Optimization of the NAS Battery Control System

Background

PG&E has purchased a 4MW, 28MWh sodium-sulfur (NAS) battery to be installed October, 2010 in San Jose at Hitachi headquarters. The site was chosen because it presents a unique opportunity to test the performance of the battery under several potential applications. PG&E will be working with EPRI and the CEC to study the effect of the battery on the performance of the local electric system as well as the feasibility of using battery storage technology to perform market functions.

Purpose

The purpose of this paper is to present a mathematical model used to optimize the controls of the NAS battery to achieve maximum return on investment.

Evolutionary Programming

To optimize the charging and discharging cycles of the NAS battery an evolutionary programming approach will be employed. The algorithm starts by initializing a population of potential solutions. Each individual is described by a solution vector containing values for all of the variables. Next the objective function is evaluated for all of the solution vectors to determine each individual's fitness. If a solution vector violates a constraint it is assigned a penalty and will likely die off as a result. The fittest individuals are chosen to survive and carried on into the next generation. They are also used to spawn new solution vectors, which is accomplished by introducing random mutations. After a sufficient number of generations the process of selection should lead to a near optimal solution.

Objective Function

The objective function being optimized is composed of the benefits that can be accrued by:

1. Improving power quality.
2. Improving reliability.
3. Performing energy price arbitrage.

All of these functions are considered to be performed simultaneously and their combined effects are not to exceed the capability of the battery. In addition to the constraints imposed by the battery, the controls will be set so that there is minimal risk of violating market agreements. In the future the battery may also be used for the following functions:

1. Providing reserves.
2. Providing regulation.

3. Providing capacity for resource adequacy.
4. Providing black start capability.
5. Providing demand response.

Constraints - Battery Limitations

The battery has a +/-4MW long term rating and +/-4.8MW short term rating. At full charge the battery holds 28MWh of energy. The maximum depth of discharge (DOD) of the battery is approximately 90%. Ramping capability is more than adequate to perform any of the desired functions. The battery is subject to thermal limitations. Unfortunately, the thermal characteristics of the battery are proprietary information of NGK and were not available for use in this study. The proposed battery schedule will be sent to NGK for evaluation. NGK will determine whether or not the battery can implement the proposed functions without exceeding thermal limitations. Because an adequate thermal model is not available the optimization will limit the maximum charging or discharging power of the battery to the continuous rating, i.e.

$$-4 \text{ MW} \leq P \leq 4 \text{ MW}$$

The battery's energy constraints are

$$2.8 \text{ MWh} \leq E \leq 28 \text{ MWh}$$

Where the minimum energy requirement, E_{min}, is computed as

$$\begin{aligned} E_{min} &= (100-DOD_{max})/100*E_{max} \\ &= (100-90)/100*28 \\ &= 2.8 \text{ MWh} \end{aligned}$$

Power Quality

The cost of power quality is

$$R_{PQ} = \$/\text{kW/event}$$

Additionally, the frequency of power quality events for Hitachi is

$$f_{PQ} = \text{events/yr}$$

The total cost of power quality can be defined as

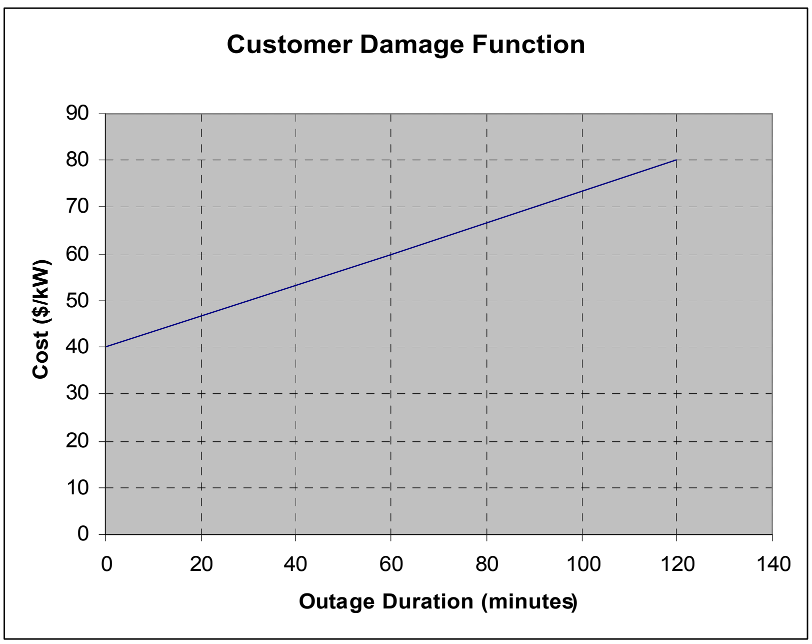
$$C_{PQ}=R_{PQ}*f_{PQ}*L_{ave}*T_{study} \qquad \$$$

Where L_{ave} is the customer's average load in kW and T_{study} is the length of the study period in years.

The installation of the NAS battery will eliminate all of the power quality events experienced at Hitachi. Therefore, the benefit provided by the NAS battery is a constant value equal to C_{PQ}. Since the cost of power quality is a constant, excluding it from the formulation of the objective function will have no effect on the optimization of the battery controls. However, the benefit of improved power quality will be included to gain insights into its importance and to determine the total earning power of the battery storage system.

Reliability

Reliability can be quantified by using value of service methodology. Value of service is quantified as a monetary amount a customer loses as a result of a service interruption via a customer damage function (CDF). A typical CDF is shown below.



The intercept of the CDF represents a fixed cost incurred as the result of any interruption and the slope of the CDF illustrates how the outage cost increases with duration. Momentary interruptions also contribute to total outage cost and in the case of sensitive industrial loads such as Hitachi can potentially cause more damage than sustained interruptions.

The cost of a sustained outage is defined as

R_{sus} = $/kW/event

The rate at which outage cost increases with duration is

R_{dur} = $/kWh

The cost of a momentary outage is

R_{mom} = $/kW/event

The total annual reliability benefit relative to the status quo cost, C_{SQ}, can be defined as

$$C_{REL} = C_{SQ} - (f_{sus}*R_{sus} + f_{sus}*MTTR*R_{dur} + f_{mom}*R_{mom}) \quad \$$$

Where f_{sus} is the frequency of sustained outages, f_{mom} is the frequency of momentary outages and MTTR is the mean time to repair.

The benefit of the battery can be viewed as the reduction in outage cost it provides. The battery will island the load at Hitachi immediately following a loss of service and will continue to serve the Hitachi load until its energy reserves are depleted. This will result in the complete elimination of momentary interruptions and a significant reduction in both the frequency and duration of sustained outages.

To capture the reliability benefit a Monte Carlo simulation of Hitachi's load point reliability will be performed. The Monte Carlo method uses a pseudorandom number generator to generate numbers uniformly between zero and one. A simple random number generator uses Lehmer's recursion, i.e.

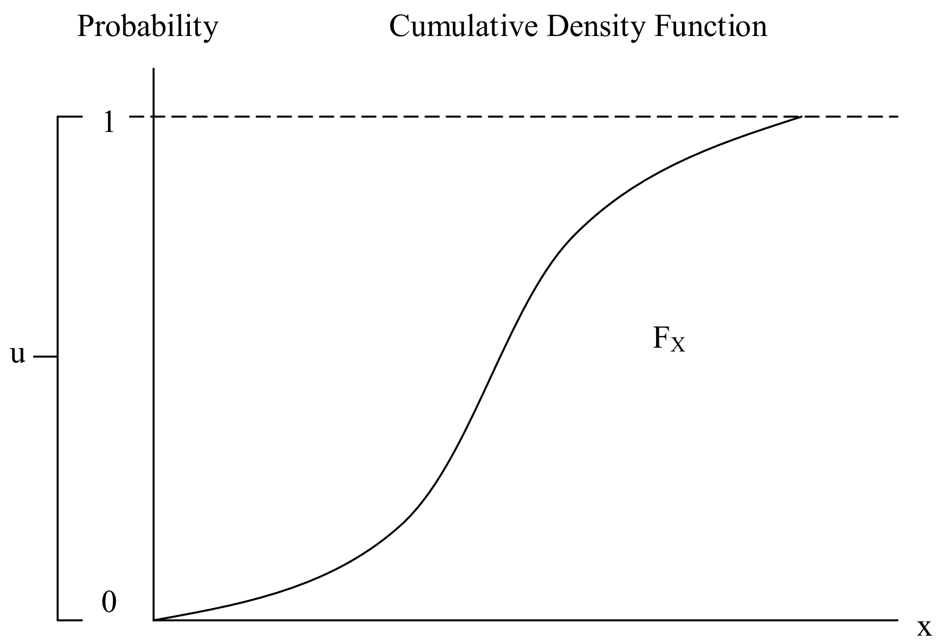
$$z_n = az_{n-1} \bmod m, \; z_o=1$$

Normalizing z_n, one obtains a uniform (0, 1) RN, i.e.

$$u_i=z_i/m$$

The period and quality of the random numbers depends upon the values chosen for "a" and "m". Choosing, a=7^5 and m=2^31-1 results in a sequence of random numbers that passes most of the diehard tests used to measure the quality of a set of random numbers. Far superior random number generators such as the complementary multiply with carry and Mersenne Twister exist. Unfortunately, they were not available for the optimization.

The uniform random number can be manipulated to simulate the characteristics of any probability density function. For this analysis the exponential and the Weibull distributions are well suited. Simulated exponential and Weibull random variables can be obtained from uniform (0,1) RNs by making use of the fact that the cumulative density function (CDF) is uniform between zero and one as illustrated in the following figure.



For an exponential probability density function (PDF) the CDF is

$$F_T(t) = 1 - e^{-\lambda t}$$

Making use of the fact that the CDF is a uniform (0, 1) RN, a uniform (0,1) RN can be transformed into an exponential RN as follows

$$F_T(t) = 1 - e^{-\lambda t} = u$$

$$e^{-\lambda t} = 1 - u$$

$$e^{-\lambda t} = u$$

$$-\lambda t = \ln(u)$$

$$t = -\ln(u)/\lambda$$

A Weibull random variable can be simulated similarly, i.e.

$$F(t) = 1 - e^{-\left(\frac{t}{\alpha}\right)^{\beta}} = u$$

$$1 - e^{-\left(\frac{t}{\alpha}\right)^{\beta}} = u$$

$$1 - e^{-\left(\frac{t}{\alpha}\right)^{\beta}} = u$$

$$e^{-\left(\frac{t}{\alpha}\right)^{\beta}} = 1 - u$$

$$e^{-\left(\frac{t}{\alpha}\right)^{\beta}} = u$$

$$\left(\frac{t}{\alpha}\right)^{\beta} = -\ln(u)$$

$$\frac{t}{\alpha} = \sqrt[\beta]{-\ln(u)}$$

$$t = \alpha\sqrt[\beta]{-\ln(u)}$$

A two state model is used to sequentially simulate the continuity of service to Hitachi. As the following figure indicates there is one random variable for failures and one random variable for repair times.

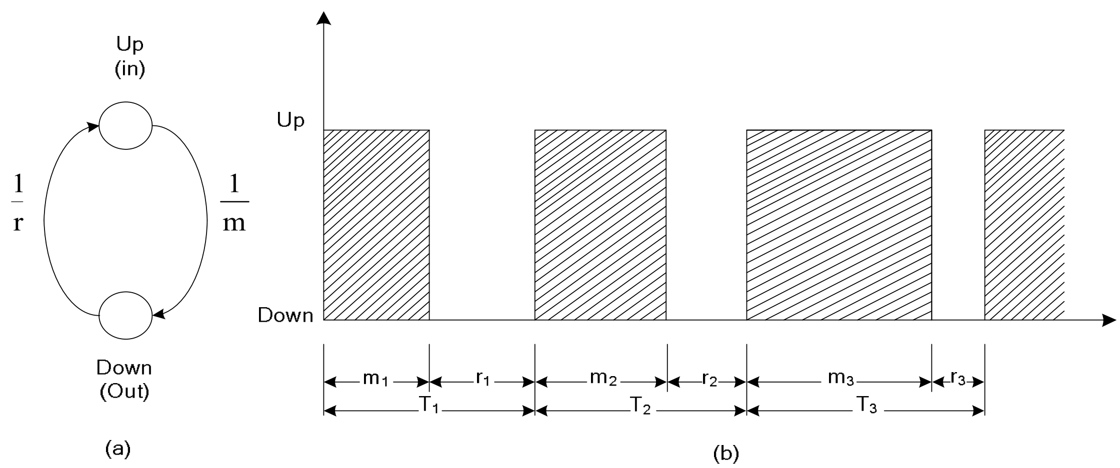
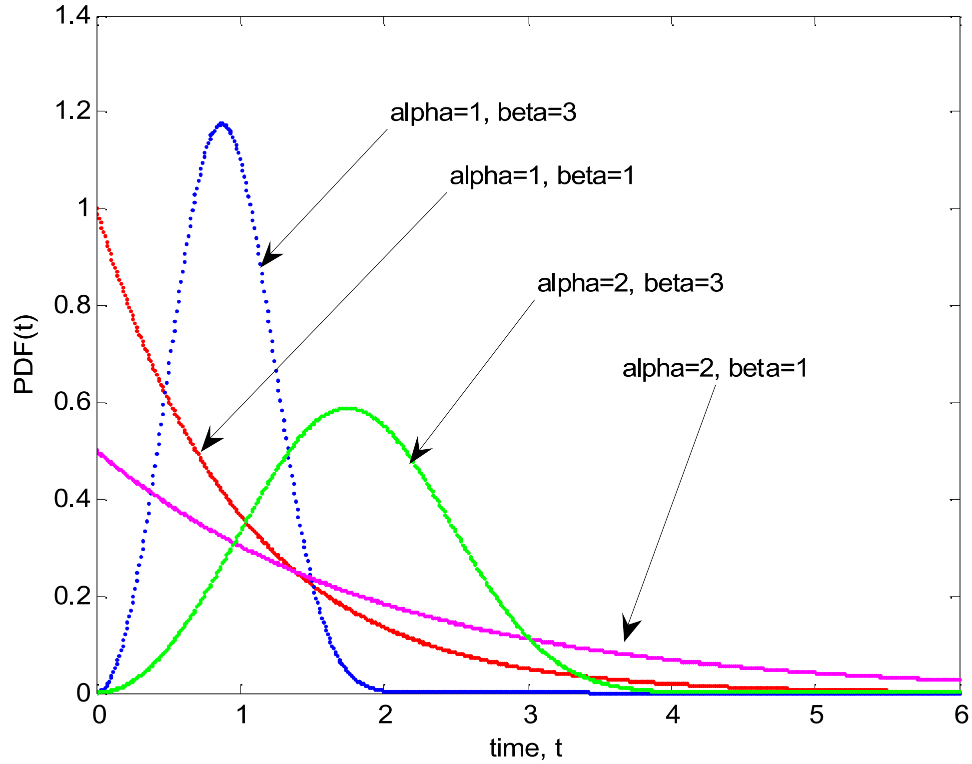


Fig. 2.10. Two-state model in terms of (a) transition diagram and (b) durations

The exponential distribution will be used to simulate random time to failure for both sustained and momentary interruptions. An exponential distribution is characterized as having a constant failure rate, λ. Over the course of a single year, the failure rates of power system components are nearly constant and the use of exponential failure density functions is common practice in power system reliability modeling.

The Weibull distribution is also commonly used to model reliability due to its flexibility. By varying the shape parameter, β, and scale parameter, α, many probability density functions can be approximated as illustrated in the following figure.

Fig. 2.3. Two Parameter Weibull PDF's



The Weibull distribution will be used to model the time spent in the down state.

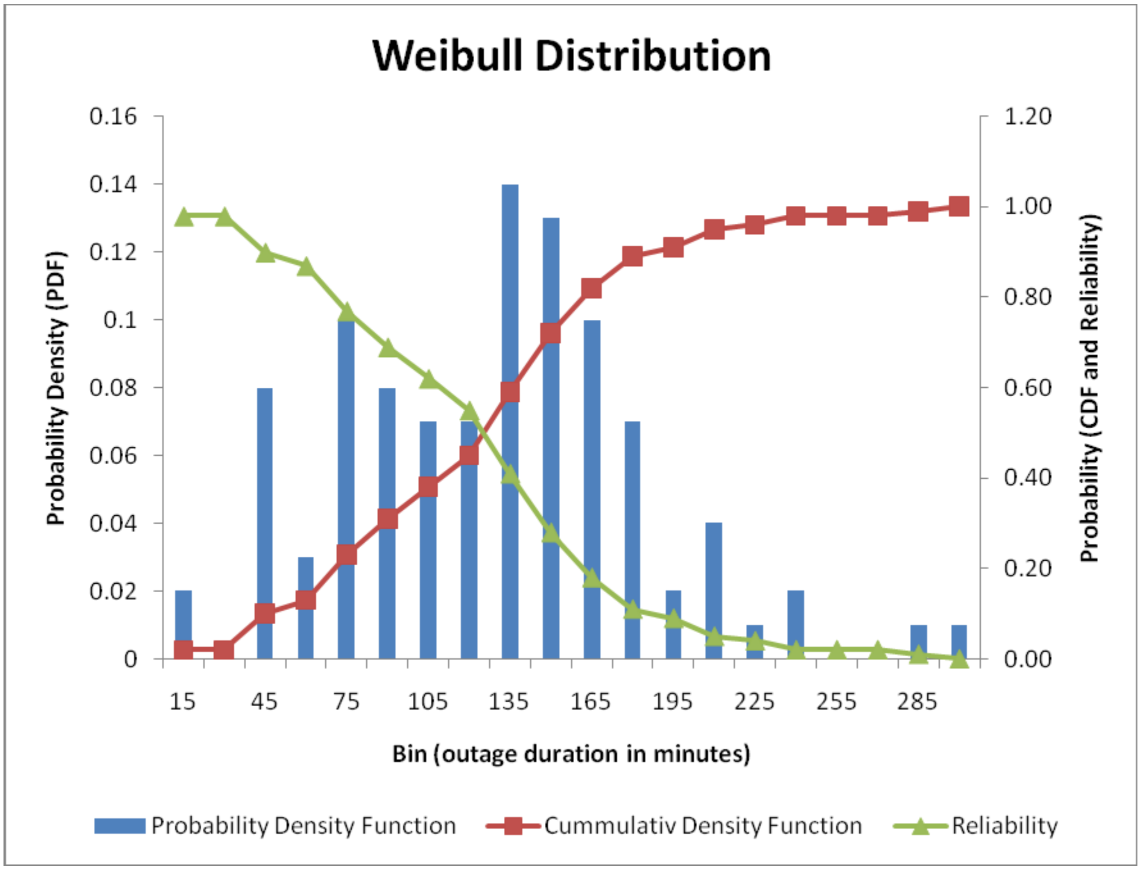
The parameters for the failure and repair time distributions can be estimated from the outage history. The failure rate, λ, can be estimated as the average failure rate over a 5 year period. The percent of momentary outages can also be determined. Then a uniform (0, 1) RN can be used to determine if a failure is a momentary or sustained outage. The parameters of the Weibull distribution used to model repair times can be determined using least-squares linear regression.

To estimate the parameters of a Weibull distribution construct a histogram of the failure density function from historical outage durations.
Integrate the failure density function to obtain the unreliability.

$$F(t) = \int_{-\infty}^{t} f(x)dx$$

Subtract the unreliability from one to obtain the reliability.

$$R(t) = 1 - F(t) = e^{-\left(\frac{t}{\alpha}\right)^{\beta}}$$



Take the logarithm of the negative logarithm of the reliability to transform the reliability function into the equation of a line

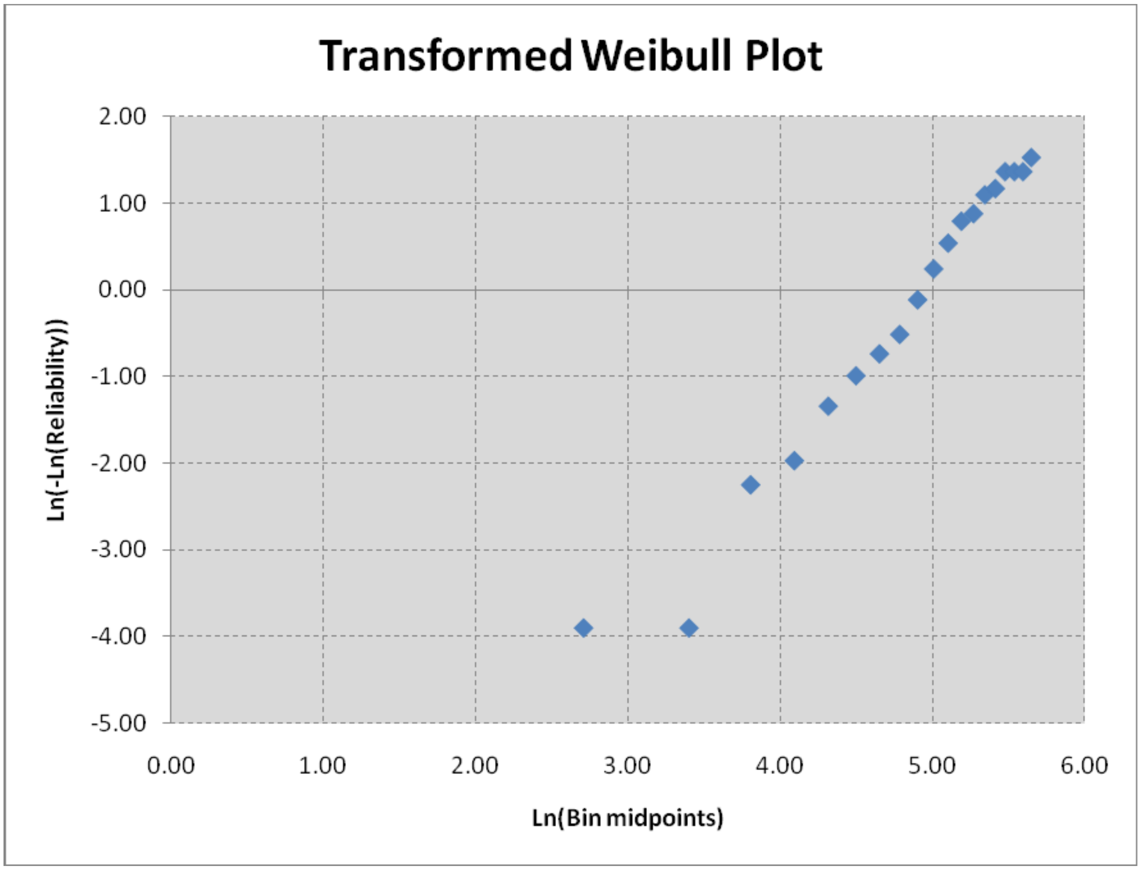
$$-\ln[R(t)] = -\ln\left[e^{-\left(\frac{t}{\alpha}\right)^{\beta}}\right]$$

$$-\ln[R(t)] = \left(\frac{t}{\alpha}\right)^{\beta}$$

$$\ln\{-\ln[R(t)]\} = \ln\left(\frac{t}{\alpha}\right)^{\beta}$$

$$\ln\{-\ln[R(t)]\} = \beta[\ln(t)] - \beta\ln(\alpha)$$

$$\mathbf{y = mx + b}$$



Use least-squares linear regression to estimate the parameters of the Weibull model.

$$\varepsilon^2 = \sum (mx + b - y)^2$$

$$\varepsilon^2 = \sum (m^2x^2 + 2mxb - 2mxy + b^2 - 2by + y^2)$$

The minimum square error occurs when

$$\frac{\partial \varepsilon^2}{\partial m} = \sum (2mx^2 + 2xb - 2xy) = 0$$

and

$$\frac{\partial \varepsilon^2}{\partial b} = \sum (2mx + 2b - 2y) = 0$$

or in matrix form

$$2\begin{bmatrix} \sum \mathbf{x}^2 & \sum \mathbf{x} \\ \sum \mathbf{x} & \sum 1 \end{bmatrix} \begin{bmatrix} \mathbf{m} \\ \mathbf{b} \end{bmatrix} = 2\begin{bmatrix} \sum \mathbf{xy} \\ \sum \mathbf{y} \end{bmatrix}$$

Solving via Cramer's rule yields

$$m = \frac{\Delta_1}{\Delta} = \frac{n\sum xy - \sum x \sum y}{n\sum x^2 - \left(\sum x\right)^2}$$

and

$$b = \frac{\Delta_2}{\Delta} = \frac{\sum x^2 \sum y - \sum x \sum xy}{n\sum x^2 - \left(\sum x\right)^2}$$

or

$$b = \bar{y} - m\bar{x}$$

The slope of the regression line is the estimate of the shape parameter, i.e.

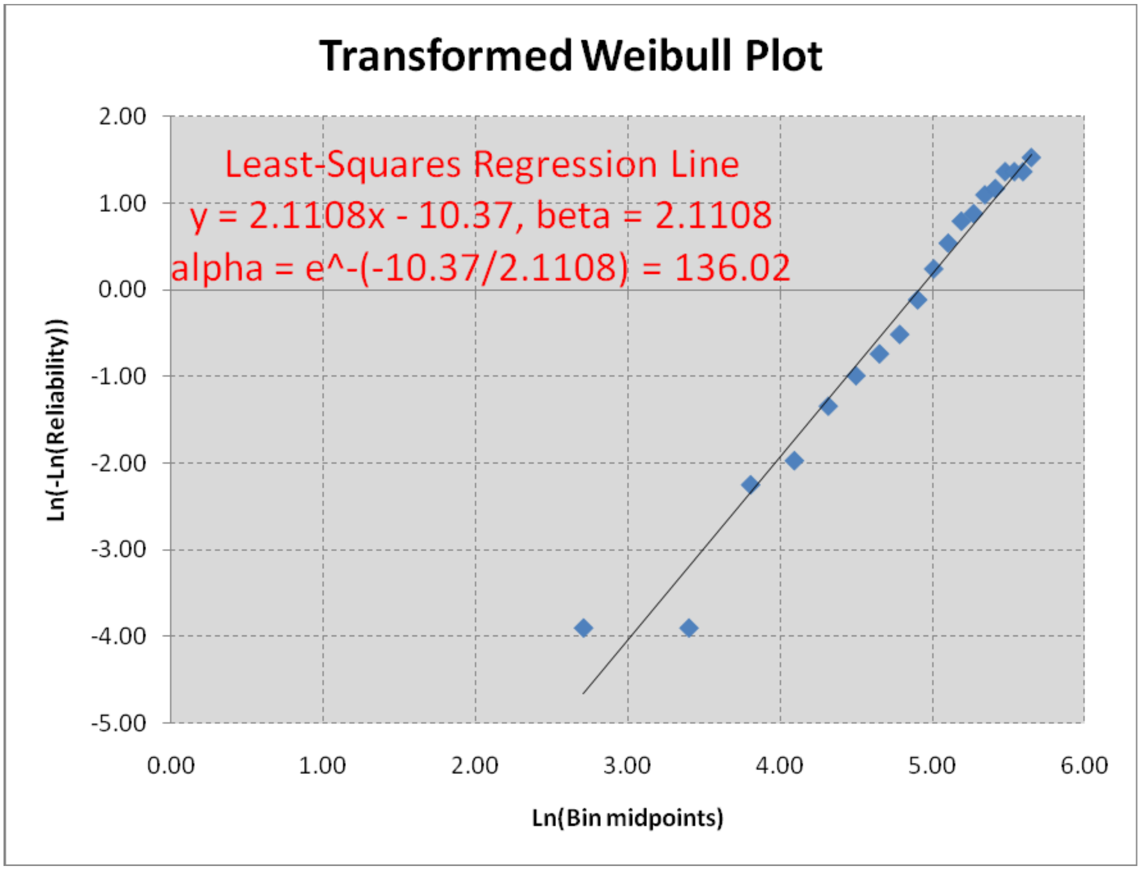
$$\beta = m$$

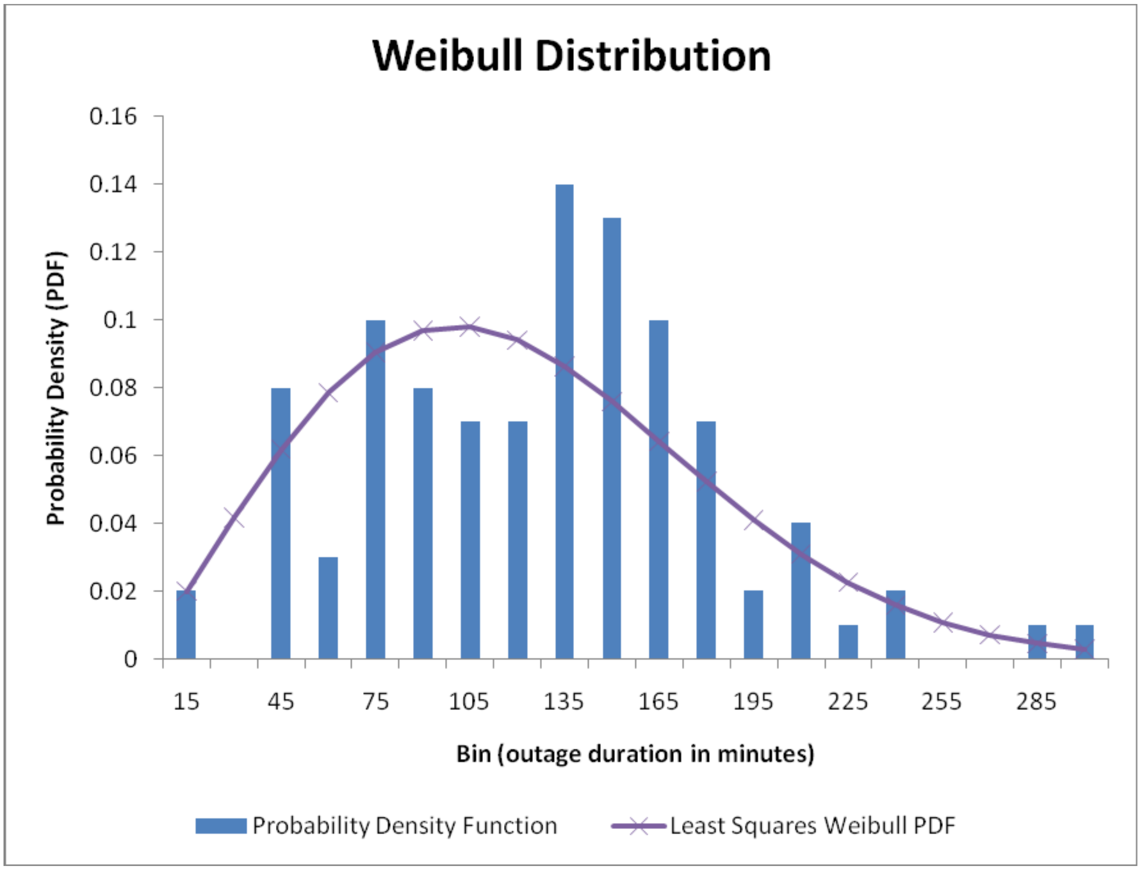
The scale parameter can be computed from the intercept and the slope via the expression

$$b = -\beta \ln(\alpha)$$

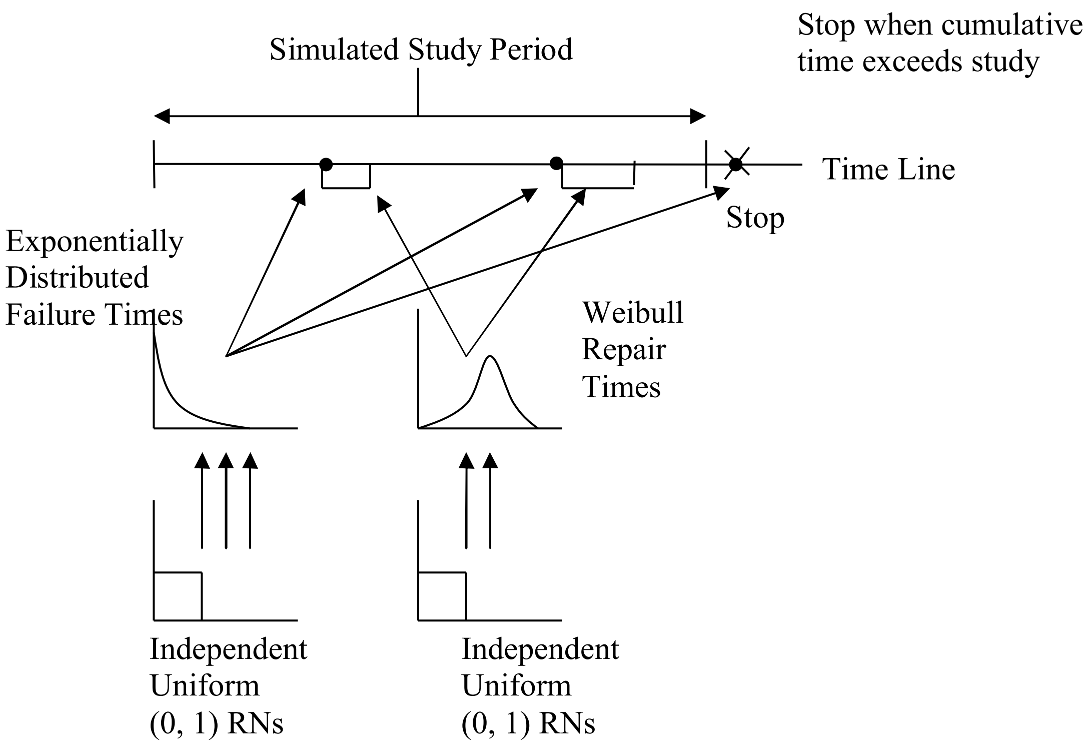
which yields

$$\alpha = e^{-\frac{b}{\beta}} = e^{-\frac{b}{m}}$$

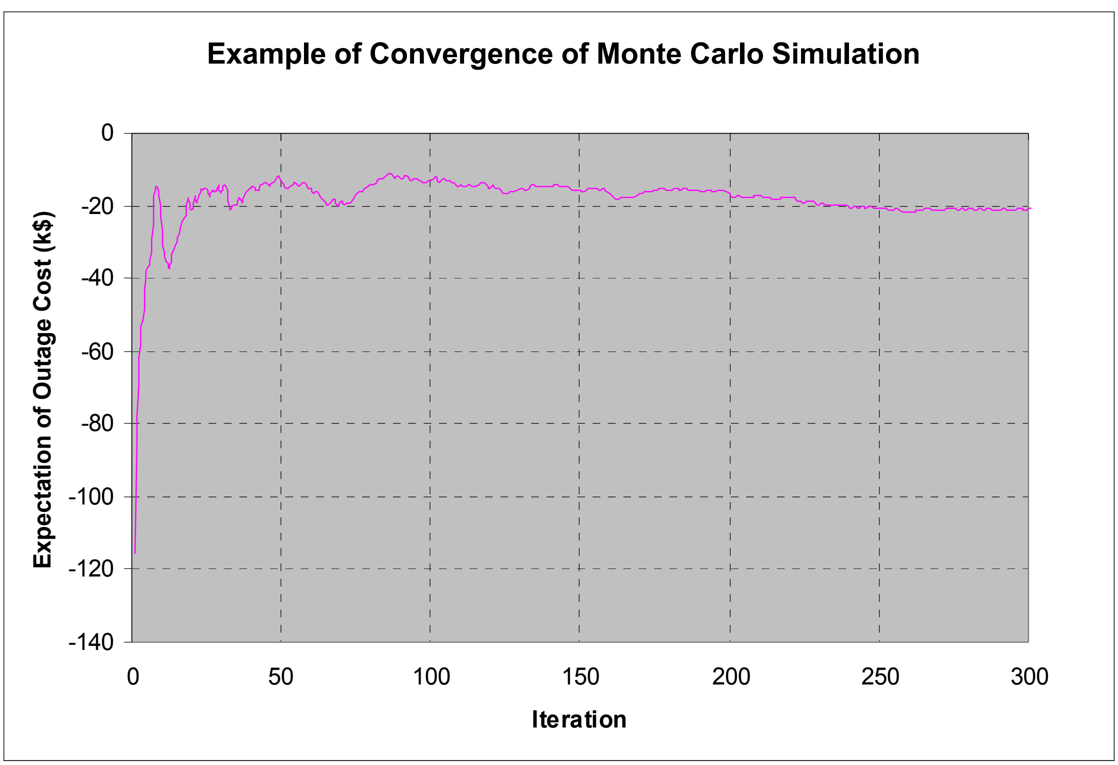

Transformed Weibull Plot
Least-Squares Regression Line
y = 2.1108x - 10.37, beta = 2.1108
alpha = e^-(-10.37/2.1108) = 136.02
2.00
1.00
0.00
-1.00
-2.00
-3.00
-4.00
-5.00
Ln(-Ln(Reliability))
0.00
1.00
2.00
3.00
4.00
5.00
6.00
Ln(Bin midpoints)



Using an exponential distribution for time to failure, a uniform distribution to determine if the failure is momentary or sustained and a Weibull distribution for the time spent in the down state it is possible to sequentially simulate the load point reliability over the study period in question. To simulate the study period failure and repair times are repeatedly generated from the RN sequence until the cumulative time exceeds the study period as shown below.



The study period is repeatedly simulated until the average outage cost converges to a steady-state value within an acceptable confidence interval.



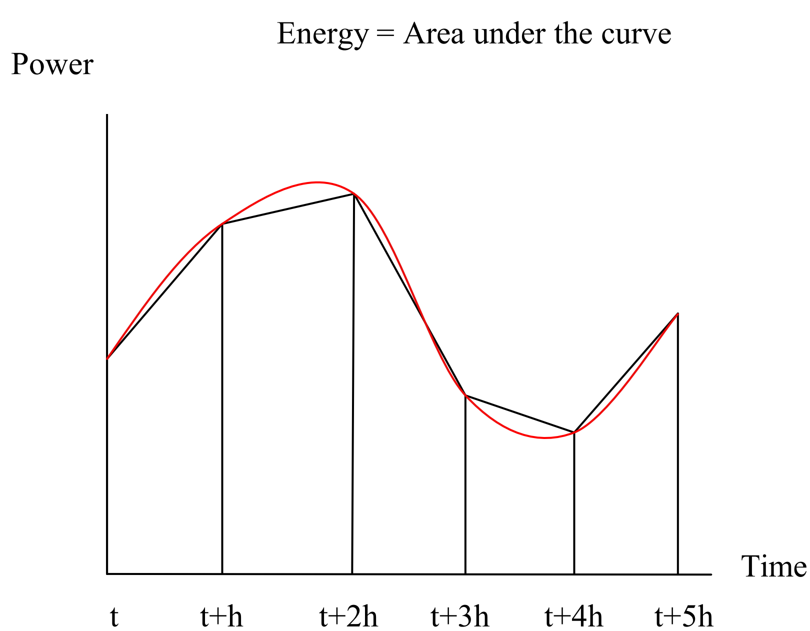
All momentary outages will be eliminated after the battery storage system is installed. The frequency and duration of sustained outages will also be reduced. When a sustained outage occurs the battery system will island the load until service is restored or the battery reaches its maximum depth of discharge and disconnects itself, whichever occurs first. The length of a sustained outage depends on the energy stored in the battery at the time of the outage and the load being islanded. For this analysis the load will be modeled using historical load readings recorded at 15 minute intervals. The energy in the battery at the time of the fault will be determined from the charge/discharge cycle of the battery. Energy is defined as the integral of power, i.e.

$$E(t) = \int_{-\infty}^{t} P(x)dx$$

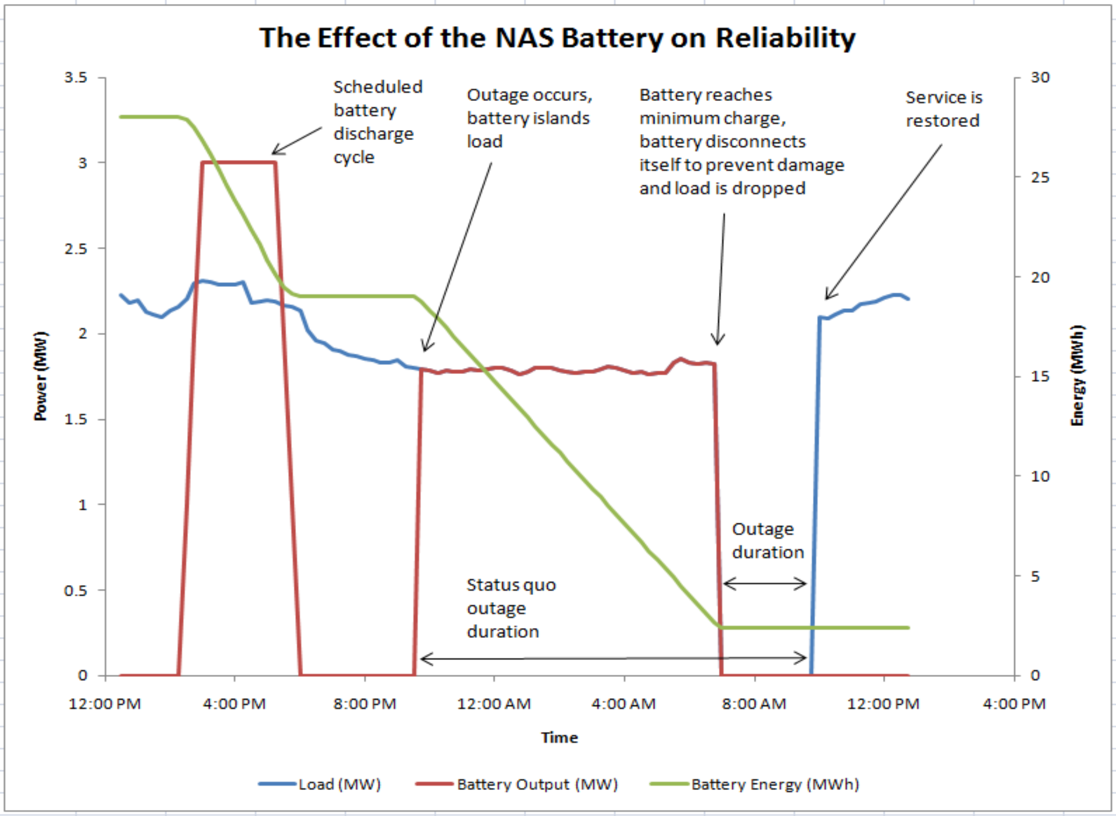
The numerical integration will be performed using the trapezoidal method. The change in energy accrued in one time step can be computed from the equation for the area of a trapezoid, i.e.

$$\Delta E = 1/2 * h * (P_t + P_{t+1})$$

where *h* is the time step.



The following figure shows an example of an islanding event.



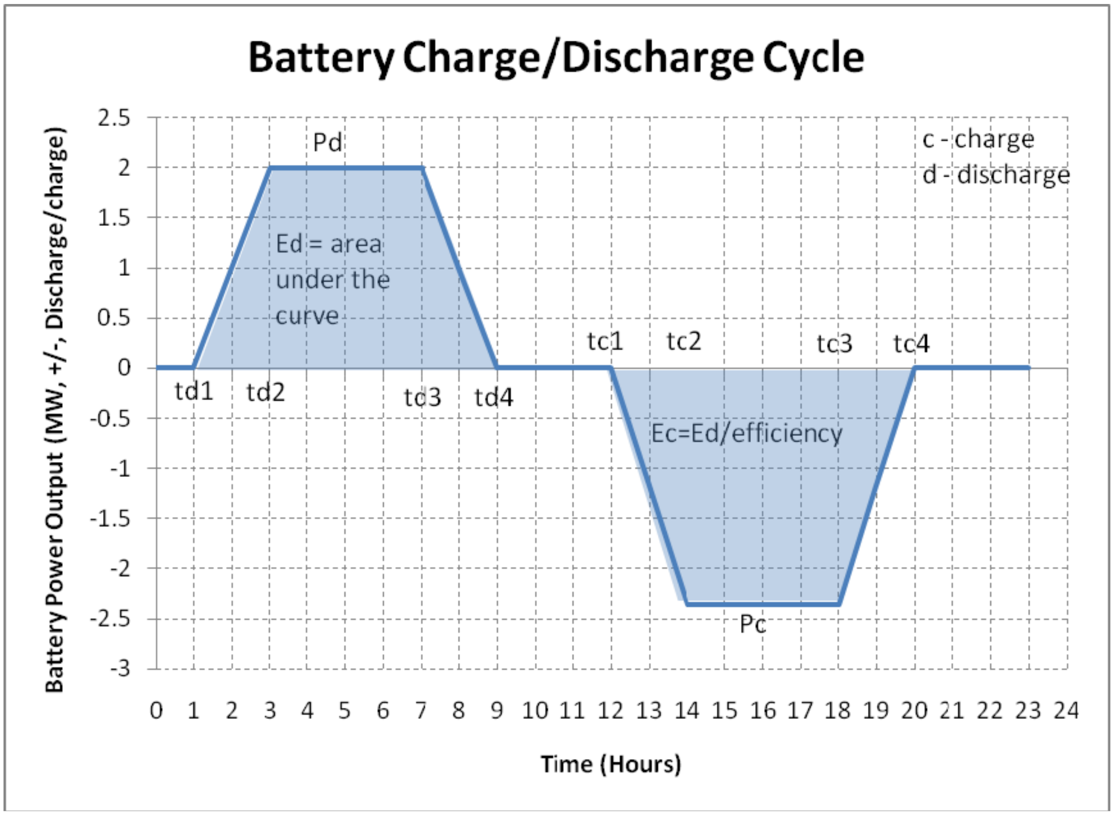
Hitachi was promised 6 hours of islanding capability from the battery. To ensure that sufficient energy was available a variable for the minimum islanding time was introduced. The maximum energy used by Hitachi over this time span is determined by integration of historical load data. This energy requirement will be considered in addition to the minimum energy requirement of the battery corresponding to maximum depth of discharge and will affect the ability of the battery to perform other functions.

Energy Price Arbitrage

A profit can be made by buying energy when the price is low (typically off-peak) and selling that energy when the price of energy is higher (typically on-peak). Charge and discharge cycles for the NAS battery can be programmed to exploit the price differential in Location Marginal Price (LMP) at the Default Load Aggregation Point (DLAP) or at a Custom Load Aggregation Point (CLAP) established specifically for the battery. Differences in the way loss factors are treated for charge and discharge cycles will be neglected for this analysis. It is also assumed that the battery is 100% self-scheduled in the Day Ahead Market (DAM). A weekend (Sat-Sun) and weekday (Mon-Fri) charge cycle will be programmed to exploit cyclical variation in LMP's. However, the battery will be limited to shifting energy from peak to off-peak over the course of a single day.

The battery has a constant heat loss of around 5% as well as variable losses. The round trip efficiency of the NAS battery is approximately 85%. The constant losses and the round trip efficiency will both be used to determine the energy needed to fully charge the battery.

The charging and discharging cycle of the battery will be modeled using trapezoids as shown below:



During the optimization the times, t_{d1}, t_{d2}, t_{d3}, t_{d4}, t_{c1}, t_{c2}, t_{c3}, t_{c4} and the discharge power, P_d, will all be variables. To satisfy the condition that the energy consumed over one charge/discharge cycle is zero the charging power, P_c, will be taken as a slack variable. In other words to satisfy the equation

$$E_c = E_d/\eta_{load} + E_{no\text{-}load\ loss}$$

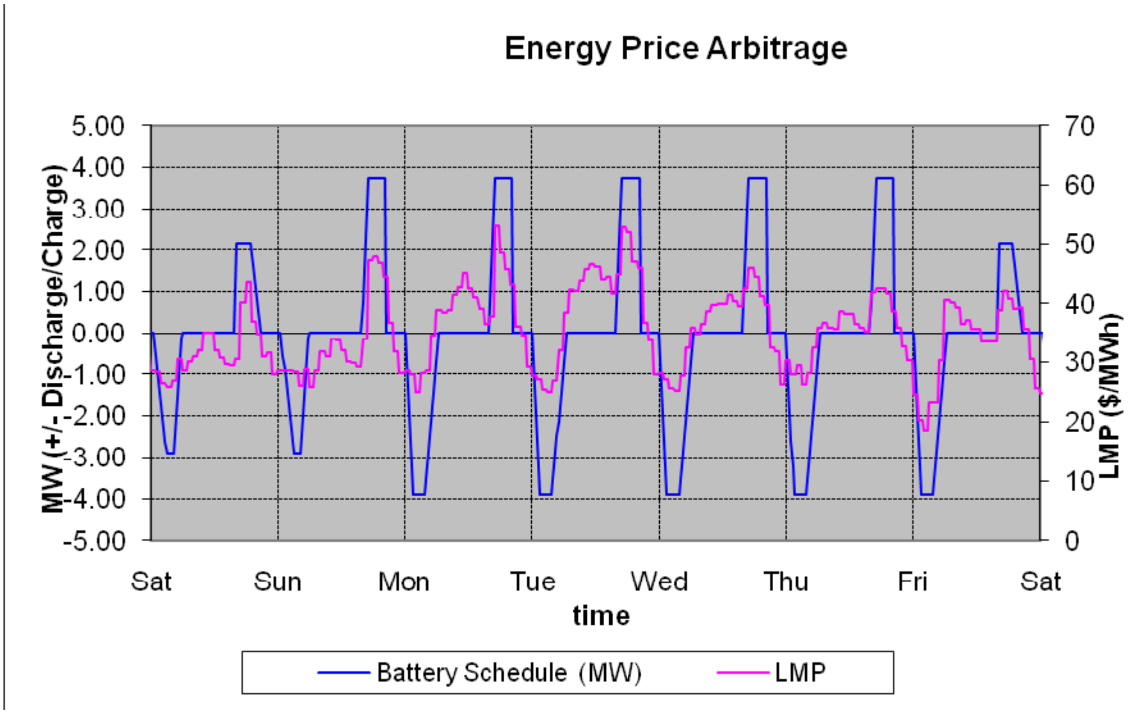
The charging power must be

$$P_c = (P_d/\eta_{load} * 0.5*(t_{d4}-t_{d1} + t_{d3}-t_{d2}) + E_{no\text{-}load\ loss}) / (0.5*(t_{c4}-t_{c1} + t_{c3}-t_{c2}))$$

To determine the benefit of performing price arbitrage the product of the LMP and the battery's power output is integrated over the course of the study period to determine the cost of buying and selling energy, i.e.

$$C_E = \sum_{i=1}^{n} LMP_i * \Delta t * \frac{1}{2}(P_i + P_{i+1})$$

Power output is defined as positive when the battery is discharging and negative during charging.



The output of the optimization algorithm is the total benefit, $C_{TOT} = C_{PQ} + C_{REL} + C_E$, and the solution vector in the form of a charge/discharge cycle that represents the optimal solution.