Battery Lifetime Analysis and Simulation Tool (BLAST) Documentation

J. Neubauer

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List of Acronyms

AC	alternating current
BLAST	Battery Lifetime Analysis and Simulation Tool
BLAST-BTM Lite	BLAST for Behind-the-Meter Applications
BLAST-S	BLAST for Stationary Applications
BLAST-V	BLAST for Vehicles
DC	direct current
ESS	energy storage system
IRR	internal rate of return
Li-ion	lithium-ion
NREL	National Renewable Energy Laboratory
OCV	open circuit voltage
PV	photovoltaic
SOC	state-of-charge

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1 Introduction

The deployment and use of lithium-ion (Li-ion) batteries in automotive and stationary energy storage applications must be optimized to justify their high up-front costs. Given that batteries degrade with use and storage, such optimizations must evaluate many years of operation. As the degradation mechanisms are sensitive to temperature, state-of-charge (SOC) histories, current levels, and cycle depth and frequency, it is important to model both the battery and the application to a high level of detail to ensure battery response is accurately predicted.

To address these issues, the National Renewable Energy Laboratory (NREL) has developed the Battery Lifetime Analysis and Simulation Tool (BLAST) suite. This suite of tools pairs NREL's high-fidelity battery degradation model with a battery electrical and thermal performance model, application-specific electrical and thermal performance models of the larger system (e.g., an electric vehicle), application-specific system use data (e.g., vehicle travel patterns and driving data), and historic climate data from cities across the United States. This provides highly realistic long-term predictions of battery response and thereby enables quantitative comparisons of varied battery use strategies.

1.1 BLAST for Vehicles (BLAST-V)

BLAST-V is specifically designed to evaluate electric vehicles, inclusive of hybrid electric vehicles, plug-in hybrid electric vehicles, and battery electric vehicles. It employs historical year-long travel histories along with travel routing logic to enable evaluation of vehicle and battery responses to infrastructure deployments (e.g., fast chargers, electrified roadway networks, battery swapping stations), as well as the ability to optimize infrastructure deployments. These capabilities have supported numerous analyses of electric vehicle use strategies, including:

- Identifying the requirements fast charging places on battery electric vehicle batteries and the possible improvements to vehicle utility under realistic conditions
- Evaluation of home, public, and workplace charging on vehicle utility and battery life
- Quantifying effects of climate and vehicle and battery thermal management on vehicle utility and battery life.

The results of BLAST-V simulations can be used in NREL's Battery Ownership Model to evaluate the economic and greenhouse gas impacts of electric vehicle scenarios as well.

1.2 BLAST for Stationary Applications (BLAST-S)

BLAST-S is intended for evaluating storage in stationary applications. Users can enter their own battery duty cycles for direct simulation to evaluate the impacts of different battery sizes, thermal configurations, climates, etc. This approach has been applied in the past to study Li-ion battery degradation and lifetime in Community Energy Storage applications. Alternatively, users can apply NREL's optimal peak-shaving control algorithm to a load profile (e.g., for a building, transformer, or substation) for simulations of specified batteries. This pathway has been employed to evaluate the effectiveness of batteries providing demand charge mitigation in commercial facilities.

1.3 BLAST for Behind-the-Meter Applications (BLAST-BTM Lite)

BLAST-BTM Lite has been developed as a quick, user-friendly means of sizing energy storage devices for behind-the-meter demand charge management applications. It trades simplified battery performance models for computational efficiency, but includes a built-in optimization algorithm to identify cost-optimal storage configurations.

BLAST-BTM allows users to supply their own demand and photovoltaic (PV) generation power profiles, but also interfaces with EnerNOC's historic commercial building load database and NREL's PVWatts tool to supply this data if necessary. A generic utility rate structure framework allows for the calculation of electricity costs under a broad array of utility rate structures with minimal user input.

1.4 Accessing and Using BLAST Tools

NREL welcomes the use of its BLAST tools by industry, academia, and others interested in applying their capabilities to the study of long-term battery use and optimization. Accordingly, BLAST-BTM Lite is freely available for download at the following site:

http://www.nrel.gov/transportation/energystorage/blast.html

Please note that NREL does not provide user support for BLAST-BTM Lite beyond this document.

Due to their complexity and anticipated need for user support, BLAST-V and BLAST-S are only accessible via specific agreements with NREL. Such agreements may include, but are not limited to, collaborative research efforts resulting in publishable papers, licensing of the models with contracted user support for proprietary studies, etc. Please contact Eric Wood (Eric.Wood@nrel.gov) to learn more.

2 Modelling Approach

As the purpose of BLAST is generally to run long-duration simulations (e.g., years), and often to perform numerous iterations across different inputs (e.g., hundreds), BLAST models are designed to favor efficiency. Accordingly, some aspects of battery performance are not accounted for (e.g., fast transient voltage response). However, the models are still sufficiently detailed as to provide the metrics necessary for assessing the performance of long term installations. The model includes three primary components, as illustrated in Figure 2.1: an electrical model, a thermal model, and a degradation model.

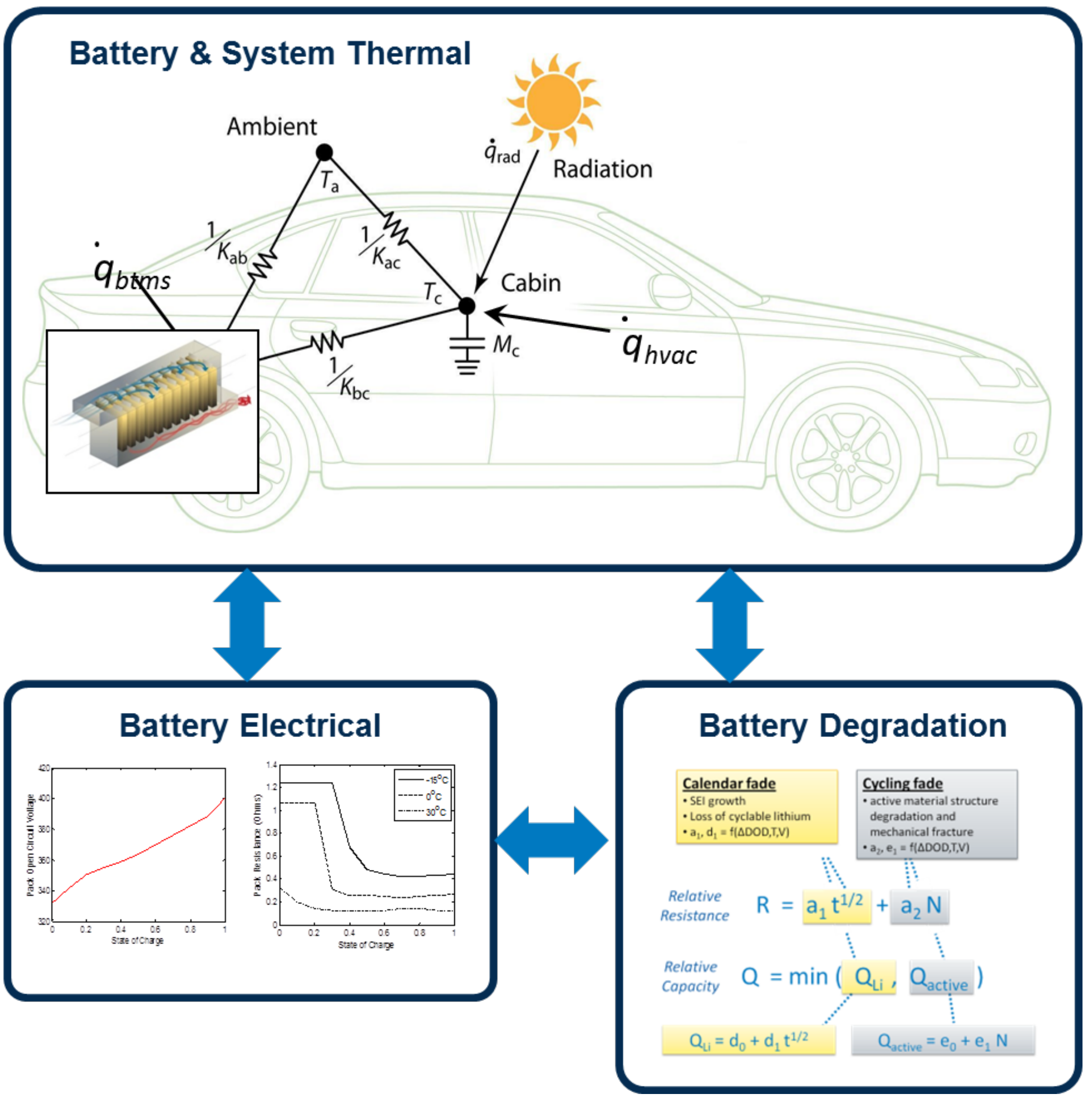

Figure 2.1. Illustration of BLAST battery modeling components

2.1 Battery Electrical Modeling

BLAST includes two options for battery electrical modeling: a simple energy accounting model, and a zero-order equivalent circuit model. The energy accounting model requires specification of available battery energy, maximum power limits, and direct current (DC) efficiency (all user specified), then computes battery SOC by integrating power flows. Allowable power is calculated from the specified power limits and SOC, and heat generation is computed using the DC efficiency value.

The equivalent circuit model calculates battery voltage and heat generation as a function of current. This model assumes a voltage source, representative of the open circuit voltage (OCV) of the electrochemistry, in series with a resistor, representative of the combined electrically and electrochemically resistive elements of the cell. The value of the voltage source is determined by a look-up table using battery SOC, while the value of the resistor is determined by a look-up table using both the battery SOC and temperature. BLAST's baseline relationships were determined by laboratory testing of a single Li-ion cell incorporating a nickel-cobalt-aluminum cathode and a graphite anode with a 41-Ah capacity. Note that in BLAST-S and BLAST-V, the user may provide their own OCV and resistance look-up tables to simulate cells of a different chemistry.

BLAST allows for adjusting the capacity and voltage of the cell to represent larger systems with a single electrical node. When cell capacity is increased, cell resistance is decreased via an inverse relationship, and vice versa. When voltage is increased, resistance is increased proportionately, and vice versa. This is similar to adding more cells in parallel or series, respectively, but forgoes the added complexity of modeling additional cells. Figures 2.2 and 2.3 show the baseline BLAST OCV and resistance values as a function of SOC and temperature when scaled to a 400V, 60.6-Ah pack.

Alternatively, user-specified OCV and resistance tables may be entered to represent different cell chemistries. BLAST also allows the number of cells modeled in series to be selected by the user rather than (or in conjunction with) scaling the voltage of the cell. As such, the user has the option to model a 400V pack as one 400-V cell, 100 4-V cells, or any other whole number of cells to yield the desired compromise of fidelity and computational efficiency. BLAST's equivalent circuit model is only single string, however; it does not allow the simulation of multiple cells or strings of cells in parallel.

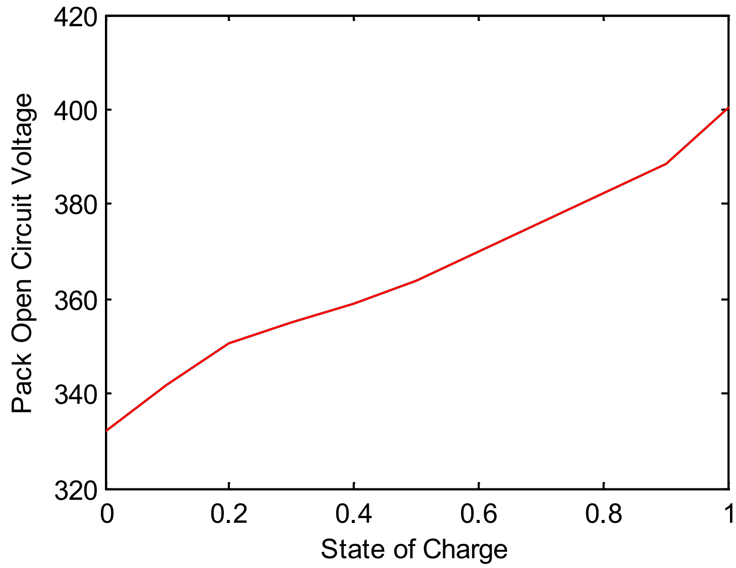

Figure 2.2. Pack OCV vs. SOC for a 400-V (max), 60.6-Ah pack

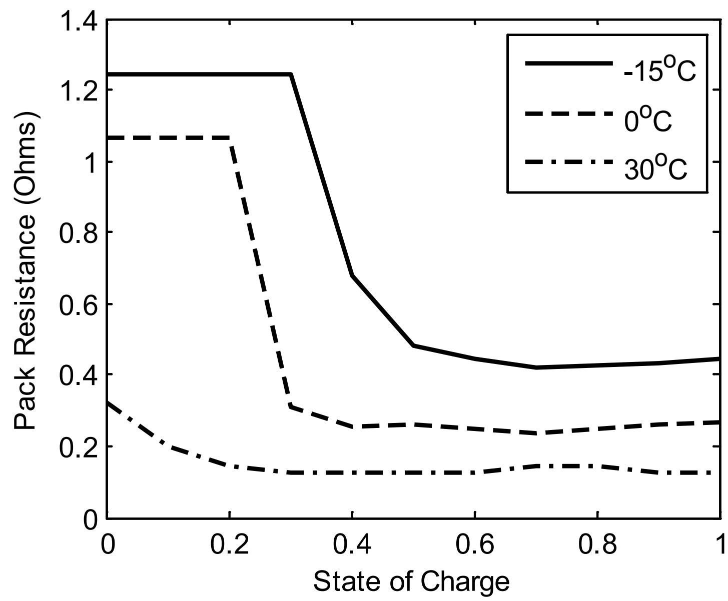

Figure 2.3. Resistance vs. SOC and temperature for a 400-V (max), 60.6-Ah pack

Due to the nature of the tests performed to acquire the resistance data, data points below 20% SOC at 0°C and 30% SOC at -15°C were unavailable. For these conditions, we have elected to hold resistance constant over low SOCs rather than extrapolate resistance trends to higher values. Similarly, for temperatures below -15°C, we apply the -15°C resistance data directly.

The terminal voltage of each cell is then given by Equation 2.1 for any arbitrary current, I, and the delivered power can then be calculated using Equation 2.2. Equation 2.3 is applied to calculate the change in SOC over time, which is in turn used to look up cell resistance and OCV from the relationships established in Figures 2.2 and 2.3. Note that this method assumes a 100% coulombic efficiency (a reasonable assumption for modern Li-ion batteries). However, inclusion of the resistance term insures accurate condition-specific accommodation of the battery's energy efficiency. Such energy losses are translated to heat generated by the cell in Equation 2.4.

$$V = OCV + I \times R \qquad \text{Equation 2.1}$$

$$P = (OCV + I \times R) \times I \qquad \text{Equation 2.2}$$

$$\frac{d}{dt} SOC = I/C \qquad \text{Equation 2.3}$$

$$Q = I^2 \times R \qquad \text{Equation 2.4}$$

Where:

I	Battery current
OCV	Open circuit voltage of battery
P	Power at the battery terminals
Q	Heat generated by the battery
R	Resistance of battery
SOC	State of charge of battery
V	Terminal voltage of battery

2.2 Battery Thermal Modeling

The capability to simulate battery temperature is included in the BLAST model using the generated heat value from the electrical model, the thermal mass of the battery, thermal connections to a system container and the ambient environment, and consideration of active cooling and heating systems. Equations 2.5–2.7 define the lumped capacitance thermal network of the battery and its environment. Representations of how this model is applied to vehicular and stationary applications are shown in Figures 2.4 and 2.5. Effective heat transfer, irradiance, and thermal mass coefficients can be supplied by the user to make this model representative of a wide range of battery systems. Ambient temperature (T_a), soil temperature (T_s), and sky temperature (T_{sky}, for calculating radiation) are sourced from historical databases.

$$M_c \frac{d}{dt} T_c = K_{ac}(T_a - T_c) + K_{bc}(T_b - T_c) + K_{sc}(T_s - T_c) + q_{rad} + q_{hvac} \qquad \text{Equation 2.5}$$

$$M_b \frac{d}{dt} T_b = K_{ab}(T_a - T_b) + K_{bc}(T_c - T_b) + q_{btms} + Q \qquad \text{Equation 2.6}$$

$$q_{rad} = \varepsilon \sigma A \left({T_{sky}}^4 - {T_c}^4 \right) \qquad \text{Equation 2.7}$$

Where:

ε	Effective emissivity
σ	Stefan-Boltzmann constant
A	Effective area
K_{ab}	Heat transfer coefficient from ambient to battery
K_{ac}	Heat transfer coefficient from ambient to container
K_{bc}	Heat transfer coefficient from battery to container
K_{sc}	Heat transfer coefficient from soil to container
M_b	Thermal mass of battery
M_c	Thermal mass of container
Q	Heat generated by the battery
q_{btms}	Heat delivered to battery from battery thermal management system
q_{hvac}	Heat delivered to container from heating, ventilation, and air conditioning
q_{rad}	Heat radiated to container from environment
T_a	Ambient Temperature
T_b	Battery Temperature
T_c	Container Temperature
T_s	Soil Temperature
T_{sky}	Sky Temperature

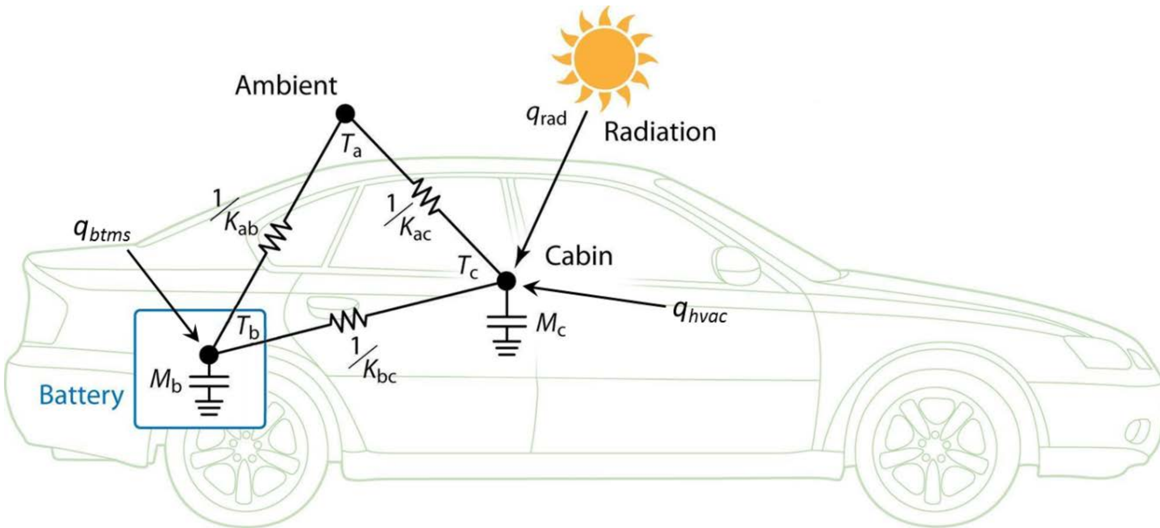

Figure 2.4. Lumped capacitance thermal model for vehicular applications in BLAST

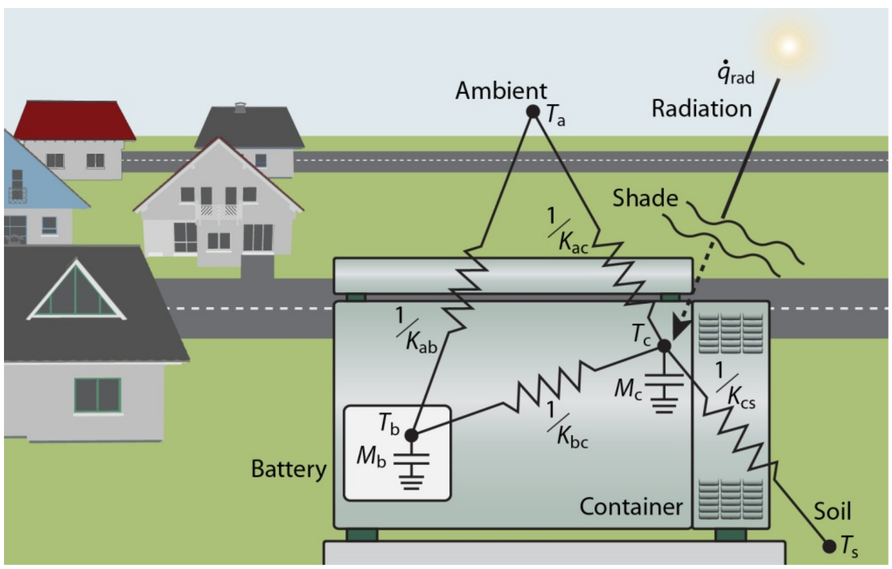

Figure 2.5. Lumped Capacitance Thermal Model for stationary applications in BLAST

Active heating and cooling of the battery and container (q_b and q_c, respectively) are available for simulation as well. The first method allows the effective heat transfer coefficient between different elements (e.g., battery and container, container and environment, etc.) to be thermostatically changed and associated with an increased electrical auxiliary load. This can be used to represent, for example, an electric fan used to move air between the environment and container. The second method allows the thermostatic removal (addition) of heat directly from (to) the battery or container, again associated with an increased electrical auxiliary load via the definition of a coefficient of performance. This method can be used to represent, for example, refrigerant-based cooling systems.

The user can also select the number of nodes to represent the battery itself from one to the number of modeled cells. Equations 2.5 and 2.6 are expanded to accommodate the number of selected nodes. Care must be taken in specifying the effective heat transfer coefficients between battery thermal nodes.

2.3 Battery Wear Model

Electrical and thermal histories of the battery calculated by the aforementioned models are passed to the battery wear model. This model is described in detail in [1]. This physically justified, empirically fit model captures sensitivity to voltage, SOC, temperature, depth of discharge, and cycling frequency to forecast irreversible reductions in battery capacity and increases in battery resistance due to loss of active sites, solid electrolyte interface layer growth, and other electrochemical degradation processes that occur within Li-ion batteries. The baseline model included in BLAST has been created from publically available data sets for a NCA chemistry. At present BLAST does not include the capability for user-defined battery life models. However, this capability is planned for the future.

3 BLAST-V

BLAST-V is the original development of BLAST designed to investigate the long-term performance of Li-ion batteries in electric vehicle applications. In addition to the models discussed in Section 2, BLAST-V includes numerous additional features to accurately simulate the long-term interaction of a battery with the vehicle in the presence of various charging infrastructure deployments. Vehicle efficiency and driver behavior are considered in detail, with integrated algorithms for tour election and rerouting travel to employ available infrastructure that accurately emulate real-world driver decisions. The ability to simulate the effects of vehicle and grid interactions (managed charging and bidirectional power flow) has also been incorporated.

Complete details on BLAST-V will be available in a future release of this document.

4 BLAST-S

BLAST-S is a variant of BLAST originally developed to investigate the long-term performance of Li-ion batteries in Community Energy Storage applications. The simulator has since been expanded to be more broadly applicable to an array of stationary applications. It builds upon the models discussed in Section 2 with additional inputs, battery control algorithms, and other features to allow analysis of peak-shaving applications as discussed below.

An intelligent, model-predictive battery controller has been developed and is included in BLAST-S for optimal peak-shaving simulations. The objective of this controller is to minimize the peak net demand for an input load profile over a specified time frame as measured over 15-minute intervals. The calculation of battery commands to achieve this end is divided into two time scales. First, an interval load target is optimized. The optimal value represents the lowest level to which the peak net meter load can be reduced with the support of the battery. Second, faster battery commands are computed and implemented every 1 minute *within* each 15-minute interval to best achieve the interval load target, taking into account hardware limitations and fluctuations in net demand.

4.1 Interval Load Targeting

This algorithm seeks to identify the minimum interval load target achievable within the energy and power constraints of the battery. The algorithm, defined at a high level below, can be run at the beginning of each new 15-minute interval, each new day, or each new month as specified by the user. It is an iterative algorithm premised on selecting a potential interval load target, evaluating the battery's response over a future forecast when said target is implemented, then comparing the computed battery SOC and meter load to desired limits. Figure 4.1 illustrates the time period of interest to the algorithm and defines relevant variables, while Figure 4.2 depicts the process described below in flowchart format.

1. Evaluate system response when the maximum observed interval load in memory is employed. If this interval load target can be achieved without exceeding battery SOC limits, use this target. If not, proceed to step 2.
2. Evaluate system response when the maximum interval load in the forecast is employed. If this interval load target *cannot* be achieved without exceeding battery SOC limits, then the battery has no ability to affect the peak interval load over the period of interest. In this case, set the interval load target to the maximum. Otherwise, proceed to step 3.
3. Reaching this step implies that the optimum interval load target is somewhere between the maximum previously observed interval load in memory and the maximum interval load in the forecast. The following iterative approach is used to identify the optimum, as illustrated in Figure 4.2:
    A. Define a starting interval load target delta as half of the difference between the maximum previously observed interval load in memory and the maximum interval load in the forecast.
    B. Define a new interval load target guess by subtracting the interval load target delta from the maximum interval load in the forecast.

C. Evaluate the system response when the new interval load target is employed. If this interval load target cannot be achieved without exceeding battery SOC limits, then define a new interval load target guess by *adding* half of the previous delta to the previous guess and repeat this step (3.C). If this interval load target can be achieved, proceed to step 3.D.

D. If the achieved minimum battery SOC is within 1% of the battery target SOC or the interval load target delta is less than 0.1% of the maximum power rating of the battery inverter, then apply the current interval target. Otherwise, define a new interval load target guess by *subtracting* half of the previous delta from the previous guess and return to step 3.C.

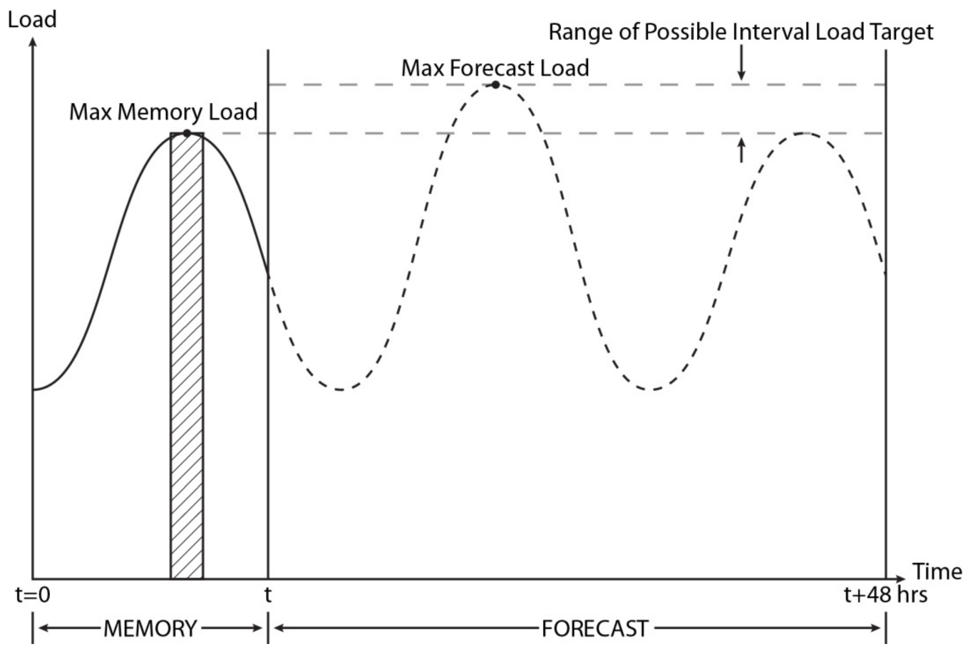

Figure 4.1. Illustration of time periods and load values employed for calculating interval load target

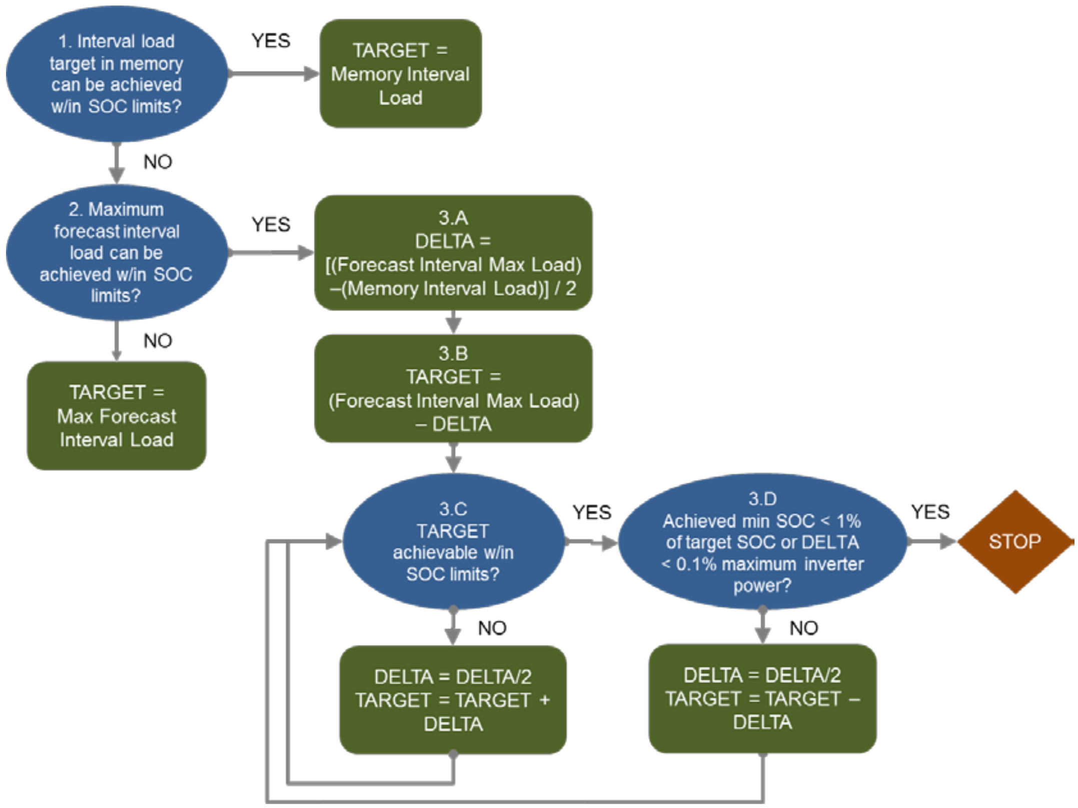

Figure 4.2. Flowchart of target interval load calculation algorithm

This optimization problem is relatively well behaved: while the relation between the interval load target and the resultant minimum achieved SOC can be highly nonlinear, it is monotonic. As such we have found that a simple bisection method for optimization is both reliable and reasonably efficient. Generally, fewer than 10 iterations are necessary to find the optimum. Combined with the need to run this algorithm relatively infrequently (at most, once every 15 minutes), it is therefore readily implementable in real time with minimal computational resources. An example convergence is shown in Figure 4.3.

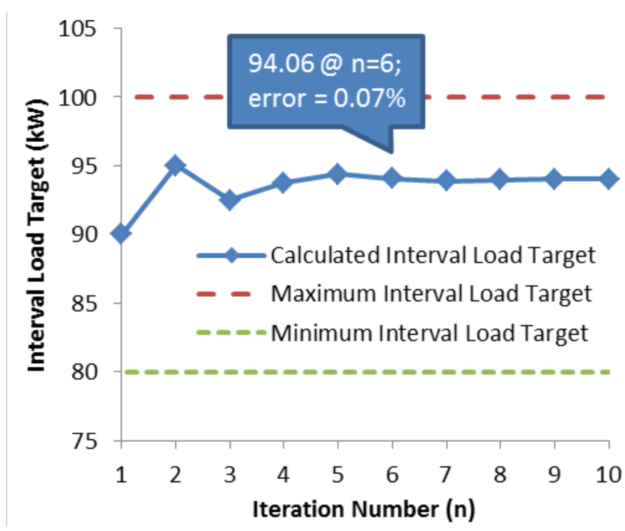

Figure 4.3. Example iterative walk to optimum interval load target (94 kW)

The maximum, minimum, and target SOC values can be set by the user within BLAST. The target SOC defines the lowest SOC that the algorithm will plan the battery to discharge to; however, this value may not be achieved when the actual net demand and/or battery response differs from that forecasted. For example, if actual net load is less than forecasted, the battery will need to discharge less than planned, and the lowest observed SOC will be greater than the target SOC. On the other hand, when actual net load is greater than forecasted, the battery will need to discharge more than planned, and the lowest observed SOC will be less than the target SOC. Thus, while setting a higher target SOC reduces the amount of energy available for peak shaving, it also increases the margin for forecast errors. As the control algorithm will not allow the battery to discharge below the user specified minimum SOC, the margin is defined by the difference in the target and minimum SOCs.

The battery model employed to evaluate system response within the interval load targeting algorithm is selectable between the energy accounting model and the equivalent circuit model. For computational efficiency, the energy accounting model is recommended. Note that using different models for evaluating system response within the interval load targeting algorithm and the subsequent simulation provides the opportunity for errors in forecasted battery response. Done properly, this can reflect the reality of applying imperfect performance models to predict real-world battery performance.

The reset frequency of the interval load target memory is controllable by the user – it can be specified as daily or monthly. The forecast period can be set to end of day, end of month, or a user-specified duration. Use of end-of-day and shorter 24-hour forecasting windows can result in overly aggressive discharging in the near term, leaving the battery at an inadequate SOC to address subsequent load peaks. Where diurnal trends exist, as is often the case, increasing the forecasting window to 48 hours or longer is recommended where consistently low peak loads are desired. Predicting out to the next ratchet (e.g., end of the month) will reduce battery activity and likely battery wear as well. However, the accuracy of long-term forecasts must be considered.

4.2 Sub-Interval Control

The sub-interval control seeks to achieve the interval load target by observing real-time net demand and commanding real-time battery power. It is important to recognize that it is not critical for the meter load to be exactly at or below the target interval load for the entire interval, but rather that the average meter load over the entire interval is equal to or less than the target. For example, consider a case where the target interval load is calculated at 100 kW. From the perspective of the monthly utility bill, it is perfectly acceptable for the instantaneous meter power to well exceed 100 kW, so long as the average power over the interval is 100 kW or less. In cases of high load variability (i.e., high PV penetration and intermittent irradiance), limitations on battery power may in fact make it infeasible to keep instantaneous meter load below the target interval load. We therefore define and continuously update a trigger value based on the observed interval loads and the interval load target to allow and accommodate for such behavior per Equation 4.1.

$$L_{trigger}(t) = \frac{L_{interval\,target}(t_2 - t_1) - \int_{t_1}^{t} L_{recorded}(t)dt}{t_2 - t_1}$$ Equation 4.1

Where:

$L_{interval\,target}$ = interval target load

$L_{recorded}(t)$ = recorded meter load, inclusive of battery action, at time t

t_2 = time at end of interval

t_1 = time at beginning of interval

t = present time

The power request from the battery is then calculated via Equation 4.2:

$$P_{request} = L_{trigger}(t) - L_{demand+PV}(t)$$ Equation 4.2

Note that when the trigger value is greater than the facility demand minus PV power, Equation 4.2 produces a positive power request to charge the battery. In this manner, we command the battery to charge whenever this is the case, resulting in a greedy charge response that seeks to maximize battery SOC when it will not imply an increase in demand charges. While this does result in on-peak charging of the battery, and thus potentially higher energy costs, it also maximizes availability of the battery for reducing demand charges.

4.3 DC Power, Hardware Limitations, and Charging

While the interval load targeting process considers the SOC, maximum power capabilities, and alternating current (AC) to DC conversion efficiency of the battery system, the power request of Equation 4.2 does not. To translate this value to an achievable battery power, we first crop the request based on the maximum AC power capability of the inverter, then account for the one-way inverter efficiency (user specified) to translate the AC request to a DC request. This specified efficiency should be set slightly low relative to peak efficiencies achieved by modern inverters to account for the fact that our simulations do not scale inverter efficiency with output power levels. Next, we calculate the DC battery current (see Section 2), then check and apply battery current, voltage, and SOC limitations. Where demand and PV power predictions as well as battery and system models are perfect, this process should not affect the power request in Equation 4.2, as these factors are accounted for in the control algorithm discussed previously. However, where forecast and/or model errors exist, these factors may limit the power request, potentially resulting in suboptimal peak shaving.

5 BLAST-BTM Lite

BLAST-BTM Lite has been developed to offer a simpler and more computationally efficient means of evaluating behind-the-meter energy storage. Subsections 5.1 through 5.4 discuss the specific changes that have been made to achieve this end. Subsection 5.5 discusses how to use the tool and describes the required inputs.

5.1 Modelling

To maximize computational efficiency, several changes and limitations to the modelling approach have been made to BLAST-S. First, the time step used for simulations is set to 15 minutes. This was selected to agree with the common peak power metering period employed by utilities in setting demand charges. The battery electrical modeling is restricted to kilowatt-hour accounting on a single cell, and thermal and degradation models are excluded.

5.2 Peak Shaving Control

Only the peak shaving controller is included. Only perfect load forecasting is employed—there is no facility for forecast error. As such, BLAST-BTM Lite is set to forecast load only on a monthly basis. Further, the peak load memory resets monthly as well. Peak shaving sub-interval control is excluded, because the simulation time step is set to 15 minutes.

5.3 Demand and Solar Power Input

The user may input both facility demand and PV power production separately. This may be done directly by importing a .csv file provided by the user. Alternatively, 98 year-long historical facility demand profiles have been acquired from EnerNOC [2] and preloaded for selection by the user. BLAST-BTM Lite has also been linked to NREL's PVWatts, which provides an estimate of hourly PV production by location on an hourly basis using typical meteorological year data [3]. BLAST-BTM Lite allows the user to specify the latitude and longitude of a location of interest, which is then used to call PVWatts and import the PV production data for use in BLAST-BTM Lite simulations. Note that as the provided data are hourly, this will underestimate the variability in 15-minute interval loads.

5.4 Energy Storage System Optimizer

To capitalize on the improved efficiency of the tool, a battery size optimizer has been added. This optimizer allows the user to specify a range of energy storage systems, then to identify the most cost-effective system for his or her facility. Internal rate of return (IRR) over a user-specified term is employed to measure cost effectiveness, as computed subsequently (see Equation 5.9).

Once an array of energy storage system (ESS) minimum durations and energy fractions are defined (see Section 5.5.1), BLAST-BTM Lite begins simulating individual combinations of these values in search of a cost optimal. The algorithm starts its search at the lowest energy, highest power-to-energy ratio ESS defined by the user. It first seeks the IRR-optimal power-to-energy ratio while holding the ESS energy constant by incrementally decreasing the power-to-energy ratio and evaluating the resultant IRR. It assumes that IRR will monotonically increase to a maximum value as the ESS power-to-energy ratio is decreased, then monotonically decreases thereafter.[1] Thus, it will continue decreasing the ESS power-to-energy ratio until an IRR is computed and found to be smaller than the previous iteration. Once this occurs, the algorithm retains the previous value as cost-optimal at the given ESS energy level.

Once the optimal ESS power-to-energy ratio has been found for a given ESS energy level, the ESS energy level is increased to the next user-defined value and the process is repeated. Similar to the search for optimal power-to-energy levels, the algorithm assumes that IRR will monotonically increase with increasing ESS energy up to its maximum value, then monotonically decrease as ESS energy continues to rise thereafter. Accordingly, once it is found that larger ESS energy levels yield lower IRR, the algorithm terminates. This entire process is illustrated by example in Figure 5.1. The algorithm begins with the lowest selected energy (87.9 kWh, purple) and finds an optimal power-to-energy ratio of 0.5 at iteration 4. Next, the process is repeated at a higher energy level (131.9 kWh, green), finding an improved IRR at iteration 9. Progression to a higher energy level (175.9 kWh, red) shows a reduced IRR once the power-to-energy ratio is optimized. Thus iteration 9 is identified as the optimal battery configuration.

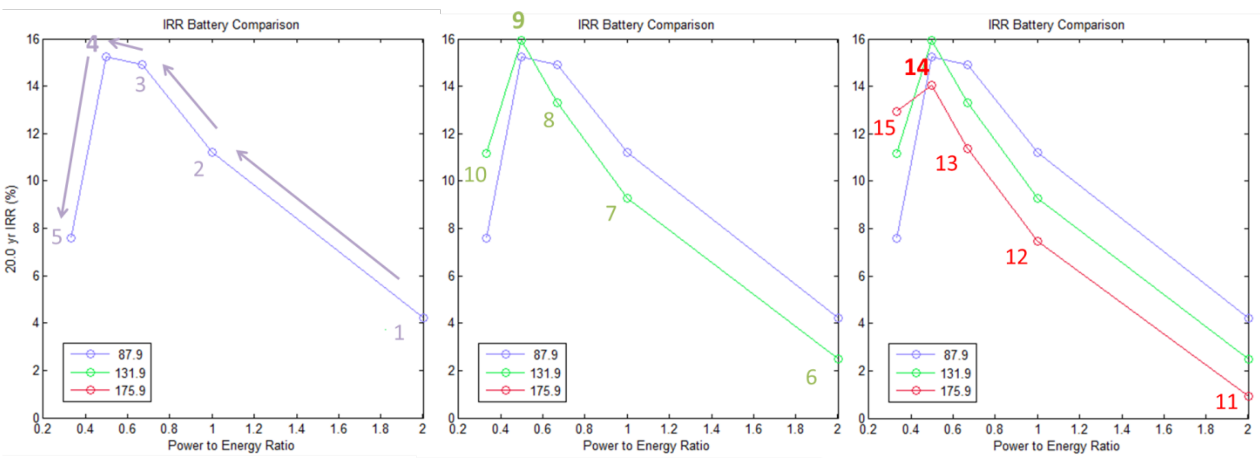

Figure 5.1. Example search algorithm for optimal power-to-energy ratio

5.5 User Inputs

The front panel of BLAST-BTM Lite is shown in Figure 5.2. Optimizing a battery for a peak-shaving application is as simple as completing the four main input sections (hardware options, demand options, PV options, and rate structure), specifying an investment term for IRR calculations, and then clicking the "Run" button. The inputs can be completed in any order as desired by the user, but they all must be completed to enable the optimization algorithm to run. The following subsections detail the required inputs.

[1] While this has not been proven to be true, it has been found to hold up over all cases explored to date.

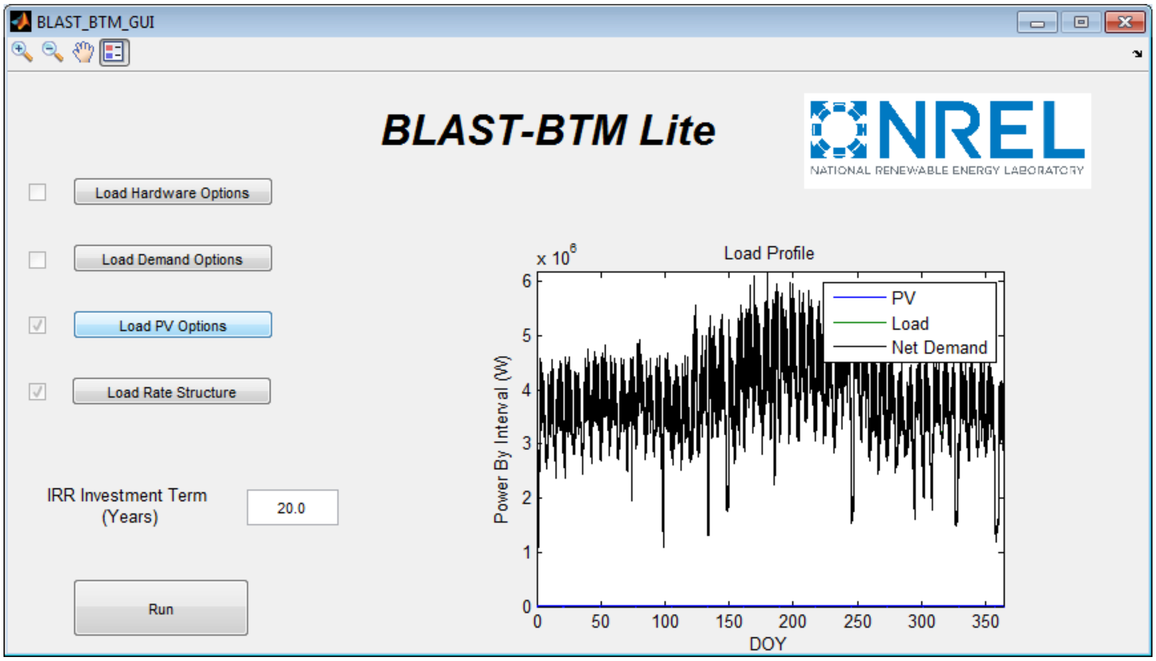

Figure 5.2. BLAST-BTM Lite front panel

5.5.1 Hardware Options

This panel serves as inputs for defining the battery performance and cost values employed by the simulation and is shown with its default values in Figure 5.3.

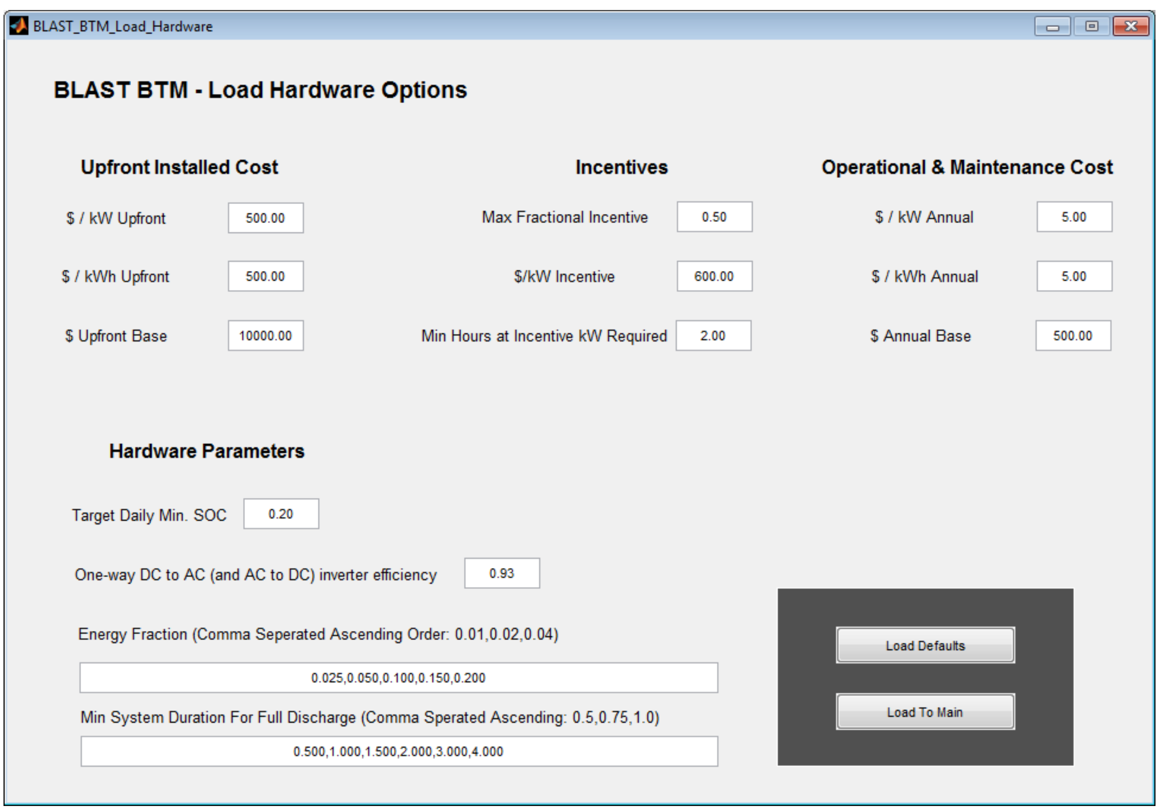

Figure 5.3. Hardware inputs

Upfront Installed Cost values define initial battery costs per Equation 5.2, where P and E are the installed ESS power (in kilowatts) and energy (in kilowatt-hours), respectively.

Installed Cost = ($/kW Upfront) * (P) + ($/kWh Upfront) *(E) + ($ Upfront Base) Equation 5.2

Incentives inputs allow definition of a third-party credit given for the installation of the energy storage device. Equation 5.3 defines how the incentive is calculated from these values.

Incentive = min[(Max Fractional Incentive) * (Upfront Installed Cost) ,

($/kW Incentive) * min(P, E/(Min Hours at Incentive kW Required))] Equation 5.3

Operational & Maintenance Costs define recurring costs resulting from battery operation. Equation 5.4 defines how these are combined to compute the recurring annual cost.

O&M = P * ($/kW annual) + E * ($/kWh annual) + ($ Annual Base) Equation 5.4

Hardware parameters bound the battery size and operation. *Target daily minimum SOC* defines the lowest SOC to which the battery will plan to operate. ESSs are specified by minimum duration and energy fraction. The minimum duration defines the minimum time in which the system can fully discharge 100% of its available energy; e.g., specifying a 2-hour minimum duration for a 100-kWh battery will yield a 50-kW system (a power-to-energy ratio of 0.5).

To define the energy fraction, we first must define the maximum energy storage value, E_{max}. This metric represents the approximate amount of 100% efficient energy storage required to fully flatten the meter load (see Figure 5.4). E_{max} can be precisely calculated over a 24-hour period for a diurnal load cycle using Equation 5.5. BLAST-BTM Lite applies Equation 5.1 over an entire year. While this approach is not perfectly accurate of the intent of E_{max}, it is sufficiently representative for the purposes of this tool.

$$E_{max} = \frac{\int_{t_1}^{t_2} |L - L_{mean}| dt}{2(t_2 - t_1)}$$ Equation 5.5

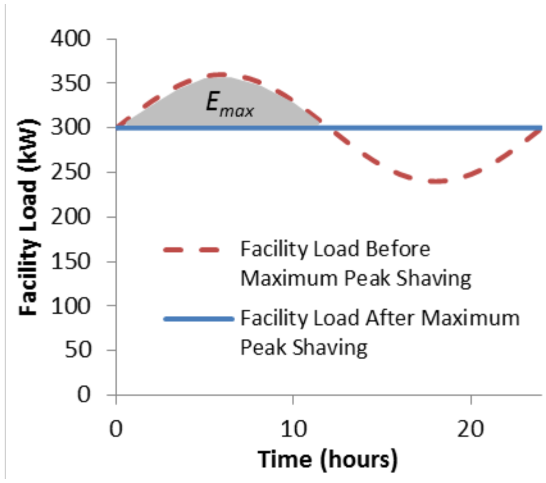

Figure 5.4. Illustration of the maximum energy storage required for maximum theoretical demand charge reduction (E_{max}) in the presence of a perfectly sinusoidal diurnal load profile

BLAST-BTM Lite calculates E_{max} automatically once the demand and PV profiles are loaded. Then, the available energy of the battery (E) is defined as E_{max} times the user-defined energy fraction. Use of energy fractions between 1% and 20% are recommended as starting points to find the most cost-effective storage systems for a given facility.

5.5.2 Demand and PV Options

These panels provide for user selection of facility demand and PV production profiles. As noted, BLAST-BTM Lite allows selection of preloaded demand profiles from EnerNOC [2], as well as PV profiles provided by PVWatts [3]. User-entered values are also allowed via CSV. Note that when providing CSV data for either demand or PV profiles, the .csv file must be a single column of data with the unit of watts. The .csv file must contain either 8,760 hourly values or 35,040 15-minute values, starting at 12:00:00 AM on January 1.

5.5.3 Rate Structure Options

Rate structure options, shown in Figure 5.5, allow for the creation of a utility rate structure to which the facility will be billed. Timing and applicability of the rate coefficients are illustrated in Figure 5.6. Different rate structures are specified by summer and winter seasons. Four demand charges can be specified in the power price fields: one each for off-, mid-, and on-peak periods, and a facility charge that applies to all hours. Demand charges are computed monthly via Equation 5.6. Monthly energy charges and the total monthly utility bill are then computed by Equations 5.7 and 5.8, respectively.

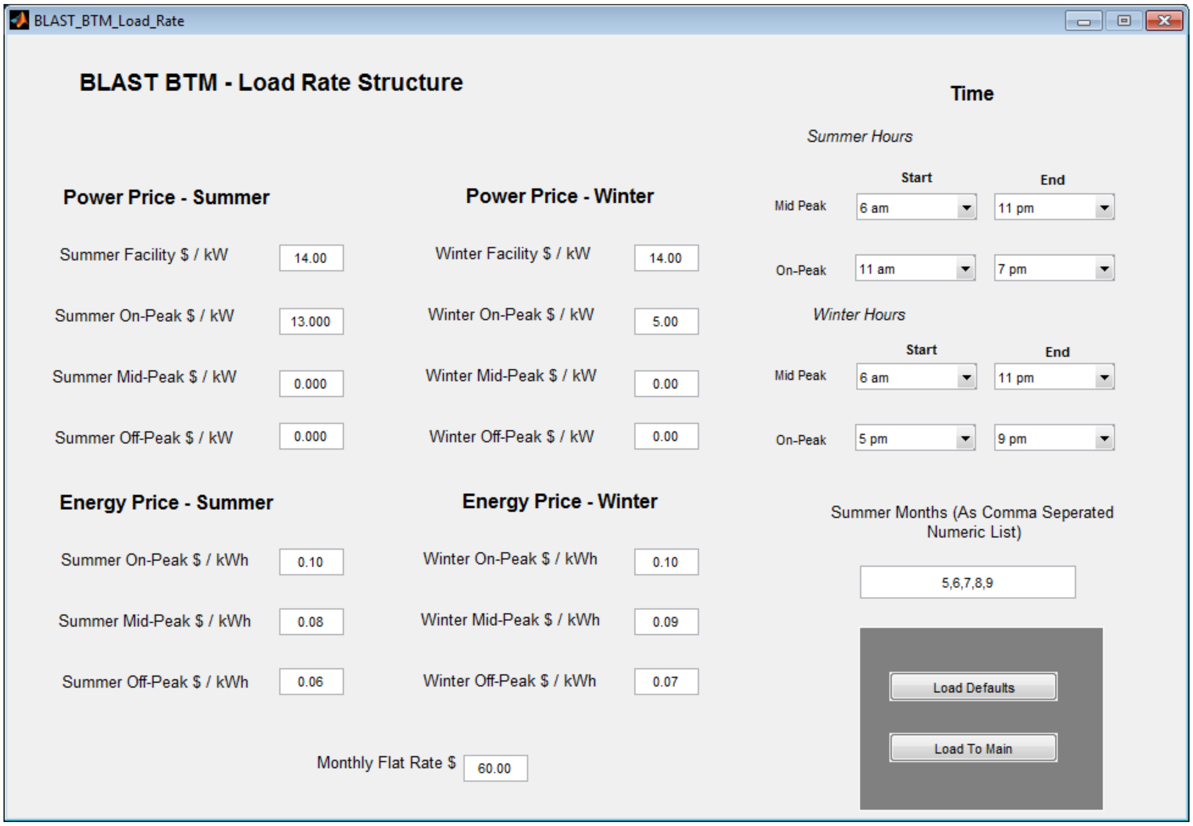

Figure 5.5. Rate structure inputs

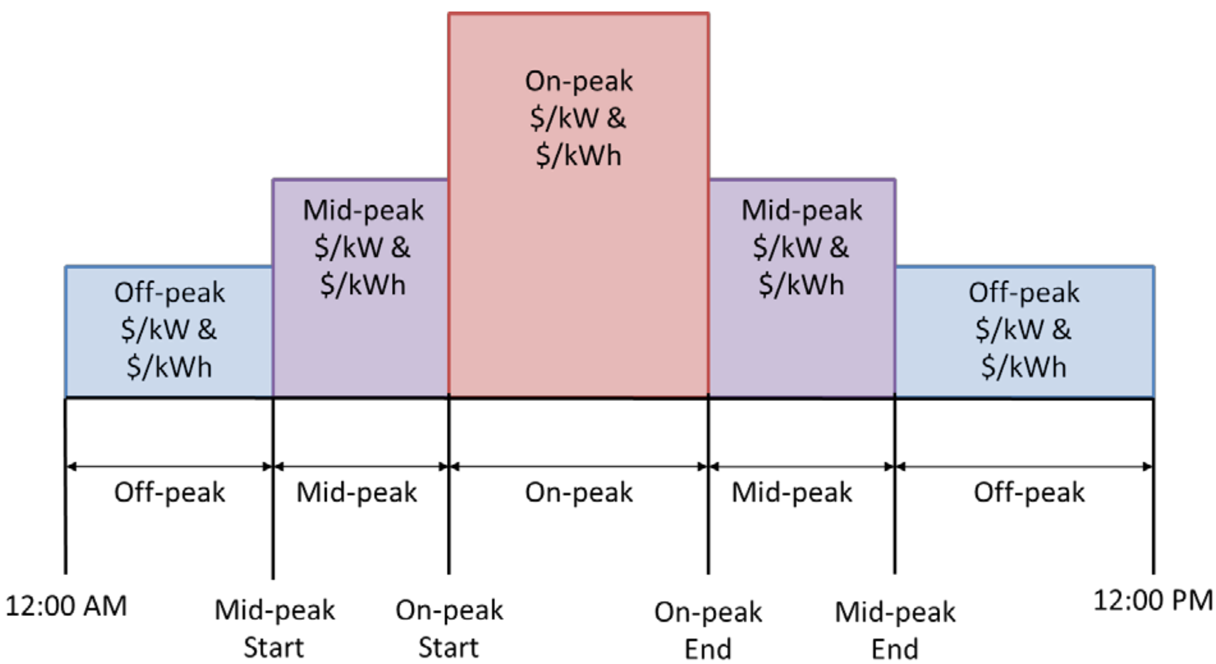

Figure 5.6. How to define off-, mid-, and on-peak time periods and applicability of cost values

Monthly Demand Charge = (maximum off-peak load) * (off-peak $/kW) + (maximum mid-peak load) * (mid-peak $/kW) + (maximum on-peak load) * (on-peak $/kW) + (maximum load) * (facility $/kW) Equation 5.6

Monthly Energy Charge = (total off-peak energy) * (off-peak $/kWh) + (total mid-peak energy) * (mid-peak $/kWh) + (total on-peak energy) * (on-peak $/kWh) Equation 5.7

Monthly Utility Bill = Monthly Demand Charge + Monthly Energy Charge + Monthly Flat Rate Equation 5.8

5.5.4 Internal Rate of Return

IRR is used for assessing the cost effectiveness of the storage system. To do this, the total annual utility bill for the assumed facility is calculated via Equation 5.8 when no storage system is assumed. Then, the annual utility bill is calculated for a specified energy storage system and subtracted from the "no storage" bill to yield the annual savings. Once the annual savings are known, IRR is computed iteratively to satisfy Equation 5.9, where *N* is the user-specified IRR term in years.

$$Upfront\ Cost - Incentive = \sum_{n=1}^{N} \frac{Annual\ Savings}{(1+IRR)^n} \qquad \text{Equation 5.9}$$

5.5.5 Evaluating and Saving Outputs

Once all of the inputs have been provided, clicking the "Run" button on the main panel will initiate the optimization algorithm discussed in Section 5.4. When the optimization is complete, two figures will be created. The first presents the calculated IRR for all of the simulated ESS, an example of which is presented in Figure 5.7. Each data point represents a uniquely sized ESS. The power-to-energy ratio of that system is defined by the x-axis; the amount of available energy defined for that system is constant within each individual trace as specified by the legend in kilowatt-hours. The figure can be saved via the "File" menu in the upper left hand corner of the window. The data can be exported to a .csv file using the "Write Results to CSV" button in the lower left hand corner of the window.

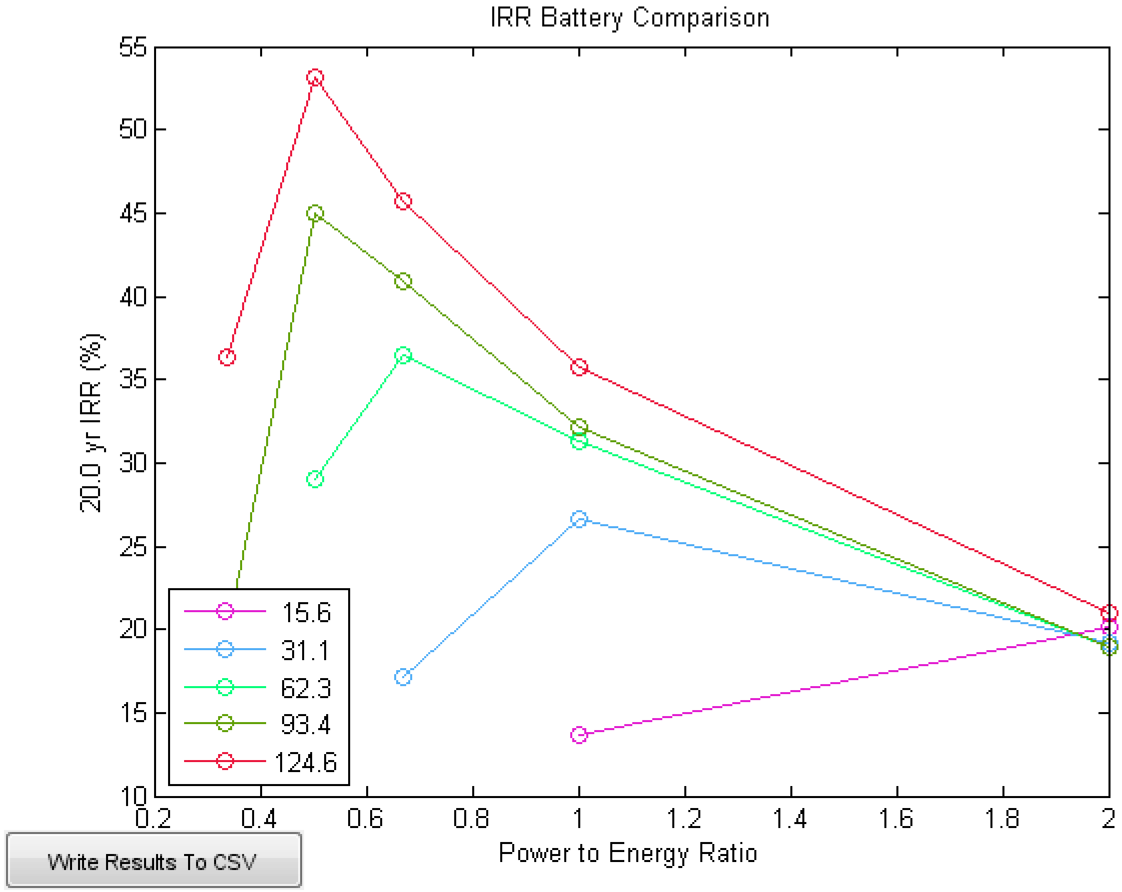

Figure 5.7. Example IRR battery comparison output of BLAST-BTM Lite

Summaries of the ESS specifications and results of operating that system on the selected facility are presented at the top of Figure 5. The top subplot compares the original load profile to the aggregate load profile with the ESS acting to reduce peak loads. Battery power and SOC are shown in the following two subplots. The figure can be saved via the "File" menu in the upper left hand corner of the window. The data can be exported to a .csv file using the "Write Results to CSV" button in the lower left hand corner of the window.

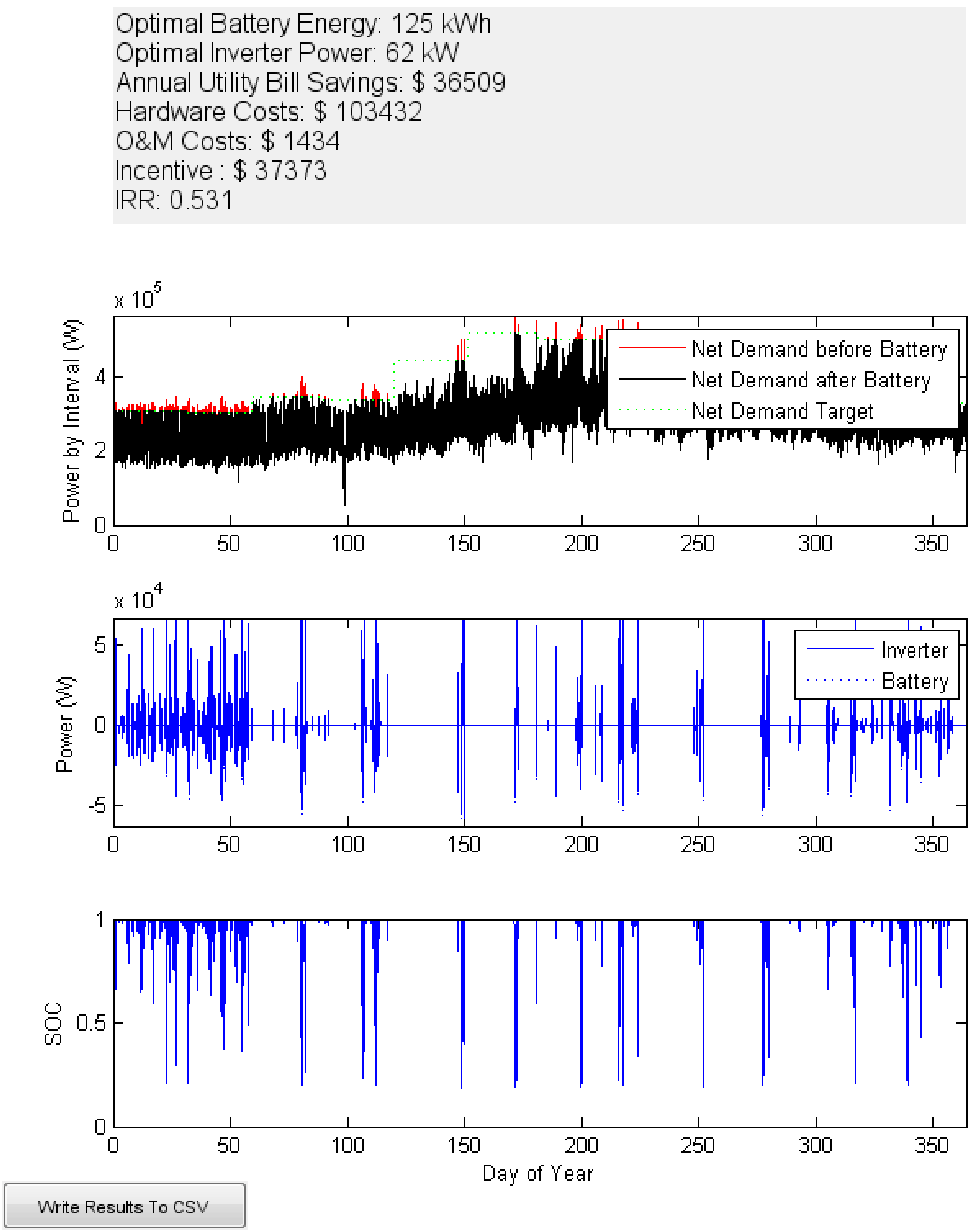

Figure 5.8. Example optimal battery configuration results output of BLAST-BTM Lite

6 References

[1] Smith, K.; Earleywine, M.; Wood, E.; Neubauer, J.; Pesaran, A. "Comparison of Plug-In Hybrid Electric Vehicle Battery Life Across Geographies and Drive Cycles." (2012). National Renewable Energy Laboratory. Presented at SAE 2012 World Congress, Detroit, MI; April 24–26, 2012. SAE paper 2012-01-0666. NREL/CP-5400-53817. http://www.nrel.gov/docs/fy14osti/53187.pdf

[2] EnerNOC. "Open Source for an Open Grid; 2012 Commercial Energy Consumption Data." Accessed January 10, 2013. http://open.enernoc.com/.

[3] "PVWatts® Calculator." National Renewable Energy Laboratory. Accessed March 23, 2014. http://pvwatts.nrel.gov/