in Barton's method which is introduced for variable loads. This addition is called the periodic variance and is again calculated at the balanced wind speed. At this balanced wind speed a net power into the storage device is calculated at each possible load. These net powers form a vector which when summed from time 0 to *t* shows the state of charge or the total accumulated energy in the store at *t*, shown in Figure 2-5.

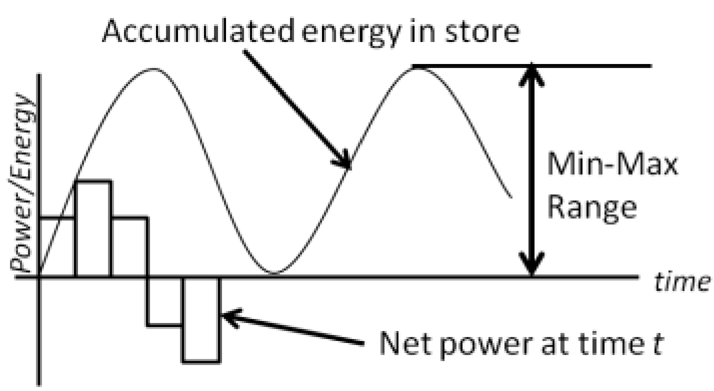

Figure 2-5: Visualization of periodic variance calculation. Where the minimum to maximum range of energy accumulated in the store is utilized to calculate the periodic variance.

The required increase in store size is calculated to be half the difference between the maximum and minimum states of charge.

$$\zeta_{Periodic} = \frac{1}{2}(E_{Net,Max} - E_{Net,Min}) \tag{2.4}$$

Barton's method for wind speeds assumes that wind power and load are independent random variables, therefore, the final storage size is then given as:

$$\zeta_\tau = \alpha\gamma\sqrt{\left(\kappa\sigma_{\Delta E_\tau}\right)^2 + \zeta_{Periodic}^2} \tag{2.5}$$

This storage size addresses the effects of efficiencies through α, the effects of wind variance through $\kappa\sigma_{\Delta E\tau}$, the effects of variable load through $\zeta_{Periodic}$, and the effects of cost and reliability through γ.

2.2 Korpaas' Method

The method suggested by Korpaas is intended to size a storage device which smoothes the variable output of a wind turbine into constant or baseload power. The requirement of constant output power allows Korpaas to design a very simple and intuitive probabilistic sizing method. This method can also be applied to system loads which are relatively constant or have low variance relative to the average load.

2.2.1 Method

Korpaas' method assumes a simple storage device with no ramping constraints and which can be characterized by charging and discharging efficiencies only. Korpaas' method also defines charging and discharging power in simple terms. When P_{Wind} is less than P_{fp} (firm power) the difference is discharging power, P_{Dch}. Alternately, when P_{Wind} is greater than P_{fp} the difference is charging power, P_{Ch}.

$$P_{Ch}(v) = \begin{cases} P_{Wind}(v) - P_{fp}, & P_{Wind}(v) > P_{fp} \\ 0, & P_{Wind}(v) \leq P_{fp} \end{cases} \tag{2.6}$$

$$P_{Dch}(v) = \begin{cases} P_{fp} - P_{Wind}(v), & P_{Wind}(v) \leq P_{fp} \\ 0, & P_{Wind}(v) > P_{fp} \end{cases} \quad (2.7)$$

These two powers are tied together by integrating over time. The integral of power with respect to time is energy, thus the integral of charging power over all times the system is in a charging state is the total energy which enters the store. Similarly, the integral of discharging power over all times of negative net power is the energy leaving the store. The amount of energy which leaves the store must be supplied by energy entering the store. Thus these two terms are set equal to each other and firm power, which affects both charge and discharge power, is used to balance charge and discharge energy.

$$\int_0^T \eta_{Ch} P_{Ch}(t)dt = \int_0^T \frac{P_{Dch}(t)}{\eta_{Dch}} dt \quad (2.8)$$

In the above equation η_{Ch} and η_{Dch} are charge and discharge efficiencies respectively. The calculation of these integrals is the key step. Firm power is a constant and will not change in time or as power from the intermittent source changes. However, the rate of power entering or leaving the store is related to the intermittent resource and the characteristics of that resource. Therefore, one might have to collect large amounts of time series power data for the intermittent resource and perform a step by step integration of charge and discharge power. This may be time consuming as the integration will need to be repeated for different firm power levels until charge and discharge energies are found to be equal. Another option is to define PDFs and cumulative density functions for the intermittent resource. This allows simple expected value calculations to be performed instead of lengthy step by step integrations. This is the option that Korpaas follows and the equations for expected value of energy entering and leaving the store are shown below, where F denotes the cumulative density function of the renewable resource and f denotes the PDF of the renewable resource.

$$E(P_{Ch}\eta_{Ch}) = \int_{v(P_{fp})}^{v_{CutOut}} \eta_{Ch}\left(P_w(v) - P_{fp}\right) f(v)dv \tag{2.9}$$

$$E\left({}^{P_{Dch}}/_{\eta_{Dch}}\right) = \eta_{Dch}{}^{-1}P_{fp}\left(F(v_{CutIn}) + \left(1 - F(v_{CutOut})\right)\right) + \int_{v_{CutIn}}^{v(P_{fp})} \eta_{Dch}{}^{-1}\left(P_{fp} - P_{Wind}(v)\right) f(v)dv \tag{2.10}$$

The variable P_{fp} is iteratively changed until $E(\eta_{Dch}{}^{-1}P_{Dch}) = E(\eta_{Ch}P_{Ch})$. The final result is the available firm power commitment and the expected values of energy entering and leaving the store, which are equal. The storage size is then this expected value multiplied by the desired store period, which in this thesis is 24hrs.

2.3 Dynamic Optimization

The Dynamic Optimization is a time-series based optimization method designed to size energy storage requirements for a wind-load energy system, as shown in Figure 1-3. This optimization is based on minimizing cost as presented in an objective function. Minimization is constrained by equations so as to create realistic operating conditions. The optimization is subject to several simplifying assumptions and is solved using Matlab's 'linprog' (R2010a, MathWorks, Natick, MA, US) linear program solver.

2.3.1 Data Requirements

This time series method requires synchronized time series of load and wind generation. In this thesis synchronization means the data sets are of the same resolution and start and end at the same time of day and year (for instance 00:00 January 1st). Synchronization of data sets ensures seasonal and hourly correlations between wind power and load are captured. In order to capture seasonal correlations, data sets must span at least one year. In this thesis, the wind generation data set is created by converting a wind speed data set, using data from the Enercon E48 wind turbine [24]. The average hourly wind speed is used to interpolate a power from the wind turbine power curve.

2.3.2 Objective Function

The objective function for this method is to minimize total cost of supplying energy and is given below as:

$$\min_{x,P} f = C_{StoreP}X_{StoreP} + C_{StoreE}X_{StoreE} + \sum_{t=1}^{T} C_{Wind}\left(P_{t,Wind}dt\right) + C_{Backup}\left(P_{t,Backup}dt\right) \tag{2.11}$$

C_{StoreP} and C_{StoreE} are the capital costs for the energy storage device's power and energy capacity respectively. $P_{t,Wind}$ and $P_{t,Backup}$ are the wind and backup power at time t and dt is the time increment, in this case hours. T is the total length of the optimization, in the case of one year at one hour time increments, T is 8760. In the model there are state variables for wind power, backup power, dumped power, charging power, discharging power, and energy state of charge. However, only wind and backup power enter the objective function as they have an attached cost, given by C_{Wind} and C_{Backup}. X_{StoreP} and X_{StoreE} are global variables representing rated store power and rated store energy.

2.3.3 Constraints

Constraints ensure the load is always met, that the store is operated correctly and that wind energy is utilized. The demand constraint balances load at each time step, t:

$$P_{t,Wind} + P_{t,Backup} - P_{t,Dump} - P_{t,Charge} + P_{t,Discharge} = P_{Load,t} \tag{2.12}$$

The backup power constraint limits the size of backup power at any point in time:

$$P_{t,Backup} \leq P_{Load,t} \tag{2.13}$$

It is required to ensure the model does not charge the store by accepting a higher backup load than the system load at time *t*. Fundamentally, this is akin to taking extra power from a larger grid or backup device and storing it for future use, which is not allowed in this model. The following three equations govern the storage device. First, the discharge power for time *t* cannot exceed the energy in the storage device at time *t*:

$$P_{t,Discharge}dt - E_{t,StoreEnergy} \leq 0 \tag{2.14}$$

Second, the energy in the device at time *t* cannot exceed the store capacity:

$$E_{t,StoreEnergy} - X_{StoreE} \leq 0 \tag{2.15}$$

Third, the energy in the storage device at time *t+1* is equal to the store energy at time *t* plus the power entering and leaving the store at time t.

$$P_{t,Charge}dt - P_{t,Discharge}dt + E_{t,StoreEnergy} - E_{t+1,StoreEnergy} \leq 0 \tag{2.16}$$

The above equation is valid only for *t* values of one to *T-1*. This constraint is copied from an account balance model [25]. The last constraint governs the final state of the storage system.

$$E_{t,StoreEnergy} = 0 \tag{2.17}$$

The above equation is for *t=0* and *t=T*, which forces the store to start and finish in an empty state.

2.3.4 Assumptions and Issues

The requirement that the store starts and finishes in an empty state has potential to cause end-effect issues. For example, consider a 24 hr window in which the first 12 hrs has a positive net power and the final 12 hrs a negative net power, as shown in Figure 2-6.

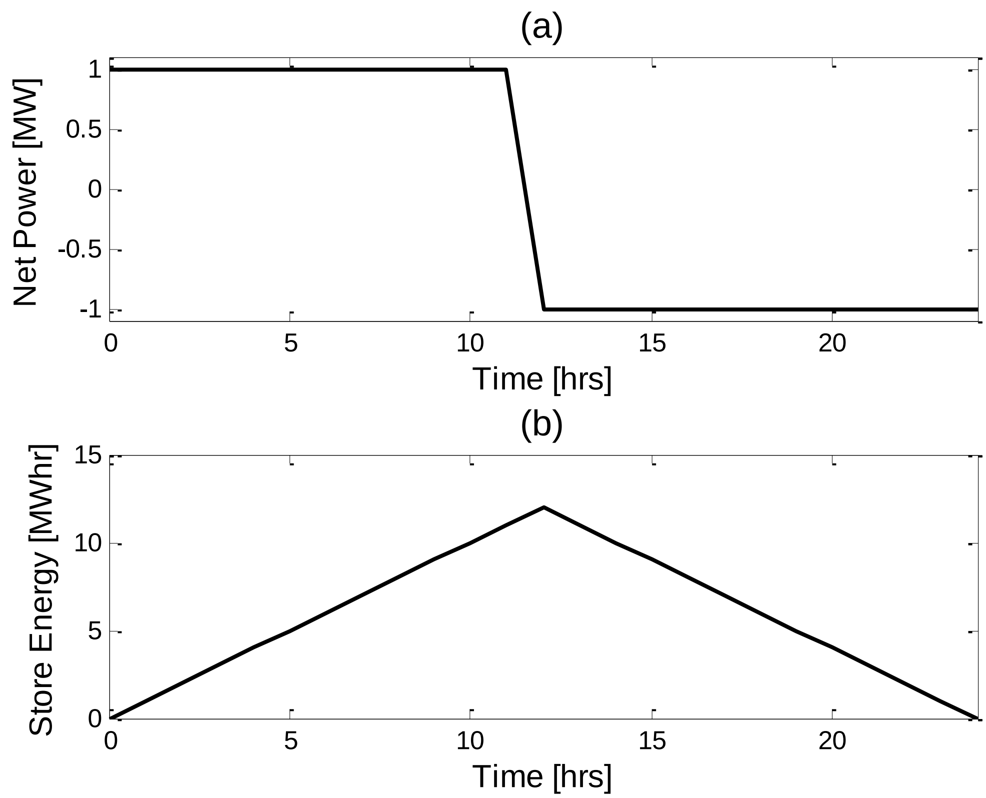

Figure 2-6: Positive end effects of storage device. In plot (a) net power starts positive and the storage device starts empty, thus it fills, shown in plot (b). Then when negative net power occurs the store has energy to discharge.

Under these conditions the start and finish empty constraint has no effect on the operation of the storage device. However, if the net power conditions are reversed, as in Figure 2-7, the storage device is unutilized as a result of the storage start and finish empty constraint.

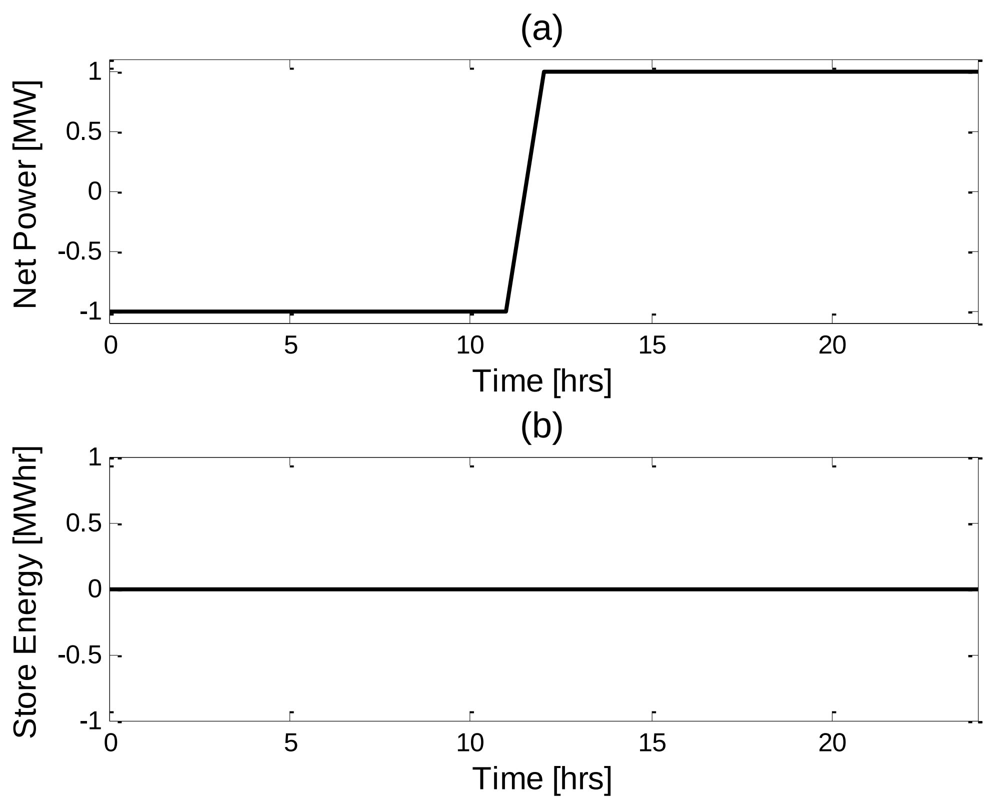

Figure 2-7: Negative end effects of storage device. The net power starts negative, shown in plot (a) but the store is empty and therefore cannot discharge, shown in plot (b). Then when the net power is positive the store remains empty due to the operating constraint which requires the store to be empty at time *t=24*.

It is worth noting that in the situation of Figure 2-6, if the store had started full it would have also remained unutilized. In this case the constraint would have been for it to start and finish full and therefore the device would have stayed full throughout. Therefore, end effects may be present regardless of the constraint on how the storage device starts and finishes. As the Dynamic Optimization is a long running model, one year, targeting a 24 hr storage device, the end effects will be small. If the model was modified to target long term storage, such as annual storage, this constraint would need to be modified, as in the Abbey Method. Another assumption present in this model is no ramping rate requirements on the storage device. The resolution of the data sets used is hourly and it is assumed that store power can ramp much faster than can be captured at this resolution [6]. Therefore, ramping rates are neglected. Furthermore, it is assumed that there are no parasitic losses or depth of discharge limitations on the storage device. This assumption reduces the complexity of the model. The final issue associated with this model is due to the length of the optimization. While the optimization is designed for a year of hourly wind and load data this results in an intractable problem for basic notebook computers due to memory limitations; therefore the model is split into four separate three month periods. Each period computes in approximately 10-15 minutes for a total time of approximately one hour. The results from each period are compared and the largest storage size is selected. Alternatives would be the use of a more powerful computer, or by selecting the storage size from the period with the largest negative correlation between load and wind. As a result of this split, the seasonal correlations have a reduced affect on the storage size. This issue coupled with end effect, ramping rate, and storage assumptions reduce the credibility of the optimized solution.

2.4 Alternative Optimization – Two Stage

The two-stage optimization is based on a method presented by Abbey [19]. The first stage sets limits for storage size and power, then the second stage optimizes for operation within these limits. This method shares many similarities with the Dynamic

Optimization, but uses probabilities to increase processing speed and improve the robustness of the result.

The first stage of the optimization sets limits for the storage size and power. While Abbey accomplishes this through a separate optimization it is also possible to simply supply a reasonable range of storage power and energy ratings and iteratively feed all possible combinations of store power and energy into the second stage. The lowest cost combination from the second stage results is the optimal solution. This iterative approach simplifies programming with negligible increase in solution speed.

The second-stage optimization calculates the operation and overall cost of the energy system. However, Abbey reduces the length of the optimization by using probabilities and scenarios rather than time series programming. Abbey assumes that two independent variables affect the results of storage size: the amount of wind energy relative to the load, and how well the wind energy matches up with the load. These variables are binned into PDFs and their probabilities are convoluted resulting in a matrix of possible scenarios for wind energy penetration and wind load correlation. The second stage optimization calculates the best case of each scenario, and then calculates an expected value based on the results of all scenarios.

2.4.1 Data Requirements

The two-stage method presented by Abbey requires synchronized data sets of wind speed or power and load. These data sets are used to make scenarios and probabilities.

2.4.2 Scenario Determination

The two-stage method optimizes for a series of characteristic scenarios which are defined by the amount of wind energy penetration and the amount of wind to load correlation. To determine these scenarios the data sets for load and wind are aligned and then divided into 365 twenty-four hour periods. Each period is then evaluated for wind energy penetration given as:

$$Pen = \frac{\sum_{t=1}^{24} P_{wind,t}}{\sum_{t=1}^{24} P_{load,t}} \tag{2.18}$$

And for wind-load correlation, given as:

$$Corr = \frac{\sum_{t=1}^{24}\left(P_{wind,t} - \bar{P}_{wind}\right)\left(P_{load,t} - \bar{P}_{load}\right)}{(24-1)\sigma_{wind}\sigma_{load}} \tag{2.19}$$

Ranges for penetration and correlation are determined from the 365 periods and these ranges are divided into equally spaced bins. The scenarios are then placed in these bins as shown in Figure 2-8.

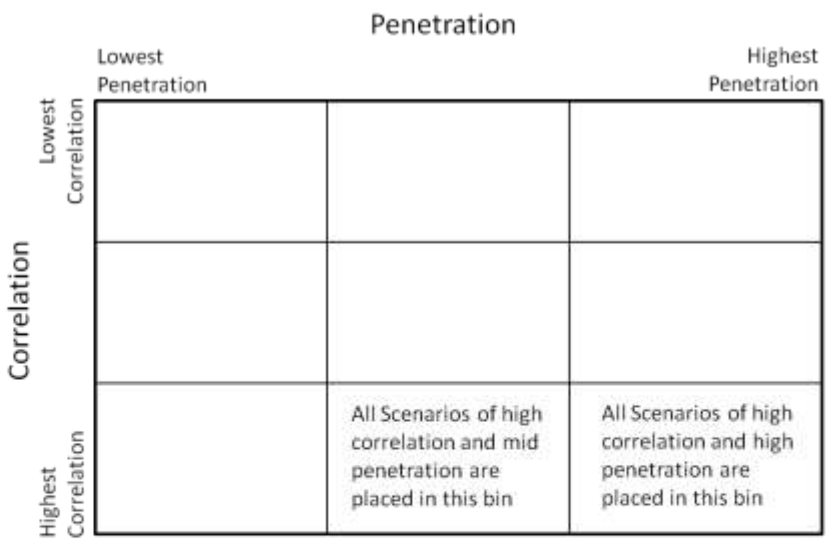

Figure 2-8: Visual representation of scenario binning. Each bin contains scenarios from which one is selected as the bin's characteristic scenario to be used in the optimization. The weight assigned to each bin's characteristic scenario is proportional to the number of scenarios in that bin.

The number of scenarios which fall into each bin gives the probability of a scenario from that bin occurring. The scenario in each bin which has values of penetration and correlation closest to the midpoint of the bin is then defined as the characteristic scenario for the bin. The optimization is performed on these characteristic scenarios only, rather than the whole data set.

2.4.3 Second Stage Objective Function and Optimization

The two-stage optimization is given storage power and energy constraints and then outputs an optimal value based on the determined scenarios. The objective function of this optimization is given as:

$$\min_{P} f = \sum_{t=1}^{T} C_{Wind} P_{t,Wind} dt + C_{Backup} P_{t,Backup} dt \quad (2.20)$$

This value represents the operating costs given the storage constraints, where C_{Wind} and C_{Backup} are the costs associated with an hour of wind or backup energy respectively, and $P_{t,Wind}$ and $P_{t,Backup}$ are the amounts of wind and backup energy at time t for duration dt. The capital cost of the given storage device is added to this value to give an overall cost and the result is stored. Therefore, equation 2.20 is similar to the objective function of the Dynamic Optimization, equation 2.11, except that the capital costs are outside the operating costs optimization. When equation 2.20 is executed, the two stage method changes the storage sizes, and then executes equation 2.20 again, producing a new optimal. This is repeated until all possible combinations of storage constraints have been executed. The lowest overall cost of operating and capital costs is the optimal. This iterative approach to optimization is not efficient but produces a solution.

2.4.4 Constraints

There are many repeated constraints from the Dynamic Optimization. This is because the modeled wind-storage energy system is identical to that shown in Figure 1-3. The first constraint requires the system load be met at all times *t*:

$$P_{t,Wind} + P_{t,Lost} - P_{t,Dump} - P_{t,Charge} + P_{t,Discharge} = P_{Load,t} \tag{2.21}$$

In the Dynamic Optimization the length of the optimization was one year, in this optimization the length is 24 hrs. Therefore *t* is from 1 to 24. Energy in the store at *t+1* is the sum of previous energy, and net power entering and leaving the store. Again, this is a similar constraint to the Dynamic Optimization and is based on an account balance model [25].

$$E_{t,StoreEnergy} - E_{Store} \leq 0 \tag{2.22}$$

$$P_{t,Charge}dt - P_{t,Discharge}dt + E_{t,StoreEnergy} - E_{t+1,StoreEnergy} \leq 0 \tag{2.23}$$

The power into and out of store must be less than the rated store power at all times.

$$P_{t,Charge} - P_{Store} \leq 0 \tag{2.24}$$

$$P_{t,Discharge} - P_{Store} \leq 0 \tag{2.25}$$

Finally, the store must start and finish at the same level. However, this differs from the Dynamic Optimization in that it starts and finishes half full. The method first proposed by Abbey included initial store energy as a factor to be optimized for, producing average values of 35%. In this thesis, 50% or half full is chosen arbitrarily.

$$E_{1,StoreEnergy} - 0.5 \times E_{Store} \leq 0 \tag{2.26}$$

$$E_{T,StoreEnergy} - 0.5 \times E_{Store} \leq 0 \tag{2.27}$$

As the store size increases there is more energy available initially. This energy must be returned to the store by the end of each time period, otherwise a net gain or loss of energy will occur. For instance, if the store started half full and finished the day empty, additional energy would have entered the system from the store. Energy is only permitted to enter this system from the scenario's wind generation and therefore the store must finish where it started. This also means energy cannot be shared from high wind days to low wind days as is possible in reality and in the Dynamic Optimization.

2.4.5 Assumptions

There are four assumptions made in Abbey's method which must be addressed. These involve the use of PDFs, the range of possible store ratings, and the storage start and finish levels.

The first assumption is that every possible scenario from the convolution of probabilities exists in the data sets. The solution lies in binning by correlation and penetration. The use of bins keeps non-existing scenarios out of the optimization. Each bin is assigned a probability equal to the number of scenarios which are represented by that bin. If a bin has no scenarios then the optimization will ignore it.

The second assumption in this optimization is in the storage ratings. As previously stated the 1st stage of the optimization is executed by iteratively changing store power and energy ratings. Therefore a range of possible store ratings is required. The lower level is chosen to be zero, or no storage device. The upper level for store power is set to the rated power of installed wind generation. The upper level for store energy is set to 150% of the result from the Barton method. This sets an upper bound for storage size. In theory this could limit the result of the two-stage optimization, however, the results indicate this does not occur when sizing for a 24hr storage device.

The final assumption involves end effects as a result of the relatively short 24hr storage period and scenario length. These effects were deemed negligible in the Dynamic Optimization, however, as the two-stage method optimizes for short scenarios the end effects are important. Therefore, the device starts and finishes half-full. This level is based on results from Abbey.

3 Modified Barton's Method

Barton's method is complex and difficult to implement; however, the basic principle is straightforward: the intermittent generator's magnitude and frequency of variance affect storage size requirements. In this chapter a modification of Barton's method is proposed.

In this modification the high and low frequency filters, the spreadsheeting calculations, and the calculations of α, κ and the periodic variance are eliminated. Figure 2-2 shows that α, κ, and periodic variance are dependent on the spreadsheeting calculations which are in turn dependent on the high and low frequency filters. Therefore, if α, κ and periodic variance are neglected then spreadsheeting and high and low frequency filtering can be avoided as well.

As previously stated, α adjusts for storage limitations and inefficiencies. It is multiplied with the state of charge variance and other conversions to give the final store power. α is calculated through the spreadsheeting results of Barton's method. In the case of an ideal storage device with unlimited charge and discharge power ratings and perfect efficiency, α would be unity. For the case of unlimited charge and discharge power ratings but an inefficient device, α would be equal to the round trip efficiency of the storage device. Adding finite power ratings would further reduce α, however the finite ratings considered in this thesis are sufficiently large so as not to affect α. Observed results, as shown in Figure 3-1, have shown that there is minimal difference between α and round trip storage efficiency.

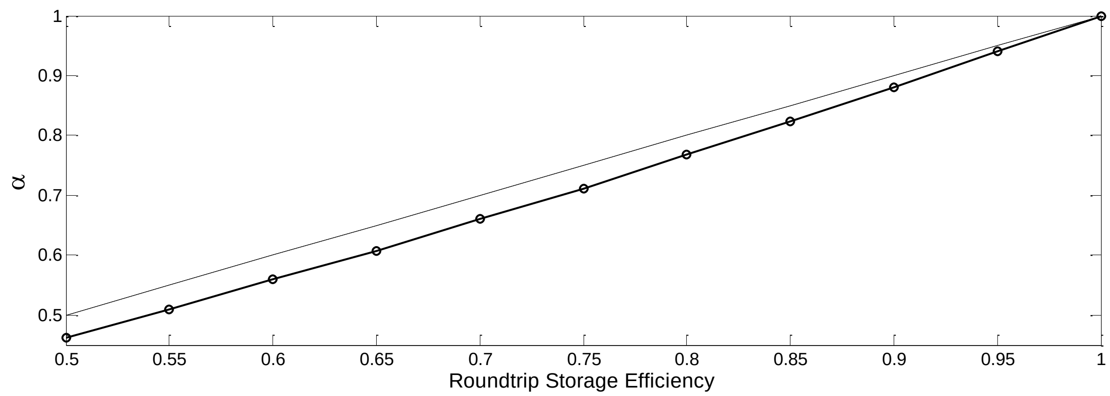

Figure 3-1: Sensitivity of α to roundtrip storage efficiency. Marked line shows α calculated by Barton's Method, solid line is y=x to illustrate the difference between α and the efficiency. This result is calculated with Sandspit wind speed data and without limitations on the storage device charge and discharge powers.

Therefore, it is proposed that α can be assigned a value equal to the round trip efficiency or neglected entirely.

The term κ is required to convert the filtered state of charge variance from variance of wind speed to variance of wind power. In Barton's method this variance is calculated from a periodogram of wind speed variance which is calculated from a time series data set of wind speed. However, if the time series data set of wind speed is first converted to a wind power and then converted to a periodogram and filtered the result is variance of wind power, making the term κ unnecessary. A comparison is shown in Figure 3-2 where there is a slight change in periodograms due to the conversion of wind speeds to wind powers. This is due to the non-linear relationship between wind speed and wind power via a turbine power curve.

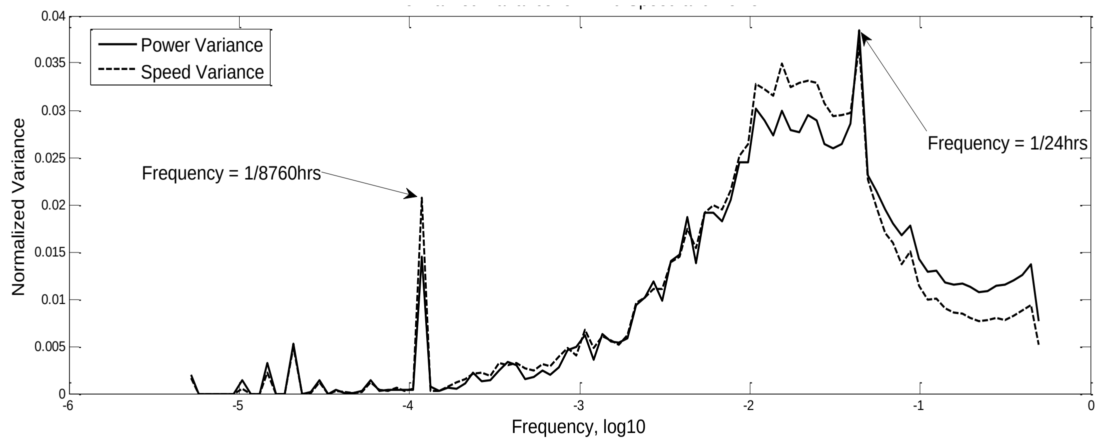

Figure 3-2: Comparison of normalized variance for wind speed and power for Sandspit and the Enercon E-48 wind turbine. Differences are due to the non-linear conversion from wind speed to wind power.

The final term modified from Barton's method is the periodic variance. The periodic variance accounts for the effects of variable load on storage size. Work by Gassner [22] has not included periodic variance. The simplified method assumes the effect of periodic variance is small and can be neglected. This assumption is verified in section 5.3

Given that the term α can be neglected, that the term κ can be made unnecessary, and that the periodic variance is ignored the spreadsheeting and high and low pass filters become unnecessary. The removal of these steps from Barton's method results in a simpler calculation of storage size.

The proposed simplified method is reduced to a few steps. First, the intermittent resource data is converted into units of power rather than being left as resource units like wind speed or water flow rate. This data is then transformed into a periodogram. At this stage the state of charge filter [13] is calculated and applied to the periodogram.

$$\sigma^2_{\Delta E_{t,i,simple}} = \left(\frac{A_i}{\omega_i}\right)^2 \left(\frac{5}{6} + \frac{1}{6}\cos(\omega_i \tau) + \frac{2}{(\omega_i \tau)^2}(\cos \omega_i \tau - 1)\right) \tag{3.1}$$

In this equation the amplitude A_i is in units of power and ω_i has units of time inverted. Therefore the overall units are energy squared. The result is an uncorrected value for store size variation based on variations in power output. Therefore the final result is the store size as calculated by the filter, $\sigma_{\Delta E\tau,simple}$, multiplied by the confidence level, γ.

$$\zeta_\tau = \gamma\sigma_{\Delta E_{\tau,simple}} \tag{3.2}$$

4 Input Data and Parametric Variations

This chapter outlines the testing and validating of the different storage sizing methods. First the financial data and methods are presented, followed by the wind data, load profiles, and time shifting methods. Results are generated using a time-series testing function detailed in Appendix B. Base case results are generated by running the testing function without storage capacity.

The validity of the Modified Barton method will be evaluated from the average result of the four existing methods.

4.1 Financial Analysis

To compare the financial costs of operating each method's proposed energy system, an investment annual cost method is used. As in Abbey's study [19] a 20 year life span is assumed for the storage device with an 8.5% interest rate. The cost of the storage system is converted to an annual cost and added to the system operating cost, yielding a yearly cost of operation. The financial metric for comparison will be supply cost of energy, C_{Supply}, given as:

$$C_{Supply} = \frac{C_{Total}}{\sum P_{Load}} \tag{4.1}$$

C_{Total} is defined in Appendix B. Reliability metrics are loss of load probability (LOLP), Eqn. (4.2), and autonomy, Eqn. (4.3).

$$LOLP = \frac{\sum P_{Backup}}{\sum P_{load}} \tag{4.2}$$

$$Autonomy = 1 - \frac{\sum T_{Backup}}{T_{Total}} \qquad (4.3)$$

Table 4-1 shows the initial financial inputs for the methods. Unless otherwise stated this information is used to compare results.

Table 4-1: Base Input Data

Store Efficiency	Store Energy [$/kWh]	Store Power [$/kW]	Wind Energy [$/kWh]	Backup Energy [$/kWh]	Term Period [years]	Interest Rate [percent]
0.85	875	213	0.4	0.6	20	8.5

These values are identical to those used in Abbey's paper; however, in this thesis the cost of diesel energy as used by Abbey is assigned to backup energy.

4.1.1 Varying Interest Rate

An interest rate is applied to the capital costs of the storage system. A high interest rate reflects the value of capital costs associated with the project and makes storage devices more expensive. A low interest rate has the effect of reducing storage costs. In this paper interest rates of 5% and 8.5% are considered as well as a no rate case where the storage costs are divided evenly across 20 years of operation.

4.1.2 Cost of Backup Energy

In theory, increasing the cost of backup energy will force the Dynamic Optimization and Abbey's method to increase storage size. An increasing cost of backup energy is akin to placing increasing value on system reliability. Therefore, backup energy cost is varied from $0.2/kWh to $2.0/kWh. This change will only impact the Dynamic Optimization and Abbey results for storage size.

4.2 Wind Data

Data sets of wind speeds are required for this study. Wind data was made available from Environment Canada [26] at hourly resolutions and a height of 10m. The height was adapted to turbine height of 64m using the power law of Peterson [27]. Additional comments on the utilized wind speed data are made in Appendix D.

By combining wind speed data sets with a turbine power curve a data set of wind power is created. This data set can then be analyzed for daily variance of wind power, seasonal variance of wind power, and mean wind power. Of these factors, mean wind power or capacity factor is selected to classify sites.

Wind sites of varying capacity factors are used by the five methods to produce required storage sizes. A normalization of system load is performed to ensure the reliability metrics can be used for comparison between sites. This ensures the energy entering through the wind turbine is equal to the energy absorbed by the system load through one year of operation. This normalization is described in Section 4.3.

Five different sites are used to examine each method's performance under different wind conditions. The table below lists five wind sites of differing capacity factors. Capacity factors range from poor (0.063) to excellent (0.42) and are shown in Table 4-2.

Table 4-2: Wind Site Characteristics. Sites A, B, C, D, E correspond to Sandspit, Penticton, Victoria, Terrace, Prince Rupert respectively [26]. Wind speed data was converted to power using an Enercon E-48 turbine power curve [24].

Wind Site	Capacity Factor	Average Wind Speed [m/s]	Wind Speed Variance [$(m/s)^2$]	Power Variance [MW^2]
A	0.42	6.30	14.29	0.14
B	0.14	3.27	6.24	0.052
C	0.063	2.34	3.54	0.020
D	0.33	5.20	8.48	0.11
E	0.21	4.01	8.09	0.083

Sites A and D have high capacity factors while sites B, C, and E have low capacity factors. Furthermore, sites A, C, and E are coastal locations whereas sites B and D are inland locations.

4.3 Load Profiles

As with a site's wind speeds, the characteristics of a load profile can affect energy system generation and storage requirements and energy system reliability. An example of a 24hr load profile is shown in Figure 4-1. This figure shows an average power of approximately 8000MW, a minimum of approximately 6500MW and a maximum of approximately 9000MW.

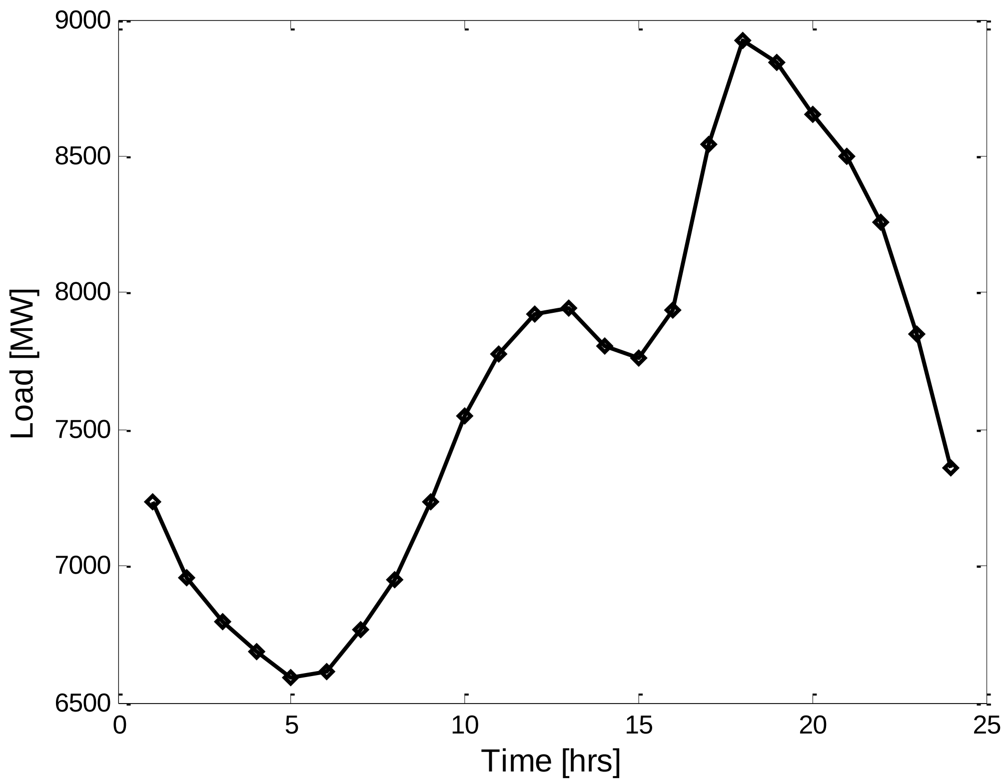

Figure 4-1: Sample 24hr load profile. This profile shows a diurnal cycle with a minimum at approximately 05:00 and a maximum at approximately 18:00 [28].

To test each method's ability to size an energy storage device a suitable load profile is required. To simulate a realistic load curve, historical load data was used from a large utility [28]. To validate the models' ability to account for load variance, tests are conducted with sinusoidal functions of 24 hour period and varying base load.

Load profiles are scaled so the total load energy is equal to the total wind energy, eliminating wind to load energy ratio as a variable when interpreting results. For example, if a load profile with an average load of 0.5 MW is combined with a 1 MW wind site of capacity factor 0.15 the reliability results will be poor regardless of the storage device. This is due to the difference in energy generated and energy demand. To counter this difference the load is normalized against its average to produce a load profile with an average load of 1. Then the load profile is multiplied by the wind site capacity factor. The end result is a site specific load profile with an average load equal to the capacity factor of the site. Over the course of the year energy supplied by the wind will approximately match the energy drawn as demand. This normalization of load with wind energy allows for comparison of results across wind sites.

The historical load profile is scaled to create five separate load profiles. The characteristics of these loads are shown in Table 4-3.

Table 4-3: Load Profile Characteristics

Load Option	Maximum Load [MW]	Minimum Load [MW]	Mean [MW]	Variance [MW^2]
1	0.632	0.292	0.424	0.005
2	0.838	0.161	0.424	0.018
3	1.092	0.000	0.424	0.048
4	0.507	0.371	0.424	0.001
5	0.437	0.416	0.424	0.00002

Load option 1 is the historical data set with only one change: it is scaled to have a mean load equal to the capacity factor of the wind site. Again, all sites will have the same mean load so that only the maximum, minimum, and variance of the load profile will affect results. Option 2 takes the historical data and shifts it down by 1/3 of the maximum load to simulate the removal of base or constant load, this increases the variance of the profile. Option 3 goes further and takes the historical data and shifts it down by the minimum load to simulate a highly variable load. In this option it is possible to have no load or periods of very low load, this is shown in Figure 4-2, plot (a). Option 4 is the historical data shifted up by the maximum load to increase the amount of baseload power. Furthermore, Option 5 takes the historical data and shifts it up by 100 times the maximum load, an arbitrary increment, to reduce the variance of the data set and simulate a near constant load, shown in Figure 4-2 (b).

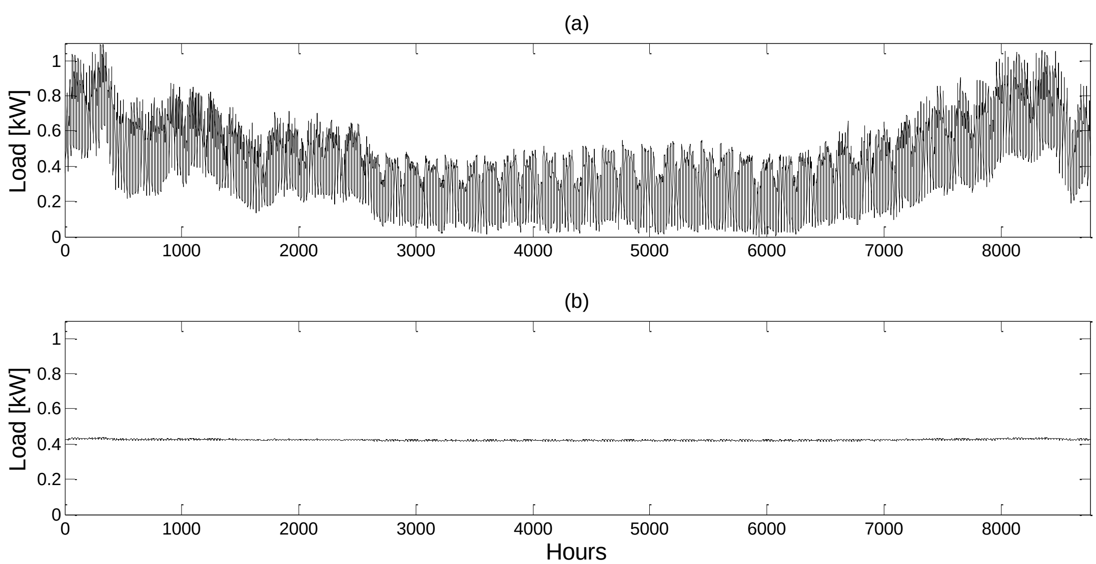

Figure 4-2: Sample plots of load options 3 and 5. They have been scaled to have a mean of 0.424kW.

4.4 Correlation between Load and Resource

The effect of correlation between load and generation on storage size and energy system performance is investigated. There are expected to be two types of correlation; diurnal and seasonal. To examine the diurnal correlation effects the wind speed profile is shifted by up to 24 hrs. To examine the seasonal correlation effects the wind speed profile is shifted by up to 12 months. This is shown below in Figure 4-3, wherein *lag* refers to the shift between data sets.

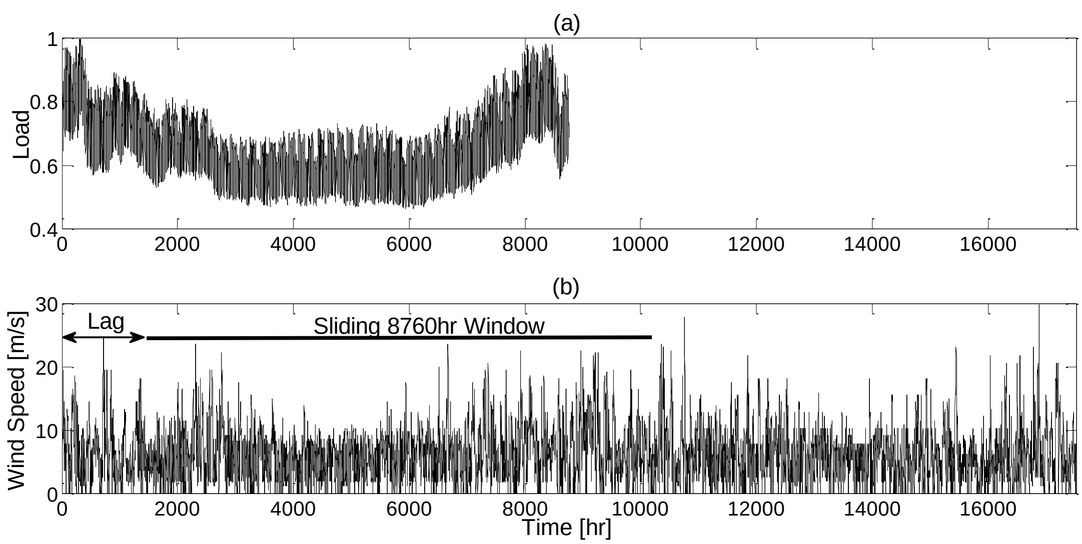

Figure 4-3: Shifting wind speed relative to load. Plot (a) shows the load data and plot (b) shows the sliding 8760hr window which determines which wind data is utilized.

This figure also shows how the input data change with lag. The change in data will have minimal effect on diurnal changes, but is potentially more significant in seasonal changes.

5 Results and Discussion

This chapter presents the results from each method and discusses areas of interest. It begins with changing costs and financial inputs, followed by varying wind sites, varying load profiles, and varying lag between load and wind resource. These testing methodologies are not exhaustive but are sufficient to show sensitivities of each method and to validate the Modified Barton method.

5.1 Costs

This section first varies the capital costs of energy storage through a changing interest rate. It then varies the operating costs of an energy storage system by changing the cost of backup energy.

5.1.1 Interest Rate

Figure 5-1 shows the effects of increasing interest rate on the supply cost for an energy system modelled with wind site D and load option 1. The cost of the no storage base case does not change with interest rate because there is no storage device present.

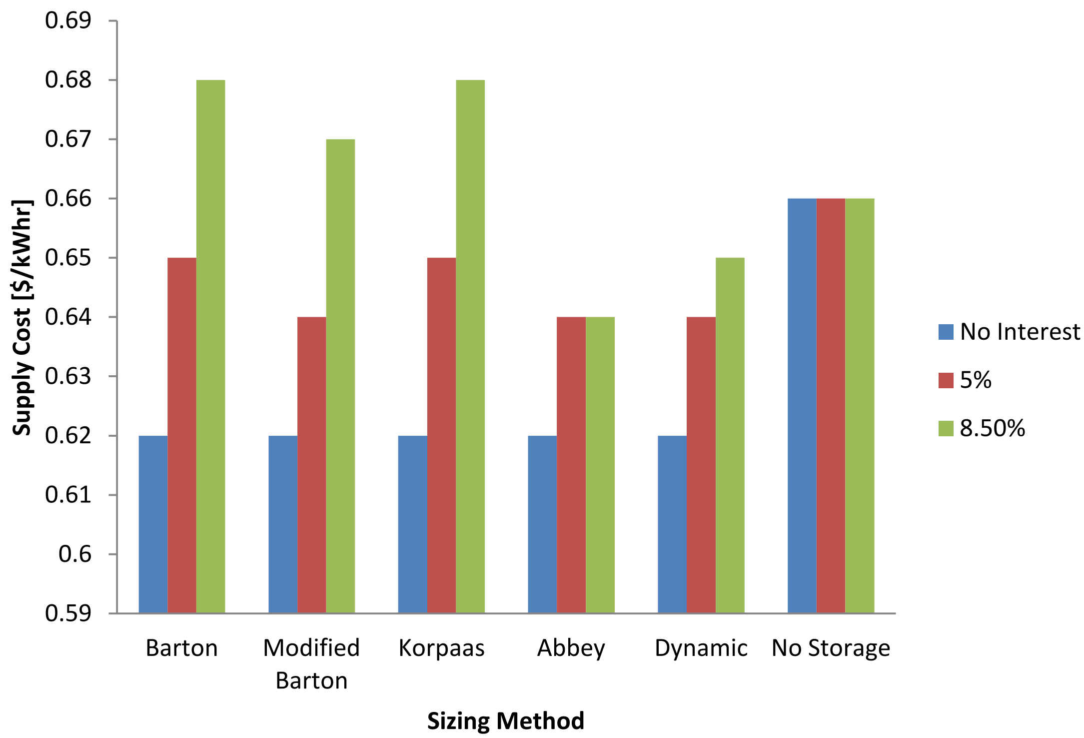

Figure 5-1: Effect of interest rate on supply cost. Abbey and Dynamic methods reduce storage size to minimize supply cost. Results can be found in Table 8-7.

Of note in Figure 5-1 is the relatively close cost across methods for the no interest rate case. This result highlights the trade off between the capital costs associated with storage devices and the operating costs associated with backup or lost energy. A larger storage device has a greater capital cost but reduces the operating costs from lost or backup energy. The Barton, Modified Barton, and Korpaas opt for larger storage sizes while the Abbey and Dynamic opt for smaller storage sizes. The results for storage size are shown in Figure 5-2. Under varying interest rate, the Barton, Modified Barton, and Korpaas results do not have a change in storage size because these sizing methods are not sensitive to cost.

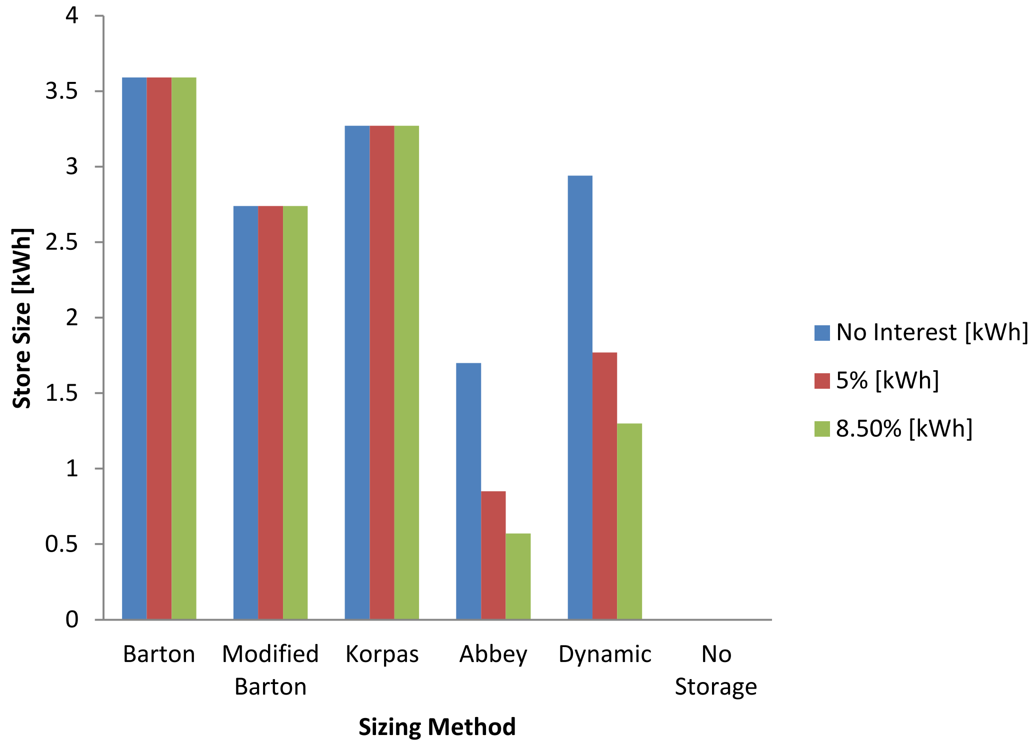

Figure 5-2: Effect of interest rate on store size. Probabilistic methods are not affected by storage cost.

The supply cost of the results from the Barton, Modified Barton, and Korpaas increase with interest rate. The Abbey and Dynamic reduce the amount of storage present to minimize the capital cost of storage and hence the supply cost. Tabled results are presented in Appendix C.

5.1.2 Cost of Backup Energy

The results from changing backup energy cost are presented in Figure 5-3, where the results for storage size from the Abbey and the Dynamic increase with the cost of backup energy. The Barton, Modified Barton and Korpaas do not change storage size as they are not affected by costs. This result combined with the results of varying interest rate show the ability of the Abbey and Dynamic to adjust storage size based on the relative capital and operating costs. The Dynamic results in Figure 5-3 show a greater sensitivity to back up energy costs than the Abbey method. This is because the scenarios for which the Abbey method optimizes are only 24 hours long, meaning there will be a maximum possible size for the storage device: equal to the greatest net store energy over all of the scenarios. The Dynamic method is not constrained to consider 24 hour storage, it is only the prices of energy and storage costs that make the Dynamic method consider 24 hour storage periods. Therefore, as the relative costs change the Dynamic method effectively lengthens the storage period by selecting larger storage devices. As the Abbey method's maximum storage size is the greatest net store energy over all 24 hour scenarios, the Dynamic's maximum storage size is the greatest net store energy over the entire one year data set.

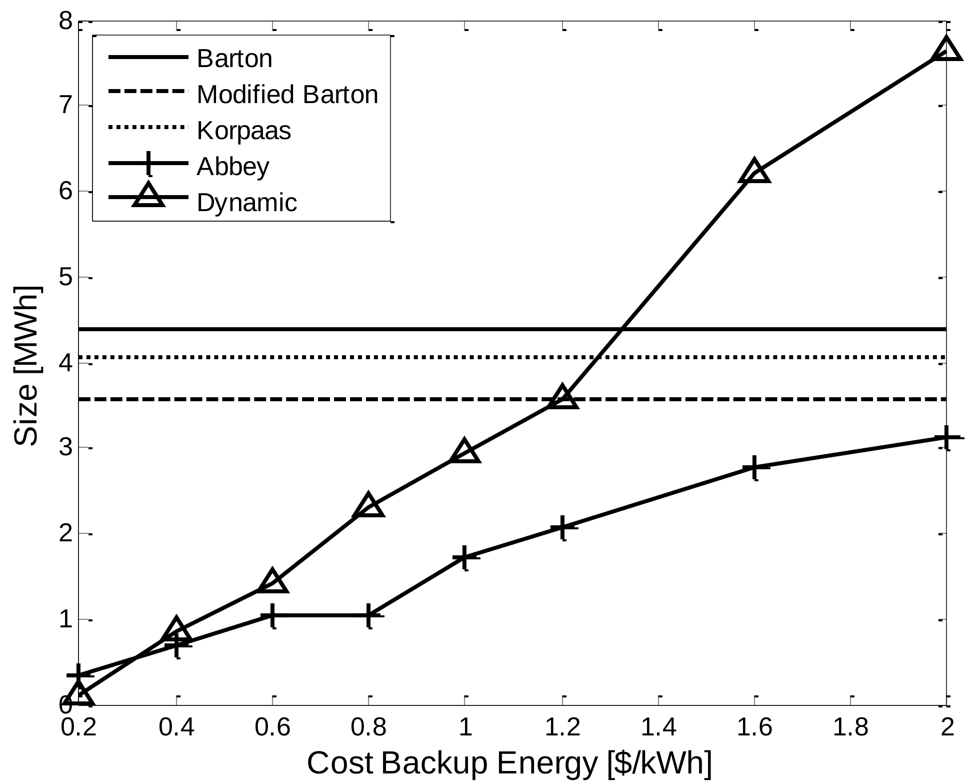

Figure 5-3: Storage size vs. Backup energy cost. As cost of backup energy is increased the optimization methods add more storage.

The results of LOLP and autonomy are shown in Figure 5-4. This figure shows that as cost of backup energy increases, the Abbey and Dynamic yield results with greater emphasis on reliability. The results from these methods for LOLP and Autonomy approach or exceed those of the Barton, Modified Barton and Korpaas methods.

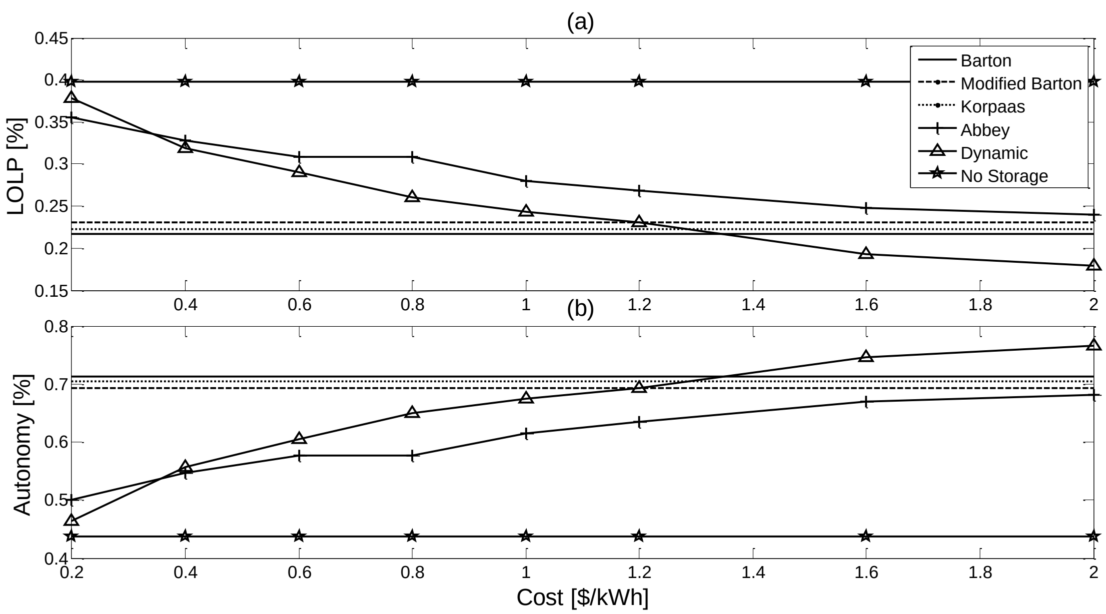

Figure 5-4: Autonomy and LOLP for varying backup energy cost. Plot (a) shows LOLP and plot (b) shows autonomy. The results of the Barton, Modified Barton, and Korpaas methods correspond best with systems which place a significant emphasis on reliability. In this instance 'significant' is when costs associated with backup energy are 3-5 times that of energy supply.

5.2 Wind Site

The Dynamic and Abbey methods are less sensitive to capacity factor than the other methods, shown in Figure 5-5. The Dynamic and Abbey are sensitive to the magnitude of both the wind profile and the load profile, which combine to equal the system's net power. As stated in Sections 4.2 and 4.3, the load profile average was scaled to equal the wind profile average and thus the values for net power may only increase slightly with capacity factor. Therefore the Dynamic and Abbey results do not increase storage size as significantly as the other methods. Korpaas and Modified Barton are sensitive only to the wind profile, and thus as capacity factor increases so should the storage size. Similarly, the Barton method increases store size with capacity factor, however, it is also sensitive to load profile. Where the Dynamic and Abbey methods size storage based on net power, the Barton method considers the load profile and the wind profile separately. Thus as capacity factor increases so does the storage size. Similarly, Figure 5-8 in the Load Profile section shows that as load variance increases so does the storage size.

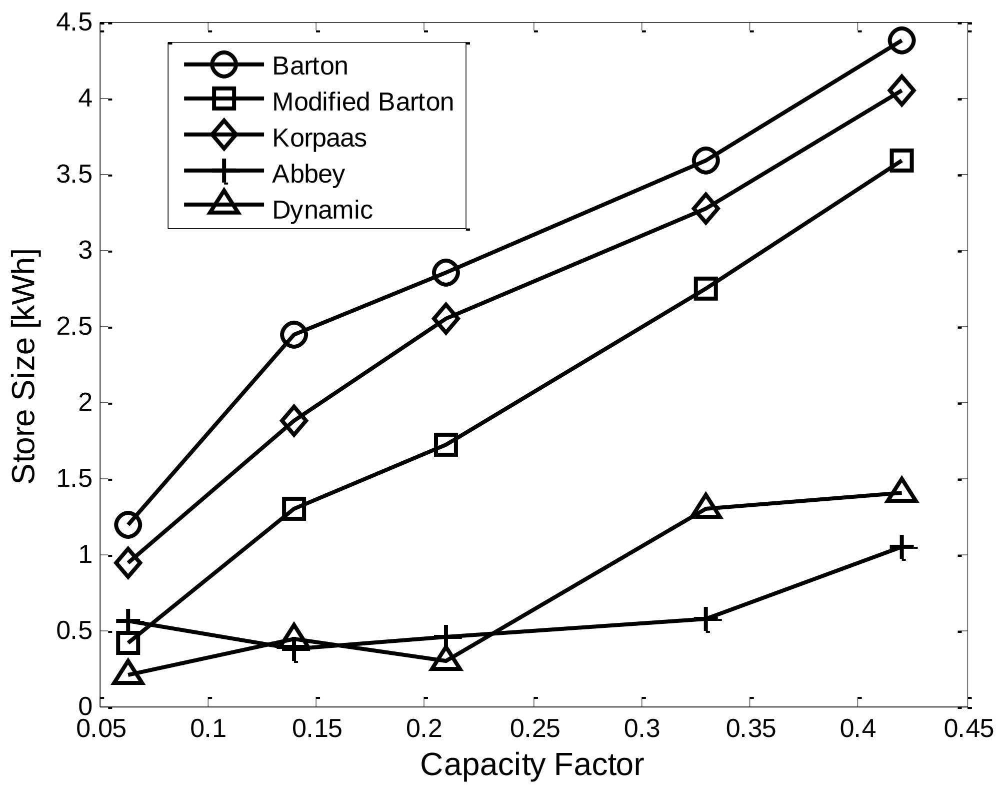

Figure 5-5: Storage size vs wind capacity factor. Note for high capacity factor sites there is a significant difference in size between the Barton, Modified Barton, and Korpaas methods' results and the Dynamic, and Abbey methods' results.

The Abbey and Dynamic methods always yield a storage size which results in the lowest cost of energy. These results are shown in the tables of Appendix C and summarized in Figure 5-6.

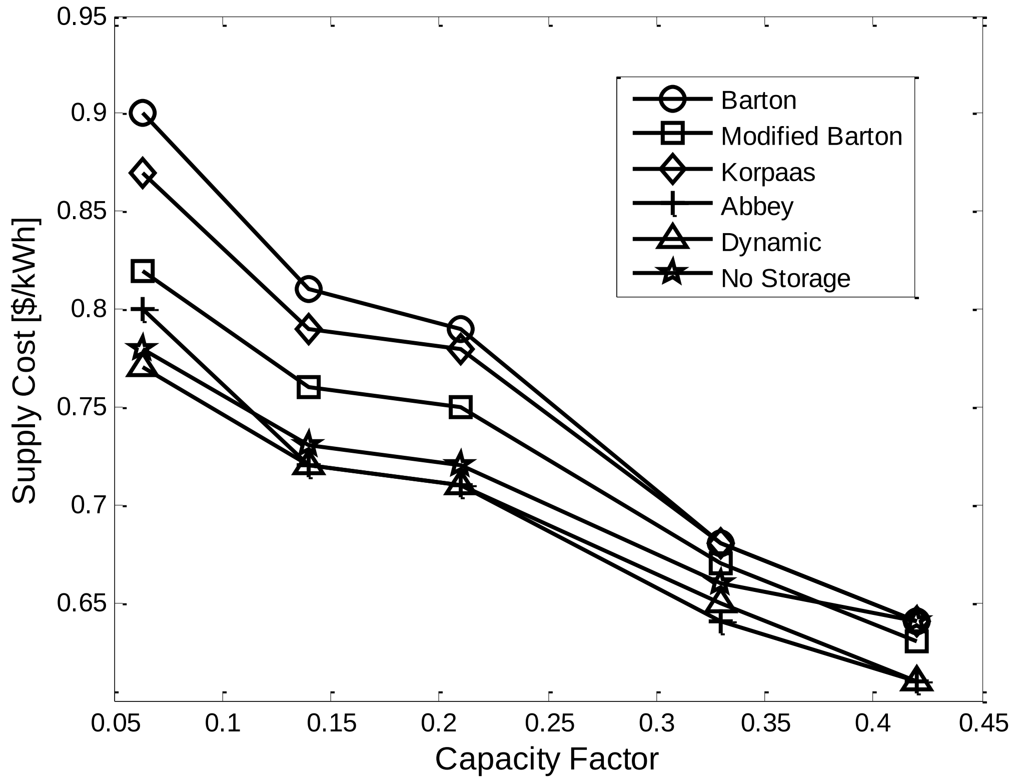

Figure 5-6: Supply cost vs. wind site. Note that the probabilistic methods cost more than the no-storage case and optimizations for most sites, but that at high capacity factor sites this increase is minimal.

It is worth noting that for high capacity factor sites the costs of the Barton, Modified Barton, and Korpaas results are very close to those of the Dynamic, Abbey, and the no storage base case results. For these high capacity factor sites the cost of supplying energy is slightly increased with the Barton, Modified Barton, and Korpaas methods, but there is also an increase in reliability, this is shown in Figure 5-7.

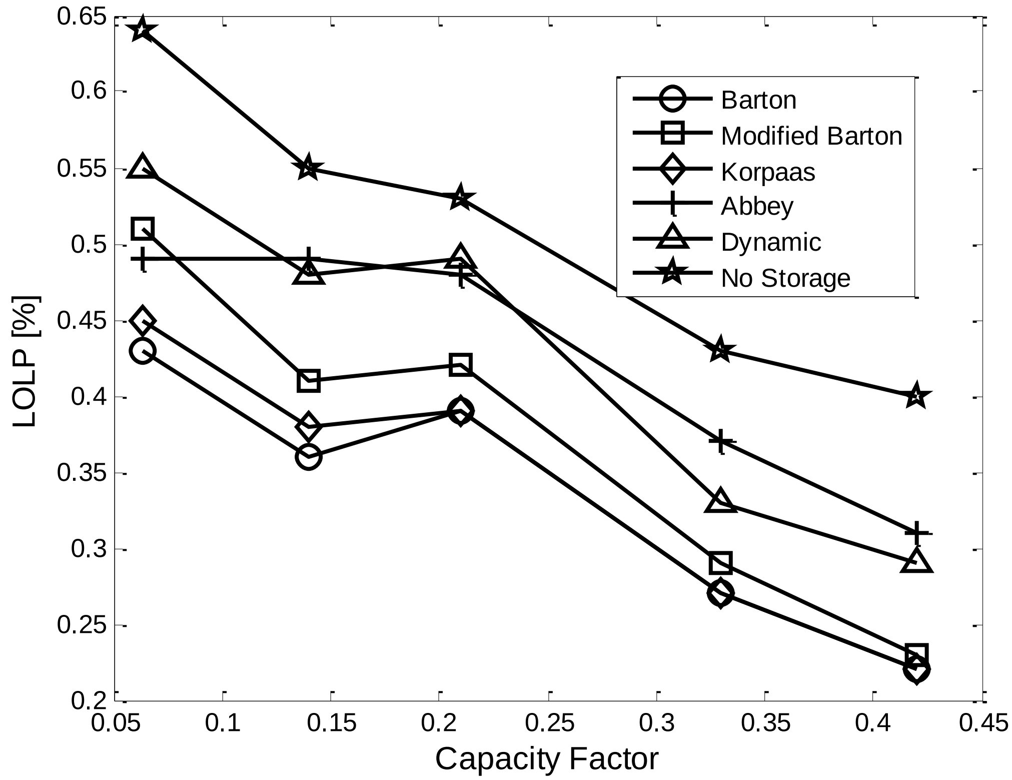

Figure 5-7: LOLP vs. capacity factor. Note the significant improvement at high capacity factors.

There is a similar effect for low capacity factor wind sites. The methods of Barton, Modified Barton, and Korpaas select larger storage devices, with improved reliability, and reduced curtailment of renewable energy. However, at the low capacity factor sites the supply costs are much greater for the results of Barton, Modified Barton, and Korpaas than for the results of the Dynamic and Abbey methods. In conclusion, the energy supply costs at high capacity factor sites were similar for large and small storage devices, however, for a slight increase in supply cost, due to a larger storage device, there is a significant increase in reliability.

5.3 Load Profiles

The results of the models' validation for sensitivity to load variance with a period of 24 hours are shown in Figure 5-8.

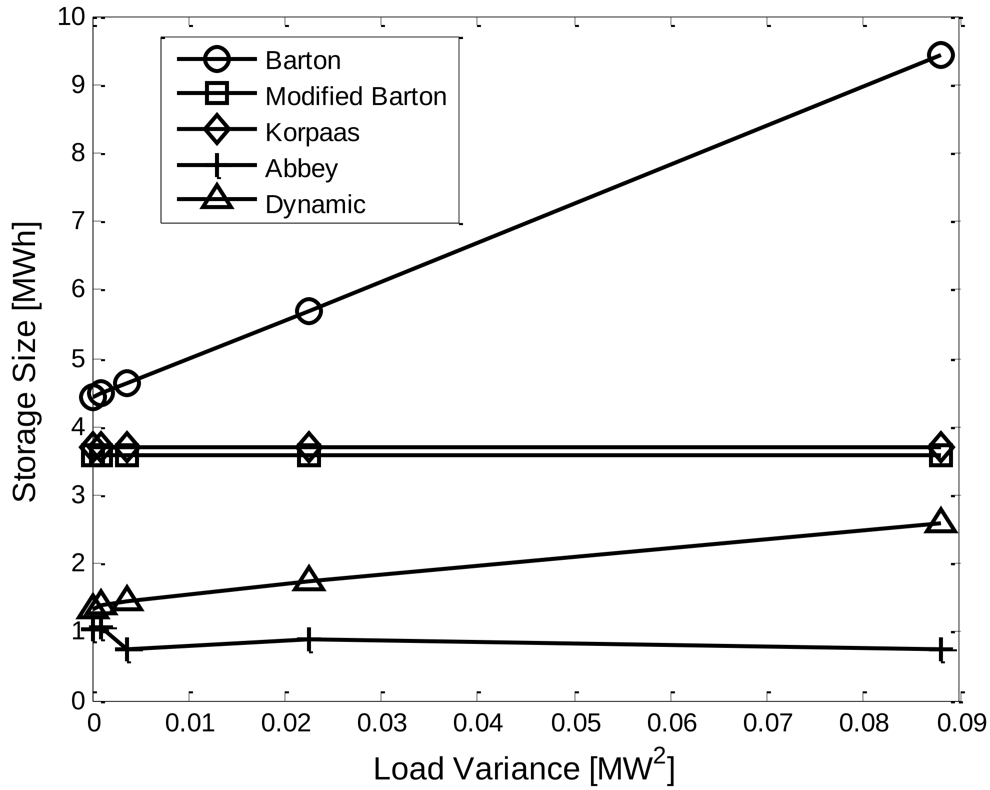

Figure 5-8: Store size vs. variance for sinusoidal loads.

The two most important results are those of Barton's method and the Dynamic method, which both show increased storage size as load variance increases, confirming their sensitivity to load variance. The result from Abbey's method is relatively constant. For the sinusoidal load profile, each 24 hour day's load profile is identical and thus Abbey's method becomes more dependent on the wind profile in each day. The Modified Barton and Korpaas methods are not sensitive to load variance and therefore produce constant store sizes.

The results for storage size under increasing load variance of the historical load profile are shown in Figure 5-9. The periodic variance in historical data has a minimal effect on storage size as Barton’s method does not significantly change as load variance is increased.

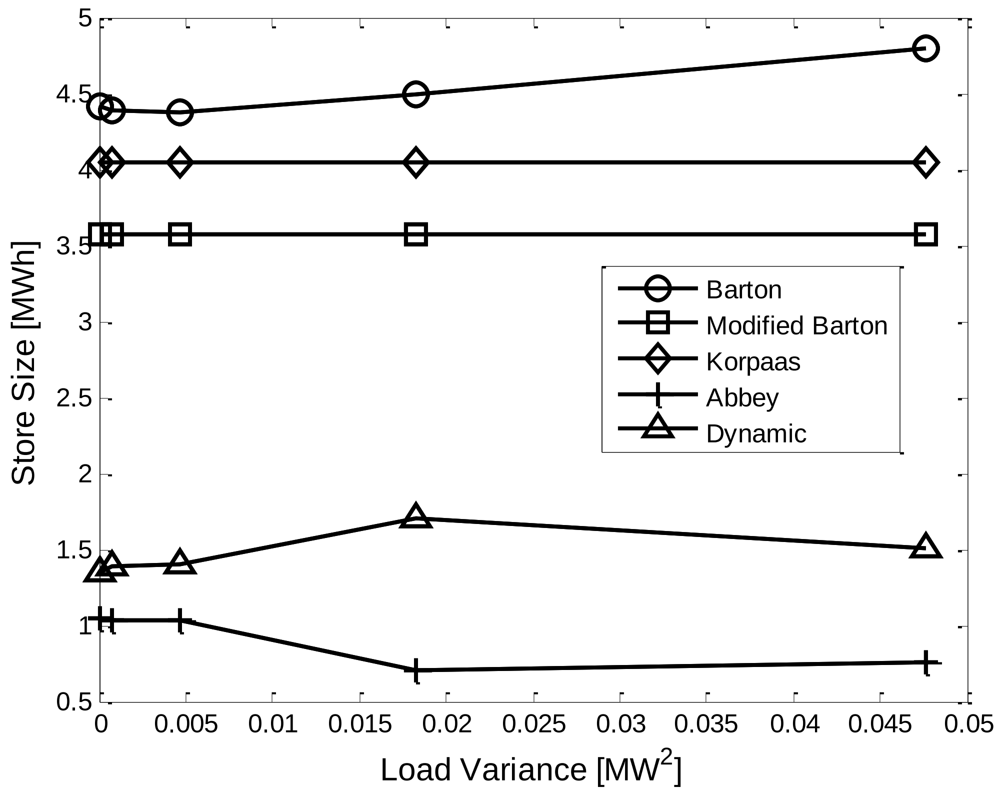

Figure 5-9: Store size vs. load variance for load profiles of Table 4-3.

All results show a slightly increased cost for low variance load, a greater increase in cost for high variance loads, and a minimum for mid variance loads. The mid variance load with minimum cost corresponds to the scaled historical data set with no shifting. While the change in supply cost is noticeable at the scale presented in Figure 5-10, the relative change is small. The explanation for slightly higher supply costs at the extremes of load profile variance is the effect of changing load on net power. At very low variance the load is nearly constant and thus net power will change with wind generation. At moderate variance levels the load power fluctuates slightly about the mean, in this instance allowing wind and load to match up positively and thus reducing net power directly, the presence of small positive correlation is confirmed in Figure 5-13. At very high load variance the net power may fluctuate rapidly if wind and load do not match up well, resulting in more periods of lost or dumped load. Results for LOLP in Figure 5-11 show there is little benefit to a large storage device under increasing load variance, the Modified Barton, Barton, and Korpaas results have a ~5-7% improvement in LOLP over the Abbey and Dynamic results despite having 2-3 times the storage.

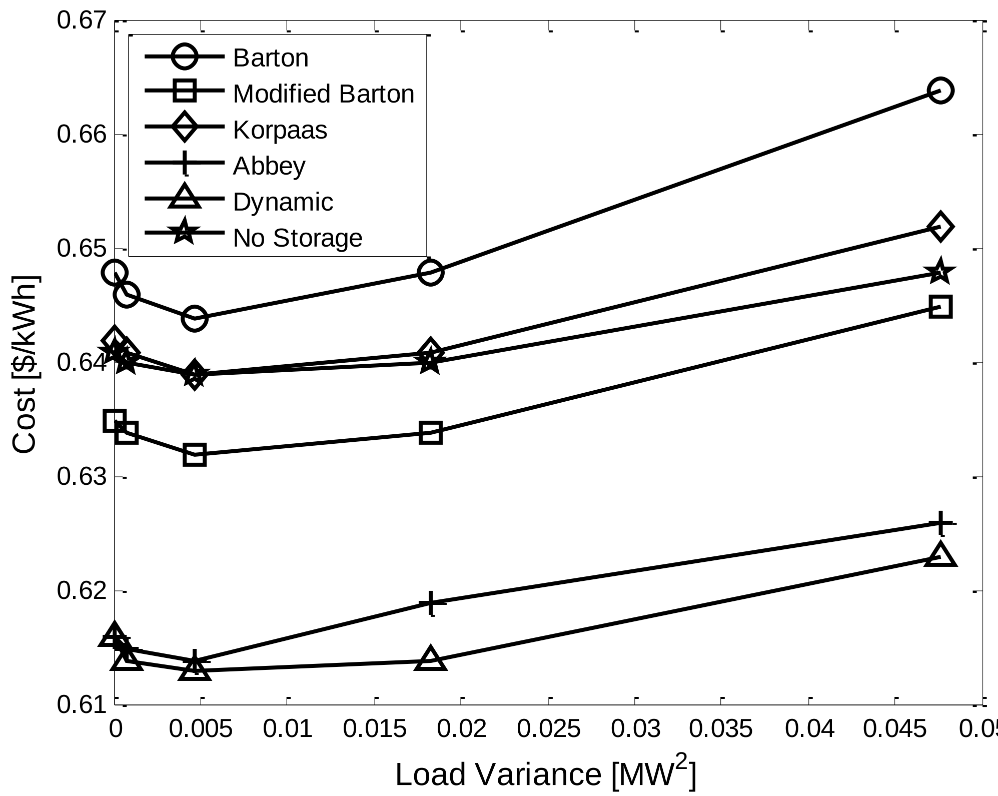

Figure 5-10: Cost vs. load variance. There is an optimal amount of variance for lowest cost of energy supply, best shown in the no storage case.

Another result of note is the effect from increasing variance on system reliability. This is shown in Figure 5-11 and Figure 5-12.

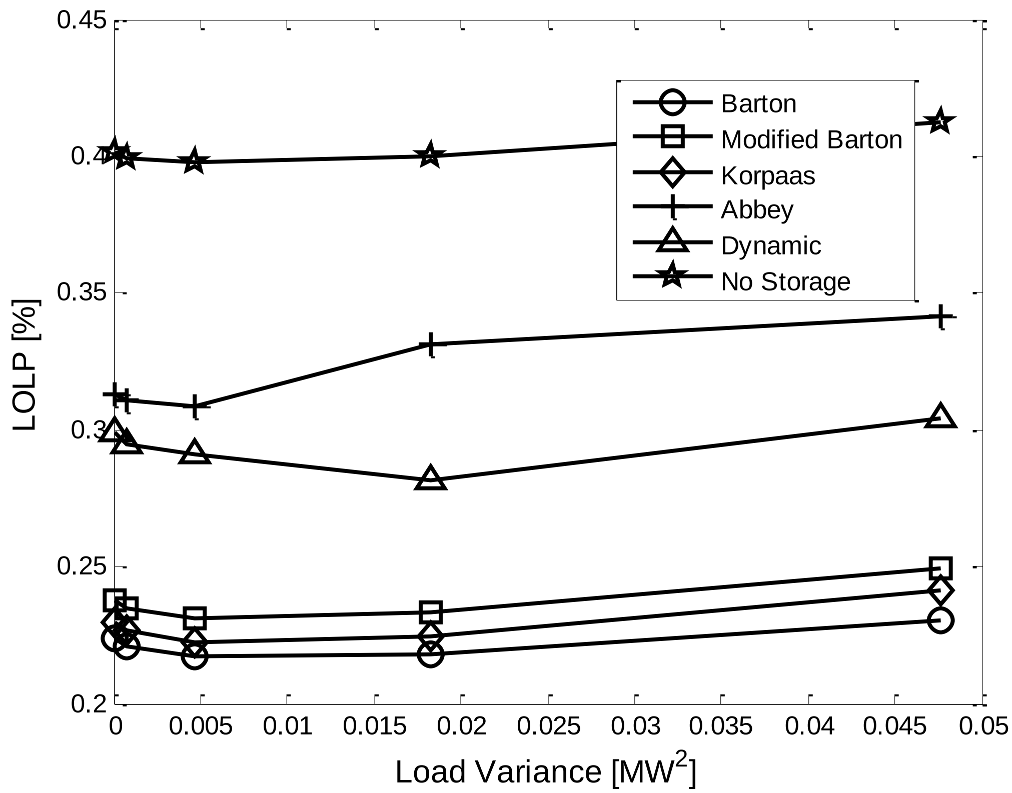

Figure 5-11: LOLP vs load variance. Note the minimal change in LOLP for all methods as variance of load increases.

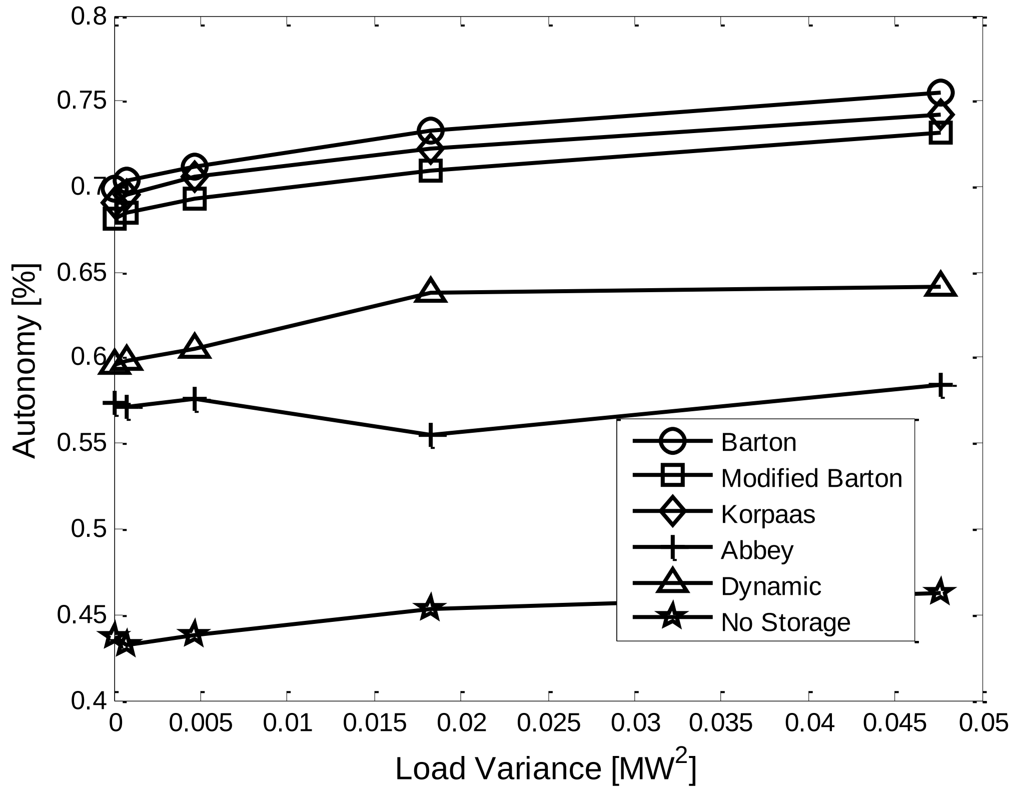

Figure 5-12: Autonomy vs. load variance. Autonomy increases with variance due to more time load is relatively small; allowing wind and storage to completely supply load.

In Figure 5-11, the LOLP increases slightly as load variance increases, this is a negative effect of load variance. In the second figure autonomy increases as load variance increases, this is a positive effect of load variance. Essentially, in high variance cases less of the total load is met, but the amount of time the load can be fully met increases. This is due to high variance profiles having more periods of low load where only a small amount of energy is needed to completely supply load. In contrast, low variance profiles spend more time at mid level or mean loads and this requires more energy to completely meet the load at each time step.

5.4 Correlation between Load and Generation

Correlation between load and generation is investigated at short term or diurnal cycles by changing lag in one hour increments, long term or seasonal cycles are investigated by changing lag in one month increments.

5.4.1 Diurnal Correlation

The diurnal correlation was investigated by shifting wind speeds by 0 to 24 hrs. The correlation between wind and load can be seen through the backup energy metric in Figure 5-13.

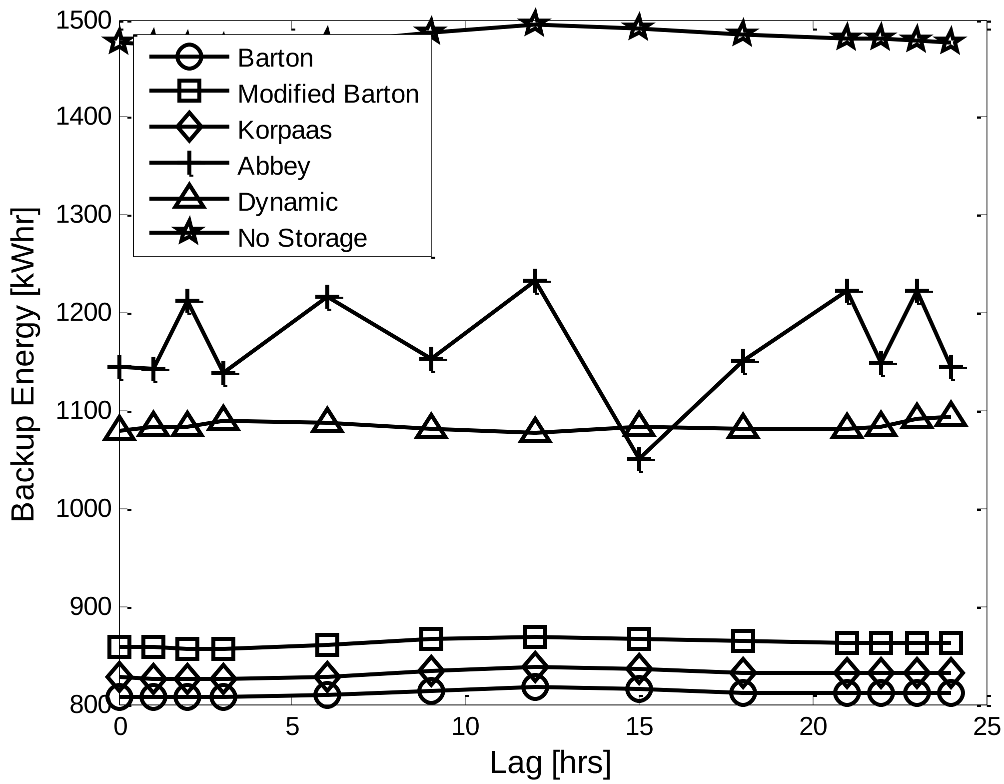

Figure 5-13: Short term correlation between wind and load. The no storage case shows there is a slight positive correlation between wind and load with maximum correlation at 3hrs.

The no storage case in Figure 5-13 shows a slight increase in backup energy as load and wind power are brought roughly 12hrs out of phase. This is shown in more detail in Figure 5-14.

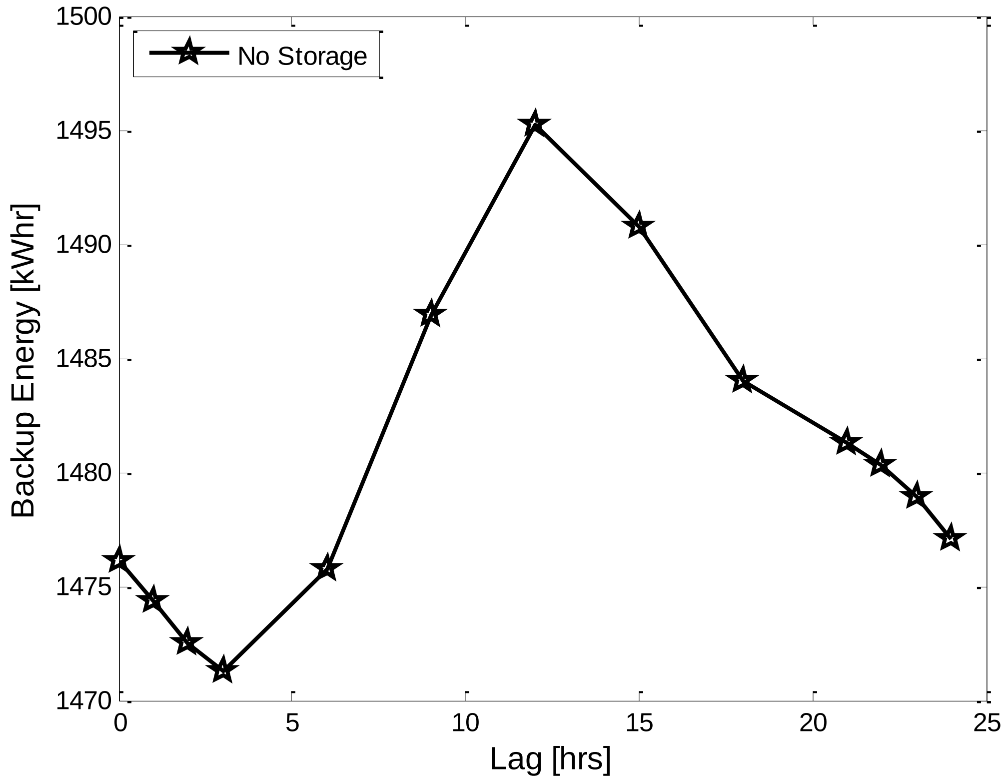

Figure 5-14: Backup energy vs. time lag for no storage case only. Note the rough cycling of the curve, with a minimum at a lag of 3hrs.

Figure 5-14 shows that in this case there are natural cycles in wind power and load, and that those cycles have a small positive correlation. However, the effect is not significant. The only significant result is Abbey's two-stage method which changes storage size erratically, shown in Figure 5-15. This highlights the sensitivity of Abbey's method to changes in data, the characteristic scenarios used in the optimization change significantly as input data changes and this affects results.

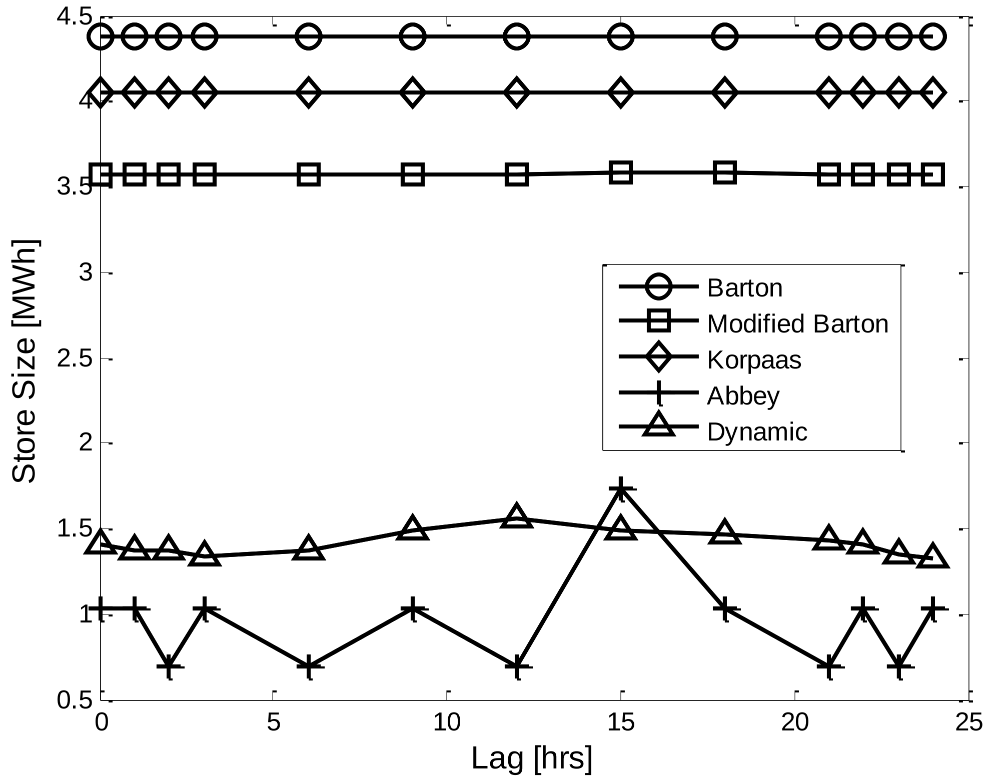

Figure 5-15: Change in store size as wind and load are shifted.

Figure 5-15 shows there is a slight decrease in the Dynamic Optimization's store size at small lags up to 3hrs; followed by increasing store size up to lag of 12hrs. The only change in the storage sizes of Barton, Korpaas, and the Modified Barton methods come from the change in the input wind data. This shows that most of these methods (excepting Abbey) are robust in that they are not overly sensitive to changes in lag. There is expected to be a larger change in probabilistic sizes when seasonal correlation is investigated.

5.4.2 Seasonal Correlation

The seasonal correlation was investigated by shifting wind data in one month (24hrs, 30days) increments. Referring to Figure 4-3, there will be new wind speed data being utilized. Figure 5-16 shows a significant seasonal correlation between the wind and load data.

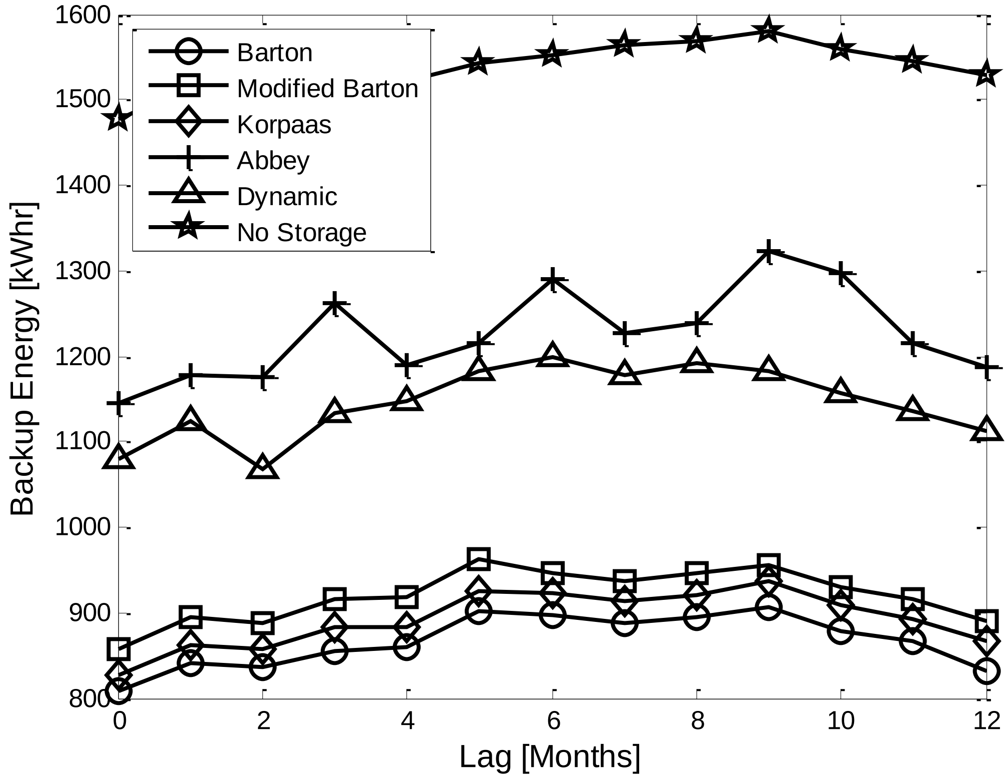

Figure 5-16: Backup energy at seasonal lags. The no storage case shows that there is a positive correlation at seasonal lags between wind and load.

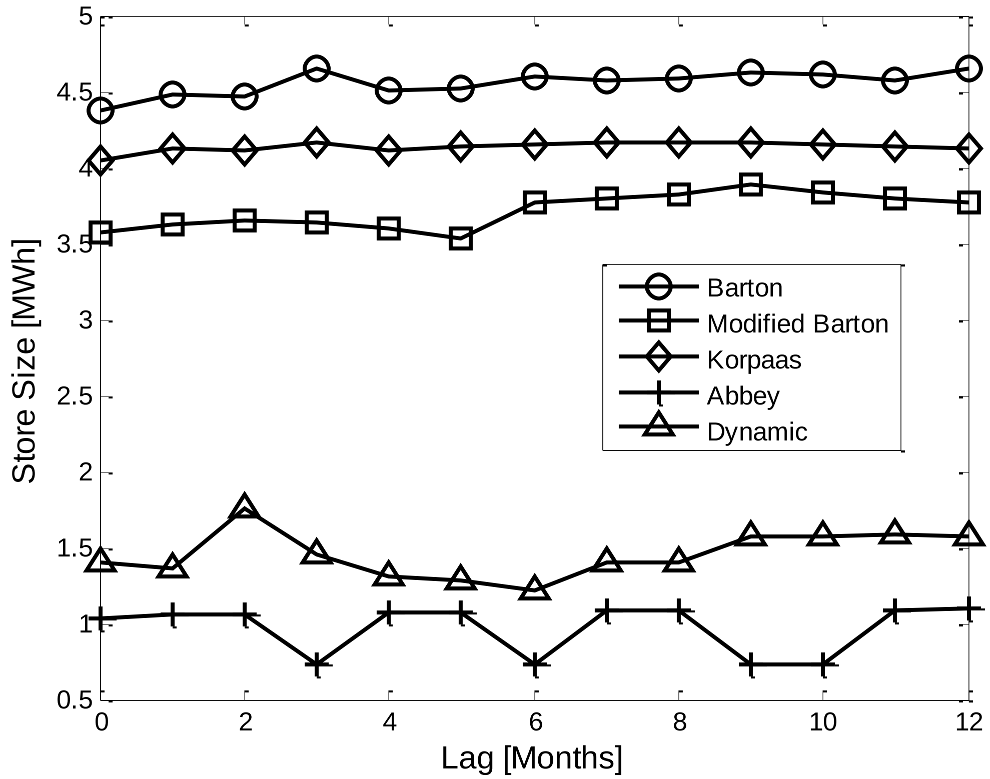

Figure 5-17 shows only slight changes in the Barton, Korpaas, and Modified Barton methods' storage sizes, which confirms that wind measurements in a specific month are similar from year to year and thus changing the window of measurement will have limited effect on results from these methods.

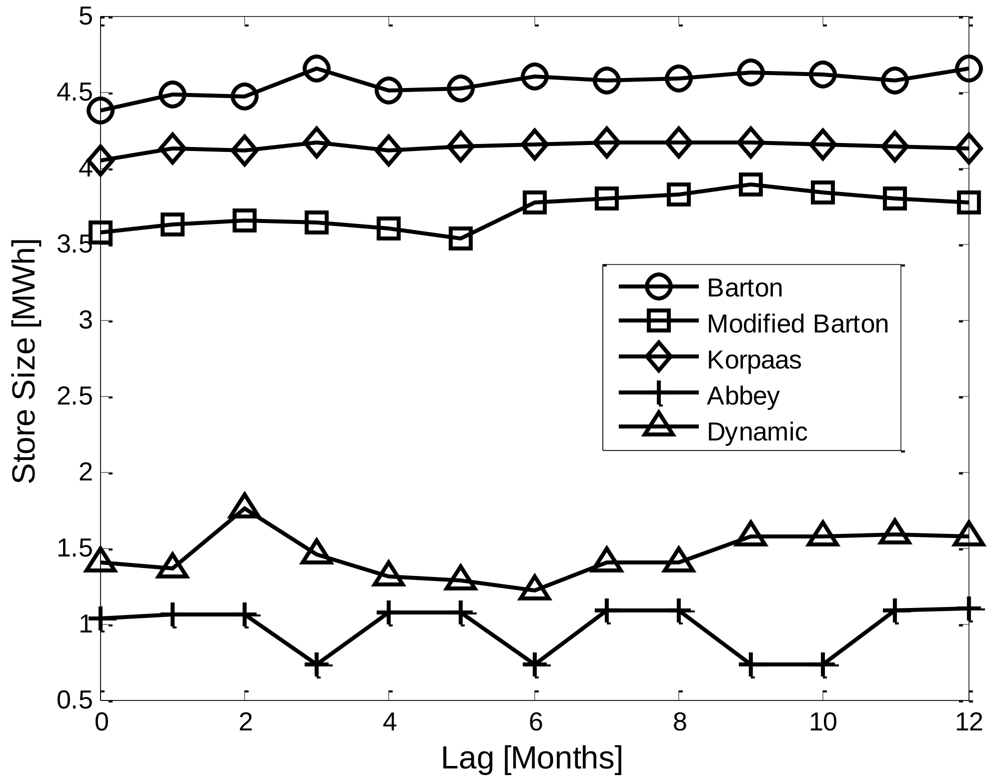

Figure 5-17: Storage size vs lag. The slight variations in probabilistic sizes are due to changes in wind data.

The results of storage size for Abbey's method, shown in Figure 5-17, are unexpected as there are relatively significant changes at approximately 3 month intervals. This method is intended to size for 24hr storage and therefore seasonal correlations are not expected to be observed in storage size, only in backup energy. In general, large seasonal correlations should be observed by either changes in backup energy (as in Figure 5-16) or a large change in storage size (not observed). The large change in storage size under seasonal lags is not observed in the Barton, Modified Barton, and Korpaas methods because the storage period is held constant at 24hrs; it is not observed in the Dynamic Optimization because the storage capital costs are prohibitively expensive; and it is not observed in Abbey’s method because it optimizes for 24hr storage.

6 Conclusion

The objective of this thesis was to develop five energy storage sizing methods, to demonstrate the sensitivity of all methods to common factors affecting energy system performance, and comment on the results from the methods. Investigation of these results has shown the Barton, Modified Barton, and Korpaas methods yield larger, more reliability-based solutions than the Dynamic Optimization and Abbey methods, which tend to yield lower cost solutions. Each method has benefits and drawbacks and, combining aspects of these methods into one simple yet efficient method may be ideal.

Table Table 6-1 summarizes the methods according to six qualitative metrics: accuracy, sensitivity, versatility, speed and cost, reproducibility, and ease of use. Accuracy refers to the appropriateness for decision making. Sensitivity lists the general inputs to which the models are sensitive. Versatility refers to the model's ability to consider different design options or system constraints. Speed and cost refers to the amount and type of data required, the time required to prepare inputs and to analyze results. Reproducibility refers to how well the models will produce a good result given slight changes in inputs. Ease of use refers to how well it can be understood and implemented by an energy systems designer, planner, or researcher.

Table 6-1: Summary of Methods

	Korpaas	Barton	Modified Barton	Two-Stage	Dynamic
Accuracy	Low: high level decision making	Moderate: can be used for planning and detailed decisions	High: improved accuracy over Barton due to removing κ, α	High: system planning and detailed decisions	High: system planning and detailed decisions
Sensitivity	Low: wind	Moderate:	Low: wind	High: wind	High: wind

	speeds, system characteristics	wind speeds, system load and characteristics	speeds and storage efficiency only	speeds, system characteristics, costs	speeds, system characteristics, costs
Versatility	Low: limited operating strategies	Low: limited operating strategies	Low: limited operating strategies	Moderate: different operating strategies, no seasonal variations	High: different operating strategies, no seasonal variations
Speed and Cost	High: quick to execute, uses readily available wind data	Moderate: requires significant wind and load data	High: requires wind data	Low: large data requirements: wind speeds, loads	Low: large data requirements: wind speeds, loads
Reproducibility	High: simple and robust method	High: if enough data is available	High: if enough data is available	Low: very sensitive to data	High: given sufficient data and computing power
Ease of Use	Moderate: simple to understand and program	Low: difficult to program	High: easy to program	Low: difficult to program	High: relatively easy to program and interpret results

The first method detailed was based on work by Barton and utilized variance filters, PDFs, and a confidence level to size energy storage. The use of filters to isolate wind speed variance at desired frequencies is effective. In this way only variance which affects storage size is considered. However, the calculations require conversion of wind speed variance to wind power variance, to adjust for storage efficiency, and to account for variable load. While the results for the output storage size show a very reliable solution, evidenced by high LOLP, the added complication of the aforementioned calculations limit this method's widespread use.

The Korpaas method utilizes PDFs of wind speed as opposed to time series data sets. This is beneficial when time series data is unavailable or when only PDFs can be obtained. The results for storage size show a reliability and cost similar to that of the Barton method. While the simplicity of execution and reduced data requirements are the strength of this method there is presently no confidence level input or other option for considering the effect of cost on storage size.

The Dynamic Optimization method relies on capital and operating costs coupled with time series data sets of load and wind power to size an energy storage device. This method uses simple constraints to simulate a real energy system and seeks out the lowest cost solution to supply energy. Therefore, the results from this solution show a low cost of energy supply when compared to the statistical methods. In some instances the supply cost is only slightly lower than the Barton and Korpaas methods' results and yet the reliability is significantly worse. Therefore, sensitivity analysis of costs should be performed when using this method. However, the size of this optimization makes sensitivity analysis difficult. Also, the deterministic nature of this type of method means solution robustness is poor.

An improvement on both computational time and solution robustness is achieved in the Abbey method. This method defines a set of characteristic scenarios based on penetration and correlation of wind power relative to load. The use of scenarios reduces the size of the optimization which improves computational time, approximately 10 minutes to a solution on a basic notebook computer. Furthermore, general scenarios should yield a more robust solution than one large data set. Where the Dynamic method optimized with certainty over one specific year of data, the Abbey method made general scenarios based on that year which are likely to apply to future years. Furthermore, while only one year of data was utilized to generate those scenarios, the Abbey method could easily utilize many more years of data, whereas the Dynamic method might suffer from computational issues due to large data sets. As the first stage selection of storage size is performed iteratively there is not a significant improvement in computational time. The results from this method are generally close to those of the Dynamic Optimization: a cost effective yet not always reliable energy system.

The Modified Barton method was developed from Barton's Method: eliminating the high and low pass filters, spreadsheeting, periodic variance, α, and κ. As a result this method is simpler to understand and execute. Rather than working in wind speeds, the method works in wind power which eliminates the calculation for κ. Other calculations are eliminated by assuming that the reduction in store size due to efficiency and the increase in store size due to variable load are both small. The resulting Modified Barton method produces results which yield smaller, yet reliable and cost effective energy storage devices. The primary weakness of this method is its requirement for time series data sets of wind power.

This thesis presents and compares five options for sizing energy storage methods, of which the Modified Barton is presented for the first time. To the knowledge of the author, these methods have not been compared before. The Modified Barton method can be said to produce similar results to the other methods because its results are within the same order of magnitude and are bounded by the other methods' results. The results section highlights the sensitivities and weaknesses of each method to common factors which affect energy storage requirements. While sensitivities and weaknesses could have been discerned from a careful analysis of the methods, only thorough execution of the methods could have revealed the relative magnitudes of energy storage size, the relative sensitivities of each method, and the relative programming complexity of each method. By comparing the various methods in detail, this thesis provides new insight for energy systems planners who have a need to understand and select appropriate energy storage sizing methods.

7 Recommendations

There are several recommendations which are supported by this work. These include when to utilize a specific type of method, on how to improve the Modified Barton method presented in this thesis, and how to combine various aspects of each method into a new method.

The factors affecting method selection are availability of data, speed and accuracy of solution, and goal of the energy system. The first factor, availability of data, may be the most limiting. If time series data sets for wind speed and load are unavailable the first choice of method would be Korpaas' PDF based method. This method can utilize more commonly available PDFs of wind speed, and has an additional benefit of requiring relatively little computational and programming time. The speed benefit also applies to the Modified Barton method which requires only a time series data set of wind power to filter for storage size. These methods can be utilized to estimate storage requirements based on available wind power. An added benefit of these methods is that they yield a system designed for reliability. However, if the goal of the energy system is lowest cost, these methods will not be sufficient as costs are not considered. Therefore, lowest cost solutions must be obtained with economic optimizations.

To achieve a low cost solution with the Modified Barton method the confidence level modifier must be further investigated. Previous work by Gassner recommended investigation of confidence level's dependence on generation and on firm power commitment. This thesis has shown that cost also influences sizing energy storage. Therefore, the confidence level should also be linked to the capital costs of energy storage relative to the operating costs of energy sources. This would improve the usefulness of the Modified Barton method by making it both simple to execute and cost efficient.

An alternative use of the statistics-based methods is to combine them with details of the Dynamic Optimization into a new method. The Modified Barton and Korpaas methods are fast to program and execute and under most circumstances yield larger storage sizes relative to the Dynamic Optimization and Abbey methods. Therefore, the results from these methods may be used to create a bound or range of possible storage sizes considered by the Dynamic and Abbey methods, causing them to execute faster. Next, the scenario's generated for the Abbey method can be utilized in a dynamic optimization model. These scenarios can be weighted and combined into one data set. This data set would be smaller than the whole data set and therefore complexities neglected in the Dynamic Optimization could be included. For instance, resolution could be increased and ramping rate constraints considered. The resulting method would be a high resolution scenario based dynamic optimization with a statistical method providing a pre-calculation for storage size.

This thesis recommends when to utilize each type of method, additional work to improve the Modified Barton method, and that a combined method to size storage should be utilized. The Modified Barton and Korpaas methods are quickly executed and can size storage with less data than a dynamic optimization method. To improve the cost efficiency of its solution it is recommended the Modified Barton method's confidence level be tied to energy system costs. Finally, when sizing storage a combined optimization method incorporating statistics and scenarios may be utilized. These recommendations may increase the utilization of statistical methods like the Barton, Korpaas, and Modified Barton method and improve the results of optimizations.

8 References

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Appendix A. Periodogram and Filtering

This appendix presents the derivation of the periodogram by first outlining the autocovariance function, the requirement of a stationary time series, and the Fourier transform. This background is followed by a description of the filter functions, the probability density functions, and the coefficient of variation.

A.1 Autocovariance Function

An analysis of a time series' variance is often completed with the autocovariance function, $\gamma_x(s,t)$. This function is a useful way to observe the amount of fluctuation (variance) about the mean at various time lags. It is given below:

$$\gamma_x(s,t) = E[(x_s - \mu_s)(x_t - \mu_t)] \tag{A.1}$$

Where $E[]$ is the expected value operator, x indicates a data series with x_s and x_t values in that data set at times s and t, finally μ_s and μ_t are the means of the time series near s and t respectively. For the special case $s=t$ this equation reduces to the variance of the time series [29]. The time series sample of wind speed is assumed to have a constant mean and a covariance that depends only on the absolute difference between s and t. Therefore the autocovariance reduces to:

$$\gamma_x(h) = E[(x_{t+h} - \mu)(x_t - \mu)] = E[(x_h - \mu)(x_0 - \mu)] \tag{A.2}$$

Where:

$$s = t + h \tag{A.3}$$

And

$$\mu_s = \mu_t = \mu \tag{A.4}$$

In the above equations h is termed the lag or the time difference between samples x_s and x_t, and μ is the mean of the time series. The autocovariance function is a useful tool for observing variance in a time series as a function of lag. However, we need to transfer this function into the frequency domain.

A.2 Stationary Requirement

The wind speed time series is assumed to have a constant mean and covariance independent of time. This assumption allows the time series to be classified as 'weakly stationary'. A non-stationary time series would have either a mean which changes in time or a covariance which is a function of time. Stationarity is required for the auto covariance function to be dependent on *h* alone.

A.3 Fast (Discrete) Fourier Transform

The time series is assumed to be of the form:

$$x_t = \sum_{n=0}^{N} a_n \cos(2\pi\omega_n t) + b_n \sin(2\pi\omega_n t) \tag{A.5}$$

This is the Fourier representation of the time series. This allows the discrete Fourier transform to be applied to the data x_t of length n as follows:

$$d(\omega_j) = n^{-1/2} \sum_{t=1}^{n} x_t e^{-2\pi i \omega_j t} \tag{A.6}$$

And a periodogram is as follows:

$$I(\omega_j) = \left|d(\omega_j)\right|^2 = \sum_{h=-(n-1)}^{n-1} \gamma(h) e^{-2\pi i \omega_j h} \qquad (j \neq 0) \tag{A.7}$$

The periodogram is the discrete version of the spectral density function which shows variance as a function of frequency. As sample size n increases to infinity, the periodogram approaches the spectral density function. It is also worth noting that the total variance of the time series, σ^2 can be calculated from the periodogram by:

$$\sigma^2 = \sum_{t=1}^{n}(x_t - \bar{x})^2 = 2\sum_{j=1}^{m} I(\omega_j) \tag{A.8}$$

where *m* is *(n-1)/2* for odd *n* and *m* is *(n/2)-1* for even *n*.

A.4 Filtering Functions

This section lists the three filter functions derived by Barton [21]. The high pass filter isolates short term variance of wind speeds. Where A_i is amplitude of variance at frequency ω_i, τ is the storage period, and i is the discrete index in the periodogram.

$$\sigma^2_{HighPass} = \frac{A_i^2}{2} - \left(\frac{A_i}{\omega_i \tau}\right)^2 (1 - cos\omega_i \tau) \tag{A.9}$$

Similarly, the low pass filter isolates long term variance for the construction of the period average PDF.

$$\sigma^2_{LowPass} = \left(\frac{A_i}{\omega_i \tau}\right)^2 (1 - cos\omega_i \tau) \tag{A.10}$$

Finally, the state of charge filter isolates variance which will affect the storage size.

$$\sigma^2_{\Delta \mathrm{E}_\tau} = \left(\frac{A_i}{\omega_i}\right)^2 \left(\frac{5}{6} + \frac{1}{6} cos\omega_i \tau + \frac{2}{(\omega_i \tau)^2} (\cos \omega_i \tau - 1)\right) \tag{A.11}$$

A.5 Probability Density Functions

Barton’s probabilistic method requires the construction of probability density functions: a long term wind speed PDF, and short term wind speed PDFs. Note that there are multiple short term PDFs. Essentially, these functions are required to answer two questions. First, what is the probability of a given average wind speed over the length of the storage period? This is referred to as the period average or mean wind speed and the PDF is a function of the low frequency variance and the overall mean wind speed. It allows one to observe the range of long term average wind speeds. The PDF is given as a normal distribution defined as:

$$f(x;\mu,\sigma) = \frac{1}{\sqrt{2\pi}\sigma} e^{-(x-\mu)^2/(2\sigma^2)} \quad \text{(A.12)}$$

Or a Weibull distribution as:

$$f(x;\alpha,\beta) = \begin{cases} \frac{\alpha}{\beta} x^{\alpha-1} e^{-\left(\frac{x}{\beta}\right)^{\alpha}} & for\ x \geq 0 \\ 0 \quad for\ x < 0 \end{cases} \quad \text{(A.13)}$$

Where α and β are shape and scale factors and are functions of the mean and variance. At shape factors greater than three Barton uses a normal distribution to approximate the PDF. The normal and Weibull distributions are similar at shape factors between three and four.

The second question is: for a given period mean wind speed what is the likely distribution of wind speeds within that period? This is referred to as the within period wind speed and the PDF is a function of the high frequency variance and the given mean wind speed. Therefore there is a separate PDF of within period wind speeds for each mean wind speed. These PDFs allow one to observe the range of short term average wind speeds. The within period PDFs are constructed in the same way as the mean wind speed PDFs with one change. As the mean wind speed for each within period PDF is different, the short term variance (which is a function of the overall mean) must also change. Assuming that variance is linearly proportional to mean wind speed, the coefficient of variation can be computed:

$$S = \sigma_{LowPass}/\bar{x} \quad \text{(A.14)}$$

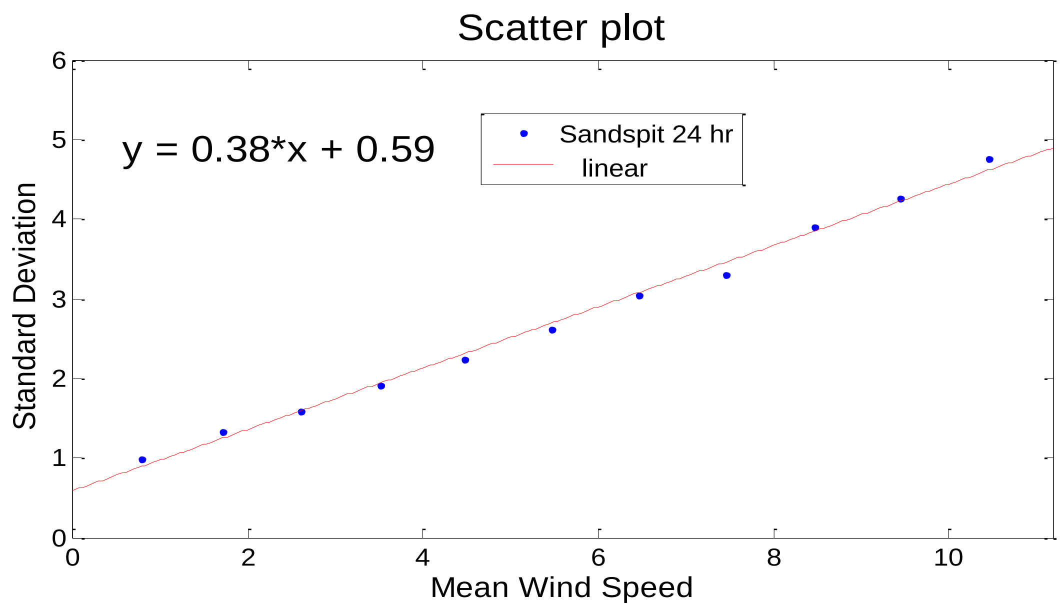
The coefficient of variance is discussed further below. Equation A.14 allows variance at different sampled wind speeds to be estimated. The variance at each sampled wind speed is then:

$$\sigma_{Sample} = S\bar{x}_{Sample} \tag{A.15}$$

This variance is then used to construct a PDF around the sampled wind speed. The end result of the PDF construction stage in the probabilistic method is one PDF describing the long term average wind speed and one PDF describing the probability of the short term wind speed for each possible period average wind speed. These PDFs are used to calculate the expected values of system performance.

A.6 Coefficient of Variance

The coefficient of variation assumes that wind speeds vary linearly with mean wind speed. A brief examination of this assumption was tested with hourly data from Sandspit, BC. This analysis revealed a strong linear relation for low daily average wind speed (0-11m/s). At higher wind speeds the result was not as strong. However, the definition of CV in Barton's method would require a CV to approach 0 as daily average approaches 0m/s mean wind speed (because a 0m/s average wind speed must have no variance because measured wind speeds must be positive). Where in reality there is some variance at daily averages close to zero. The CV could be modified to accept a constant or 'y-intercept' term. In the plot below, CV could be calculated from the line of best fit.


Scatter plot
y = 0.38*x + 0.59
Sandspit 24 hr
linear
Standard Deviation
Mean Wind Speed
0
1
2
3
4
5
6
0
2
4
6
8
10

Appendix B. Time Series Testing Function

In order to compare results a testing function was developed. This testing function takes in the same data sets and store efficiencies as the sizing methods. It also takes in the storage size result from one of the methods. The function then acts as an energy system controller; it balances load using the available wind power, available storage device charge or discharge capability, a dump or curtailed load, and a backup or unmet load option, shown in Figure 1-3. At each time step, *t*, the following calculations are carried out. First, a net power is calculated from the load and the available renewable power. As the time series data are hourly averages, powers and energies can be used interchangeably.

$$P_{Net,t} = P_{Load,t} - P_{Wind,t} \tag{B.1}$$

The load and wind power come from the time series data sets. A positive net power is a time of surplus energy. Therefore, excess energy is sent to the storage device according to the equation below.

$$E_{Store,t+1} = \begin{cases} E_{Store,t} + \eta_{RT} P_{Net,t} dt, & E_{Store,t} + \eta_{RT} P_{Net,t} dt < E_{Store,Limit} \\ E_{Store,Limit}, & E_{Store,t} + \eta_{RT} P_{Net,t} dt \geq E_{Store,Limit} \end{cases} \tag{B.2}$$

In this equation, $E_{Store,Limit}$ is the storage size from sizing method and η_{RT} is the round trip storage efficiency. In the case that the input exceeds the available size energy is dumped according to the following equation.

$$P_{Curt,t} dt = P_{Net,t} dt - \left(E_{Store,Limit} - E_{Store,t}\right)/\eta_{RT} \tag{B.3}$$

Similarly, in times of negative net power energy is drawn from the storage device. The storage device equations for a discharging state are:

$$E_{Store,t+1} = \begin{cases} E_{Store,t} - P_{Net,t}dt, & E_{Store,t} - P_{Net,t}dt > 0 \\ 0, & E_{Store,t} - P_{Net,t}dt \leq 0 \end{cases} \qquad \text{(B.4)}$$

If the storage device is unable to meet the negative net power, the difference is calculated as the unmet or backup power.

$$P_{Backup,t}dt = E_{Store,t} + P_{Net,t}dt \qquad \text{(B.5)}$$

In the above equation $P_{Net,t}dt$ is negative and of greater magnitude than $E_{Store,t}$ thus $P_{Backup,t}dt$ is negative. At this stage the power at time *t* has been balanced through charging, curtailing, discharging, and dumping energy. These calculations are performed at each time step of the time series data sets. A partial flowchart is shown in Figure 8-1.

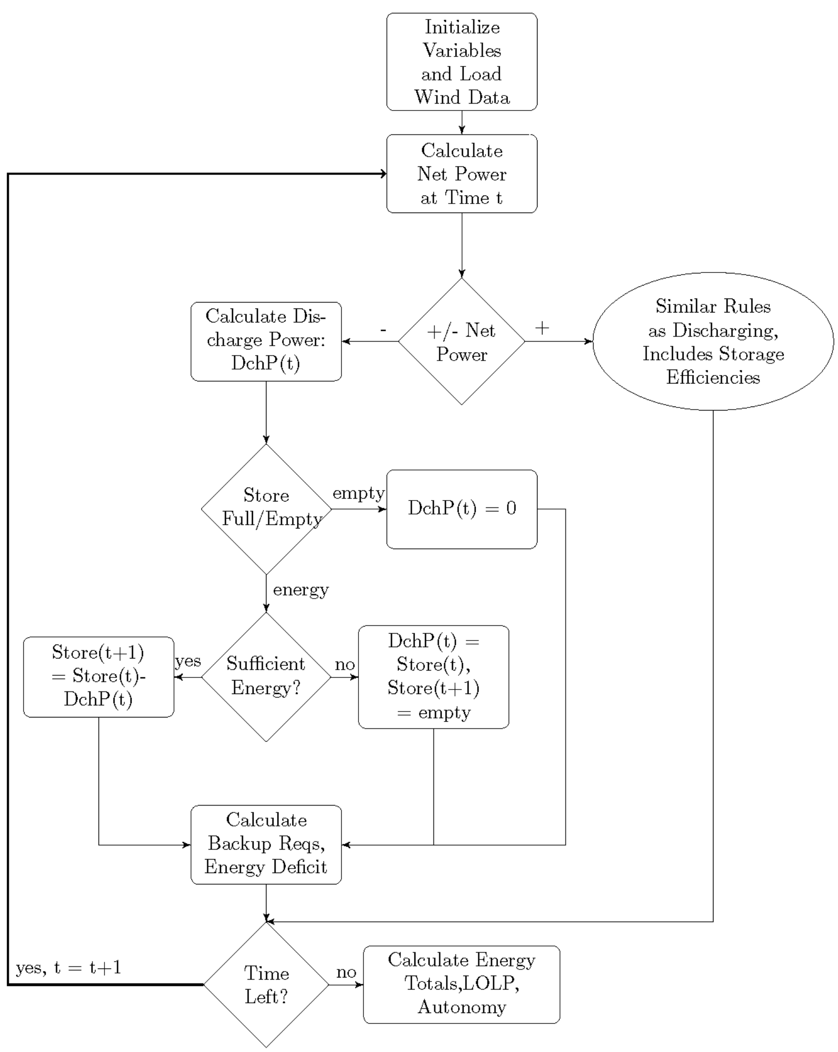


Figure 8-1: Partial flowchart of time series testing function. The case of positive net power is neglected for simplicity.

The time series function then calculates a total operation cost by summing the amount of renewable power generated and unmet power.

$$C_{Operating} = \sum_{t} C_{Lost} P_{Lost,t} dt + C_{Wind} P_{Wind,t} dt \tag{B.6}$$

A total yearly cost is calculated from the operating and capital costs in the equation below, where $A_{20,IR}$ refers to a 20 year investment annual cost with interest rate, IR.

$$C_{Total} = C_{Operating} + A_{20,IR}\left(C_{Power} P_{Installed} + C_{Energy} E_{Store,Limit}\right) \tag{B.7}$$

Therefore, output results from the testing function include an overall cost consisting of capital plus operating costs, system reliability in the metrics of autonomy and loss of load probability. In addition, energy flows are tracked and include renewable energy curtailed and load energy backup. The reliability metric Loss of Load Probability or LOLP is the total unmet or backup load, given by P_{Backup}, divided by the total required load.

$$LOLP = \frac{\sum P_{Backup}}{\sum P_{load}} \tag{B.8}$$

The other reliability metric, autonomy, is similar to LOLP except it tracks the amount of time the load is not completely met. A similar version is defined by Ekren [30] but is modified for use here and is given below.

$$Autonomy = 1 - \frac{\sum T_{Backup}}{T_{Total}} \tag{B.9}$$

These two reliability metrics indicate the overall reliability of the system.

Appendix C. Tabled Results

C.1 Wind Site Results

Table 8-1: Wind site A results. Results generated from load option 1and input data from Table 4-1.

Site A, Load: 3717kWh Method	Store Energy [kWh]	Curtailed Energy[kWh]	LOLP	Cost per kWh
Barton	4.38	689	0.22	0.64
Modified Barton	3.58	748	0.23	0.63
Korpaas	4.05	712	0.22	0.64
Abbey	1.04	1083	0.31	0.61
Dynamic	1.40	1007	0.29	0.61
No Storage	0.00	1476	0.40	0.64

Table 8-2: Wind site B results. Results generated from load option 1and input data from Table 4-1.

Site B, Load: 1254 kWh Method	Store Energy[kWh]	Curtailed Energy[kWh]	LOLP	Cost per kWh
Barton	2.44	416	0.36	0.81
Modified Barton	1.29	489	0.41	0.76
Korpaas	1.87	445	0.38	0.79
Abbey	0.38	594	0.49	0.72
Dynamic	0.44	585	0.48	0.72
No Storage	0.00	695	0.55	0.73

Table 8-3: Wind site C results. Results generated from load option 1and input data from Table 4-1.

Site C, Load: 553 kWh Method	Store Energy[kWh]	Curtailed Energy[kWh]	LOLP	Cost per kWh
Barton	1.19	221	0.43	0.90
Modified Barton	0.42	271	0.51	0.82
Korpaas	0.94	233	0.45	0.87
Abbey	0.56	259	0.49	0.80
Dynamic	0.21	296	0.55	0.77
No Storage	0.00	352	0.64	0.78

Table 8-4: Wind site D results. Results generated from load option 1and input data from Table 4-1.

Site D, Load: 2862 kWh Method	Store Energy[kWh]	Curtailed Energy[kWh]	LOLP	Cost per kWh
Barton	3.59	683	0.27	0.68
Modified Barton	2.74	748	0.29	0.67
Korpaas	3.27	706	0.27	0.68
Abbey	0.57	1038	0.37	0.64
Dynamic	1.30	902	0.33	0.65
No Storage	0.00	1237	0.43	0.66

Table 8-5: Wind site E results. Results generated from load option 1and input data from Table 4-1.

Site E, Load: 1810 kWh Method	Store Energy[kWh]	Curtailed Energy[kWh]	LOLP	Cost per kWh
Barton	2.85	653	0.39	0.79
Modified Barton	1.72	721	0.42	0.75
Korpaas	2.54	668	0.39	0.78
Abbey	0.45	850	0.48	0.71
Dynamic	0.29	877	0.49	0.71
No Storage	0.00	967	0.53	0.72

C.2 Tabled Results for Effect of Interest Rate

Table 8-6: Storage size under various interest rates. Results generated from load option 1, wind site D, and input data from Table 4-1.

Method	No Interest [kWh]	5% [kWh]	8.50% [kWh]
Barton	3.59	3.59	3.59
Modified Barton	2.74	2.74	2.74
Korpas	3.27	3.27	3.27
Abbey	1.70	0.85	0.57
Dynamic	2.94	1.77	1.30
Base Case	0.00	0.00	0.00

Table 8-7: Overall Costs under various interest rates. Results generated from load option 1, wind site D, and input data from Table 4-1.

Method	No Interest [$/kWh]	5% [$/kWh]	8.50% [$/kWh]
Barton	0.62	0.65	0.68
Modified Barton	0.62	0.64	0.67

Korpas	0.62	0.65	0.68
Abbey	0.62	0.64	0.64
Dynamic	0.62	0.64	0.65
Base Case	0.66	0.66	0.66

Appendix D. Comments on Wind Speed Data

The quality and quantity of data in wind speed data sets affects results. The available data sets give hourly averages for many years; allowing many effects to be considered in the models. However, there are also some effects which cannot be considered as a result of these data sets.

Wind speed effects considered in this research are daily variance, seasonal variance, and mean wind speed. The daily variance can be captured in data sets which span multiple days at relatively low resolutions (hourly). Furthermore, as the length of these data sets spans several years any yearly or seasonal trends present can be captured as well. Finally, the length of sets also allows for long term averages to be taken for mean wind speeds. These long term data sets can be converted to a power and the sites can be classified by their average generation or their capacity factor. Sites with low variance and high capacity factor are preferable because this research has shown they supply energy at a lower cost.

Wind speed effects ignored in this research are gusting or short term variance, and direction changes. The large number of hourly average data previously mentioned is useful for determining capacity factors or average generation. However, hourly averages are at an insufficient resolution to consider power quality effects. In a high resolution model of wind generation there will be power fluctuations which may affect quality of supply. Additional fluctuations in power may come from rapid changes in wind direction, both horizontal and vertical [31],[32]. Under these circumstances a small meteorological tower may react to the change in direction and give a seamless reading for wind speed. However, a large wind turbine may take time to adapt to this change in direction and as a result the generated power may not be proportional to the wind speed recorded by a meteorological tower. Furthermore, aggregation effects like shadowing and turbine hysteresis may also affect the conversion from average wind speed to average wind power [33]. This research assumes that the average measured wind speed over one hour is equivalent to the wind speed facing the turbine and that it gives an accurate measure of the wind speed available for power generation.

An improvement to this research would be to use either high resolution wind speed data which includes wind speed direction or to use measured wind power. High resolution data with directions could be converted to a more accurate wind power and then averaged. Similarly, if generation data existed for a given site it would be preferable to measured wind speeds.