Dispatch Strategy Development

for Grid-tied Household Energy Systems

By

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ABSTRACT

The prevalence of renewable generation will increase in the next several decades and offset conventional generation more and more. Yet this increase is not coming without challenges. Solar, wind, and even some water resources are intermittent and unpredictable, and thereby create scheduling challenges due to their inherent "uncontrolled" nature. To effectively manage these distributed renewable assets, new control algorithms must be developed for applications including energy management, bridge power, and system stability. This can be completed through a centralized control center though efforts are being made to parallel the control architecture with the organization of the renewable assets themselves—namely, distributed controls. Building energy management systems are being employed to control localized energy generation, storage, and use to reduce disruption on the net utility load. One such example is VOLTTRON™, an agent-based platform for building energy control in real time. In this thesis, algorithms developed in VOLTTRON simulate a home energy management system that consists of a solar PV array, a lithium-ion battery bank, and the grid. Dispatch strategies are implemented to reduce energy charges from overall consumption ($/kWh) and demand charges ($/kW). Dispatch strategies for implementing storage devices are tuned on a month-to-month basis to provide a meaningful economic advantage under simulated scenarios to explore algorithm sensitivity to changing external factors. VOLTTRON agents provide automated real-time optimization of dispatch strategies to efficiently manage energy supply and demand, lower consumer costs associated with energy usage, and reduce load on the utility grid.

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Chapter 1. Introduction

Fossil fuels have long been the mainstay of the energy economy. In 2012, fossil fuels made up about 80% of the resources used to meet the energy demand and account for 70% of electricity generation (IEA, 2014). Yet future projections indicate that renewable resources such as solar photovoltaic (PV), wind, and hydro-electric energy will increase in prevalence in the United States and across the world (Ellabban, Abu-Rub, & Blaabjerg, 2014). This increase in renewable energy generation is often purported to be the result of declining costs and reduced environmental impact (Ellabban, Abu-Rub, & Blaabjerg, 2014).

Yet the advantages to renewables come with a few challenges. Much of these challenges stem from renewable resource intermittency and hence the inability to control output. For example, solar PV energy generation is highest on clear days with dips in power output with intermittent cloud cover, and wind energy generation fluctuates with changing wind conditions. These factors create variability on how much power is available for consumption at any given time. Electric utility companies must provide sufficient operating reserve to maintain power reliability and mitigate renewable intermittency. This is sometimes known as bridge power, which is provided by generation or storage assets to “bridge” periods of change in the system net load caused by dramatic decreases (or increases) in power output from renewables, power output from conventional sources (as in the case of a unit failure), or spikes in demand. The intermittency associated with on-site power generation, as with rooftop solar PV on households, can be mitigated through localized storage, controlling inverter power output, and load management.

Household loads change throughout the day with typical peaks occurring in the morning and evening as residents wake up, leave for work/school and return home from work/school, respectively. Greater changes occur on smaller minute-to-minute intervals. This higher-resolution data is suitable for capturing changes in large loads, such as in summer months when air conditioning units switch on and off. These fluctuations may be more pronounced when looking at the aggregate demand of multiple buildings. These aggregate effects are translated to the electric utilities and prompt the utilization of “peaker plants” that are used only periodically during the year to provide power during periods of high demand. These units often have a higher cost of energy than typical base loading stations. Utilities commonly apply differential rate structures to prompt users to reduce their usage during times when demand is peaked. Users can take advantage of changing rates and employ demand response control mechanisms to reduce power usage in high-cost periods of day, or move power usage from high-cost period to low-cost periods in a practice known as load shifting.

Energy storage devices and advanced energy management devices have facilitated the effort to shift loads to different times of day (Nottrott, Kleissl, & Washom, 2013). Demand response helps users reduce cost during peak times and if implemented on a larger scale, could help reduce pre-set time-of-use (TOU) costs. Several storage devices featuring electrochemical, flywheel, pumped hydro-electric, and compressed air configurations can be used to store excess energy production when it is available and then offload energy as needed to meet demand (Koohi-Kamali, et al., 2013). Load shifting involves scheduling times when deferrable loads operate to off peak times when non-deferrable load is relatively low. Controlling these two factors forms the basis of renewable resource control algorithms and technology.

This paper develops, implements, and tests the efficacy of dispatch strategies for a solar-storage energy management system implemented on a single household with the objective to reduce energy costs and shave the net household peak load. These goals are accomplished by implementing a set of control algorithms within a multi-agent environment called VOLTTRON™. Simulations are implemented using data read to-from file with the software architecture and interfaces developed for application in a run-time environment on an operational system.

Chapter 2. Background

2.1 High Penetration Renewables

Considering the multiplicity of factors involved in the highly complex infrastructure of today's power systems, integrating renewable resources is challenging and takes considerable time and effort. Numerous studies have been focused on the subject resulting in a vast compilation of literature sources. The ultimate goal of these studies is to effectively control the way renewable energy is harvested, distributed, and transmitted such that utility generation costs are reduced and the overall consumption of non-renewable resources is decreased.

Although higher renewable penetration has the potential to reduce dependence on fossil fuels (conserve non-renewable energy), they do not necessarily reduce energy demand (Yalcintas & Kaya, 2009). Power consumption (energy demand) is dependent on the efficiency and number of devices using electricity at any given time. It is suggested that retrofitting inefficient or constructing more efficient buildings should accompany, or precede, increased penetration of renewable power sources (Yalcintas & Kaya, 2009). Yalcintas & Kaya provide evidence that the payback time of retrofitting can be significantly less than the payback time associated with PV solar array installation, depending on what retrofitting options are available (2009). Consequently, it can be reasoned that reducing the instantaneous energy demand of buildings will also reduce the required initial investment of renewable power generation sources, providing shorter overall payback times.

When cost effective, higher renewable penetration will be realized either by centralized or distributed renewable power generation. Centralized generation assets require large PV arrays or wind farms where large amounts of power can be generated and transmitted to off-site locations or stored in large energy banks. Distributed generation assets commonly include small-to medium-sized residential and commercial PV arrays and wind mills where power is generated on-site and may then be used on-site or sent back to the utility if the energy generation output exceeds local power consumption. However, challenges to distributed generation may arise when trying to implement large amounts of distributed renewable power sources such as: higher installation costs associated with specialized technology, custom engineering, development of interconnection standards, control and protection hardware, and maintaining synchronization with the utility grid (Bauzid, et al., 2015).

2.2 Building Energy Systems

Research initiatives have been driven by environmental concerns and Government regulations such as those that have recently been imposed in Europe regarding net-zero energy buildings (NZEBs) (Kylili & Fokaides, 2015). This legislation calls for buildings to reduce energy usage by 20% by the year 2020 (European Union, 2010). Similar goals have also been set in California which aims to reduce energy usage by 20% in residential buildings by 2020 and in commercial buildings by 2030 (Deng, Wang, & Dai, 2014). Broadly, a NZEB is a building with significantly reduced energy needs (Cawley, Pless, & Torcellini, 2009). With enough renewable energy generation and more efficient building design, net zero energy sites can be made into net positive sites. Four definitions of NZEBs, adapted from (Torcellini, et al., 2006), are given as follows:

1. **Net Zero Energy Site:** Energy generated on-site is at least as great as the amount of energy the site uses over a one year period.
2. **Net Zero Source Energy:** Annual energy generated is equal to the amount of annual energy used in reference to the source. In these cases, the energy imported and exported is multiplied by a multiplication factor to account for energy losses incurred during conversion, storage, and transmission. Conditions for a net zero energy site may be reached when a site is not net zero in source energy, and vice versa, depending on the source of energy and associated losses.
3. **Net Zero Energy Costs:** The credit of generating energy on site is equal to or greater than the cost to buy energy from the utility over the course of one year.
4. **Net Zero Emissions:** The amount of emission-free energy produced in one year is equal to or greater than the amount of energy generated in one year from emission producing sources.

To handle distributed power sources, microgrid power structures have emerged as a viable energy control network (Bauzid, et al., 2015). Cox & Considine define microgrids as a "group of devices with self-management, and optionally storage, generation, and consumption of energy" (2013). Energy distribution can be controlled such that energy requirements from the larger grid system (if connected) remain relatively constant (Bauzid, et al., 2015). A microgrid structure could consist of a single

NZEB or the integration of several NZEBs. Ideally, following the "Net Zero Energy Site" definition, a microgrid structure could operate independently of the larger grid system and function normally in the case of a black-out condition. In any case, microgrid networks utilizing renewable energy control try to handle three levels of power fluctuations including:

- Power Arbitrage (hours): shifting certain loads to different times to take advantage of differences in TOU rates.
- Bridge Power (minutes): relating to power intermissions where back-up systems may need to be turned on or loads need to be reduced to handle instances of decreased power generation or power generation failure. This may be resulting from sudden power disruptions due to clouds and other objects passing over PV arrays and sudden changes in wind speeds for wind turbines (Beaudin, et al., 2015)
- Power Quality control (seconds): relating to brief power intermissions where voltage and frequency fluctuate and a fast response time is required to maintain system stability and keep voltage and frequency levels within tight tolerances. Power stability is critical in applications such as large datacenters that are sensitive to even small voltage fluctuations or changes in frequency.

Handling power fluctuations in most situations requires some sort of back up storage device. Several options for storage systems exist such as pumped hydro-storage, compressed air, electrochemical, superconducting magnetic, hydrogen, flywheels, capacitors, and supercapacitors (Beaudin, et al., 2015). Each of these have different advantages and disadvantages which can be readily found in literature (Beaudin, et al., 2015) (Koohi-Kamali, et al., 2013). Different devices are better suited to meet different arbitrage, bridge power, and power quality requirements.

The ability to utilize power arbitrage has more to do with device capacity than response time. On the other hand, bridge power and power quality control are more reliant on device response time. Storage device functions relating to arbitrage include renewables capacity firming, renewables contractual time of production payments, smoothing macroscale wind variations, peak shaving, central generation capacity, and TOU cost management (Beaudin, et al., 2015). These only require response times measured in minutes or hours making pumped hydro-storage and compressed air viable storage options (Schoenung, 2001). Managing bridge power requirements require response times in the minutes to seconds range to handle functions such as transmission congestion relief, demand charge management, spinning reserves, providing uninterruptible power supply, and for emergency back-up systems (Beaudin, et al., 2015).

To manage power quality, device response times are measured in terms of seconds and portions of duty cycles and handle functions like smoothing microscale generation assets like wind turbines, removing effects of intermittent clouds on PV, and other stochastic factors that affect frequency and voltage (Beaudin, et al., 2015). Since the response time for bridge power and power quality are smaller, devices such as batteries, flywheels, and capacitors are better suited (Schoenung, 2001). Pepermans et al. also suggests energy security issues relating to the natural variability of renewable distributed power sources that then require more extensive back-up systems to maintain grid stability and power quality delivered to loads (2005).

Many residential and commercial units employ rooftop PV array panels to generate electricity. In 2014 there was a 30% increase in PV installations resulting in over 600,000 homes and businesses having on-site solar with total capacity reaching 6,201 MWdc (GTM Research/SEIA U.S. Solar Market Insight, 2014). These installations provide residential and commercial buildings with renewable power during the daytime and can offset the costs of loads that are on during the daytime, such as HVAC units. They can also provide opportunity for other deferrable loads to be turned on during the daytime when there is extra PV power. Although on the decline, the greatest hindrance to implementing such systems is the initial cost of PV system installation, which at the end of 2014 was $3.48/Wdc for residential units and $2.25/Wdc for commercial units (GTM Research/SEIA U.S. Solar Market Insight, 2014).

Although they add to the initial investment and increase maintenance costs of renewable energy generation systems, storage devices may provide more power stability and power arbitrage opportunities. Extra renewable energy generated can be stored for later use or energy from the grid can be stored when the cost of energy is low. Despite these advantages, it is not always cost effective to implement energy storage. This is particularly true in winter months when rate structures are fairly constant. However, as many electrochemical batteries are seeing a reduction in price and increase in capacity, particularly lithium based technologies, more batteries may be used in home energy management systems (Yoshino, 2014). Johnson et al. points out that in order for batteries to be utilized most effectively, a 90% reduction in initial cost must be realized (2011). However, other ancillary uses, such as back-up storage and power regulation may justify their use (Johnson, Lilienthal, & Shoechle, 2011).

Strategies for energy management have included controllers that manage when various loads are on and off. Many such devices can be programmed by the user based on their personal preferences while other “smart” devices such as the NEST thermostat (www.nest.com) utilize learning algorithms to adjust load settings to optimize user comfort and reduce overall energy demand. Such devices are often stand-alone units and only have control over single loads. A household energy management system may collect data from multiple loads, on-site power generators and online sources to handle power distribution. In contrast, centralized energy management systems used by utilities are not capable of managing individual loads. Rather, utilities monitor system-wide variations in demand and respond automatically or manually by reducing energy generation or by bringing additional energy generation assets online. Utilities also manage energy by providing varying rate structures and incentives for users to reduce their overall load, load variability, or both.

Although microgrid networks and household energy management systems aim at reducing local reliance on the utility grid, there are also economic opportunities for distributed energy sources and microgrid networks (Rahimi & Ipakchi, 2012). Recently, terms such as “Transactive Energy” have been used to lump the movement from centralized utility networks to distributed energy networks. The term transactive energy refers to the utilization of energy as a commodity with market value. Energy is bought and sold among different parties that either produce, consume, store, or transport energy within an energy based economy (Cazelet, 2014). Similar to monetary economics, energy related services can either be paid for in advance, or in real time. When paid in real-time, pricing variability depends on the supply and demand of energy (Cazelet, 2014). In addition to energy transactions, in a transactive energy market there needs to be an exchange of information between systems, devices, and users for purposes of enrollment, scheduling, monitoring and control (Rahimi & Ipakchi, 2012). It is projected that transactive energy market strategies will be deployed over the next several years, but will not reach maturity for several decades (Cazelet, 2014).

2.3 Electricity Rate Structures

Implementation of distributed renewable resources put increased strain on utility companies as energy sales decrease and power stability concerns increase (Hledik, 2014). Consequently, utility companies are seeking new ways to increase their revenue. One option utility companies have implemented is to increase their fixed service charges. This is of less concern to users who already face substantial energy costs, but to those with relatively small energy costs, or are implementing renewable resource generation facilities, this is problematic (Hledik, 2014). For NZEB sites measured by cost, higher fixed charges will require more generation sources to offset utility charges. Such charges also provide little incentive to reduce overall demand.

Most utilities offer basic rate plans that have a constant rate throughout the day. The average rate of electricity in the U.S. in 2013 was \$10.1/kWh (U.S. Energy Information Association, 2015). Often these rates will increase or decrease depending on the season with summer days incurring higher rates. To influence users to reduce their energy use during times of high demand, utility companies often offer time of use (TOU) "peak time" rates. These rates vary from different utilities and have different associated times with many utilities offering multiple rate structure options. Utility companies determine these rates based on fairly predictable daily regional demand fluctuations and on historical trends. During these peak times, or times of higher load, the power company must supply more power to meet increased demand providing incentive for many users to reduce their load during peak times. This type of rate structure provides incentive for users to employ renewable resources to reduce the amount of required energy from the grid during peak times and even sell back energy to the utility company if such options are available (Ratnam, Weller, & Kellett, 2015).

Commercial and industrial buildings also face demand charges resulting from sudden, and often drastic, increases in power consumption as large machines are turned on. Demand charges involve a monthly charge based on peak usage over 15 minute intervals (Nottrott, Kleissl, & Washom, 2013). On utility bills, these charges are usually separate from charges associated with total energy usage. Residential units may also start facing demand charges as utility companies try to reduce the maximum required output on their generation facilities (Hledik, 2014)

2.4 Real Time Operation

With PV and other renewables being generated and stored on site, loads can be shifted to mitigate the load spikes incurred on and managed by utility companies. These demand response mechanisms are the focus of many control algorithms implemented in renewable resource management technologies. Many utility companies employ a supervisory control and data acquisition (SCADA) system to manage energy transmission and distribution (Mehta & Reddy, 2015). This type of system provides a hierarchal control network usually consisting of three levels. The first, or lowest level consists of instrumentation and control devices; the second level consists of remote terminal units (RTUs) that collect data and control local equipment; and the third level consists of a master terminal unit (MTU) that sends commands, collects and stores data, and interfaces with the operator (Nan, Eusgeld, & Kroger, 2013). This type of system is ideal for microgrid applications as it allows for localized control and distributed generation networks. Nan, Eusgeld, & Kroger suggests an agent based model to simulate the interactions occurring within the system and discusses vulnerability issues that arise when elements of the system are disrupted (2013). A similar system implementing programmable logic controllers is described by Figueiredo & Sa da Costa, in this system energy waste is minimized using a predictive controller developed in Matlab (www.mathworks.com) (2012).

Another method of control that is decentralized utilizes agent based modeling. Agent based modeling and Multi-Agent Systems (MAS) in and of themselves do not rely upon a centralized control mechanism to function (Lockemann, Kirn, & Herzog, 2006). They are capable of interacting and responding to non-deterministic environments without requiring information about the entire system as a whole (Lockemann, Agents, 2006). Such a network may be ideal for distributed renewable resource generation networks reliant upon stochastic weather conditions. According to Yoo, et al.,

> "Compared to the conventional centralized control, multi-agent systems (MASs) have strengths to distribute computational burden to local agents and can consider the characteristics of individual entities by using intelligent algorithms. The agents can obtain information by monitoring local systems and spontaneously communicating with other agents. The agents can make a decision on behalf of microgrid entities with artificial intelligence through negotiating and cooperating with other agents." (2013)

Lagorse, Paire, & Miraoui also suggests that an agent based design that implements a "bottom-up" approach is more flexible than a centralized "top-down" approach because it requires less adjustment when new elements are added (2010). MAS are also more suitable for transactive energy markets where agents within a microgrid structure bid for energy resources according to their needs and cost structures (Olivares, Canizares, & Kazerani, 2011).

The flexibility and modularity of multi-agent systems has inspired the development of a platform called VOLTTRON specifically designed to support multi-agent based microgrid control. VOLTTRON was developed at Pacific Northwest National Laboratory (PNNL) to provide an environment to build interconnected power grids on a localized scale. According to Akyol, et al., "the intended use of VOLTTRON is in the distribution system for managing distributed generation, demand-response, and plug-in electric vehicles" (2012). VOLTTRON allows for multiple agents to communicate via an information exchange bus (IEB) to publish and subscribe to information regarding their current status and needs. Although written in Python™

(www.python.org), VOLTTRON is language agnostic and utilizes ZeroMQ™ (www.zeromq.org) to allow diversity in agent developmental languages such that agents can be written in languages other than python and still communicate via the IEB (Haack, et al., 2013).

Agents within the VOLTTRON framework can be classified under one of three general groups: platform agents, cloud agents, and control agents. Platform agents are those that are embedded in the platform itself and perform service for other agents. Cloud agents interact with remote applications such as online weather services like Weather Underground (www.wunderground.com). Control agents interface with devices such as PV arrays and employ Modbus and BACNET device drivers (Haack, et al., 2013).

When a device has an energy need, it publishes that need on the IEB along with a priority for meeting that need. Three priority levels exist within the VOLTTRON framework, namely HIGH, LOW, and LOW PREEMPT. Energy requests with HIGH priority receive first rights to available energy. Such requests can come from non-deferrable loads such as lighting or kitchen appliances. When energy is requested from these loads, energy is immediately supplied to the load and other loads with lower priority may be turned off. Requests with LOW priority, such as an HVAC unit may be asked to wait to be turned on if they have not been activated yet, but once an on cycle has started, cannot be turned off. Requests with LOW PREEMPT priority can be turned off at any time when preempted by a HIGH priority request (Pacific Northwest National Laboratory, 2014). Requests with LOW PREEMPT priority may come from devices like a PEV, electric water heater, or pool pump. Priority can also be determined based on circumstance. For example, if a PEV battery is depleted and it is early in the morning, a request to charge the PEV may have a higher priority. A microgrid network in such a configuration allows for loads within a single unit, or across multiple units to be regulated to maintain a more even system-wide energy demand.

2.5 Summary

Renewable penetration is increasing at a steady pace and will continue to do so for several decades. With increased renewable penetration will come increased building efficiency and incentives to retrofit inefficient buildings and install distributed renewable resource generators. Distributed generation facilities will bring with them added complexity as utility companies struggle to provide adequate infrastructure and power system stability. Utilities compensate increased maintenance costs with various rate structures and demand charges adding economic strain on many energy users. To reduce this strain, the goal of many energy management systems is to become less reliant on the utility grid and provide more even load profiles. Several countries have employed initiatives for NZEBs to be implemented. These buildings will feature efficient appliances and construction and on site renewable generation technology to offset energy demands and costs imposed by the utility grid.

In addition to efficient buildings and renewable generation facilities, real-time control schemes are being implemented to reduce and stabilize energy demand. SCADA systems implement a hierarchal control network with multiple units receiving and transmitting information about local energy demand and system performance. Although effective, MAS may provide a better solution to handle complex distributed load networks. VOLTTRON is a MAS designed to support microgrid networks by implementing a priority based IEB to exchange information regarding energy needs and environmental conditions. It is the goal of this study to demonstrate some of the basic capabilities of VOLTTRON in developing control agents and simulating how the agents would respond to varying load conditions to reduce user costs associated with power consumption and demand charges.

Chapter 3. Methodological Approach

The main objectives of this study are to (1) increase renewable resource utilization, and (2) reduce the delivered cost of energy to the user. Simulations of real time operation of a home energy management system are performed using the VOLTTRON software platform. Time series solar PV and load data is read from file, processed using the energy management control schemes developed herein, with results including control actions that address study objectives. Sensitivity analyses are performed on various model parameters (e.g., time-of-use electricity rates) to examine the efficacy of control schemes under different scenarios for a residential rate-payer. Control algorithm efficacy is evaluated on technical and economic merits between a reference case—solar PV with no intelligent controls—and a study case that includes additional equipment for battery storage, solar PV curtailment, load control, and a household energy management system with computational agents and control logic developed on VOLTTRON.

3.1 Case Study Dataset

3.1.1 Load and Solar PV Dataset

Load data is obtained from Pecan Street (Pecan Street Inc., 2014). The Pecan Street database contains hourly, 15-minute, and one-minute resolution data on a variety of end loads and renewable energy generators for households in Austin, Houston, Dallas, and other parts of Texas along with Boulder, CO and San Diego, CA. One minute resolution is collected for a large 4518 square foot home and a PV array in the year of

2014. The home utilizes several devices that potentially use large amounts of energy such as a pool pump, and a plug-in electric vehicle (PEV).

3.1.2 Case Study Rate Structure

Pecan Street does not provide information regarding utility rates or demand charges. Because utility rate data is not provided, a hypothetical rate scheme is constructed. As TOU rates are of most interest in this study a 50% increase in utility charges is applied during peak hours. The values associated with this rate scheme are given in Table 1. On-Peak hours are specified as occurring from 1:00 PM to 7:00 PM during weekdays of summer months starting in May and extending through October. Winter months (November through April) do not implement peak times and have a constant "flat" rate throughout the entire day. The rate structure presented also allows energy to be "credited" back to the user. For simplicity in analysis purposes, the value of energy credit is equal to the TOU cost of energy.

Table 1. Off and On Peak TOU Utility Rates ($/kWh).

TOU Rate Period		
Winter (flat)	Summer (Off-Peak)	Summer (On-Peak)
0.12	0.16	0.24

3.2 Energy Balance and Cost Equations

3.2.1 Energy Balance Equations

Energy transfer within the battery is simulated according to a series of energy balance equations represented in Equations 1 and 2. The battery state of charge (SOC) is also calculated based on remaining battery levels and the maximum energy capacity of the battery according to Equation 3.

$$E_{dis} = \frac{t \times P_{bat}}{\sqrt{\eta}} \tag{1}$$

$$E_{char} = t \times P_{bat} \times \sqrt{\eta} \tag{2}$$

$$SOC = \frac{E_{rem}}{E_{max}} \times 100 \tag{3}$$

where

E_{dis} = Energy Discharged from the battery (kWh)

E_{char} = Energy charged into the battery (kWh)

E_{rem} = Energy in battery at any given time (kWh)

E_{max} = Maximum amount of energy that can be stored in battery (kWh)

t = time duration of interval (hr)

P_{bat} = Battery Load (- if discharging, + if charging) (kW)

η = Battery round-trip efficiency

SOC = Battery state of charge (%)

3.2.2 Cost and Rate Equations

Power consumption and its associated costs are also calculated according to Equations 4 – 9. These calculations assume there is no cost in operating the battery or the PV array and that energy supplied by them is of zero cost when it is discharged. It should be noted, however, that there is a cost associated with charging the battery from the grid.

$$P_{net} = P_h + P_{bat} - P_{pv} \tag{4}$$

$$C_{control} = t \times P_h \times R \tag{5}$$

$$C_{pv} = t(P_h - P_{pv}) \times R \quad (6)$$

$$C_{bat} = t \times P_{net} \times R \quad (7)$$

$$R_{net,pv} = \frac{C_{pv}}{t \times P_h} \quad (8)$$

$$R_{net,bat} = \frac{C_{bat}}{t \times P_h} \quad (9)$$

where

P_{net} = Net Load (kW)

P_h = Household Load (kW)

P_{pv} = Available Photovoltaic Power (kW)

$C_{control}$ = Control Cost without PV or Battery ($)

R = TOU Rate or Utility Credit depending on load relationship to zero ($/kWh)

C_{pv} = Cost using only PV to supplement ($)

C_{bat} = Cost using PV and Battery to supplement ($)

$R_{net,pv}$ = Net Rate of Use using only PV to supplement ($/kWh)

$R_{net,bat}$ = Net Rate of use using PV and battery to supplement ($/kWh)

3.2.3 Battery Characteristics

The battery is assumed to be ideal in that charge and discharge rates and temperature do not affect battery efficiency, and there is no battery capacity degradation over time. This assumption results in the roundtrip efficiency and nominal voltage remaining fixed at 90% and 24 V respectively. Battery capacities are represented in kWh after a unit conversion from Amp-hours (Ah) as shown in Equation 10. Charge rates are presented as a percentage of the battery capacity (C) available to be discharged in a single hour. For example, a charge rate of 1C would charge the entire capacity (0 – 100%) of the battery in one hour, a charge rate of .5C would charge the battery in two hours.

$$kWh = \frac{Ah \times V}{1000} \tag{10}$$

Where

V = Nominal Battery Voltage

3.3 VOLTTRON Agent Development

VOLTTRON provides several examples and templates for developing agents including a step by step user guide to install the VOLTTRON platform and develop a simple agent (Pacific Northwest National Laboratory, 2014). Five agents are developed that together provide the necessary data input (monitoring and sensing), control logic, and data output (control signal) for energy management and bridge power applications as applied to the simulated single-family home. These agents communicate with each other and with a master home energy management system (HEMS). In the VOLTTRON framework, a scheduler agent would represent the HEMS and would make decisions regarding resource allocation. Functions of these agents are described below:

1. <u>Load Agent:</u> This agent is designed to retrieve the amount of power being consumed at a pre-determined interval. Data input resolution when collecting for days and years are one minute and 15 minutes respectively. The load is assumed to be constant over the interval specified, resulting in an effectual average for that time frame. After reading in from file one instance of power consumption (in kW) the agent publishes its needs to the VOLTTRON IEB. The agent subscribes to any offers to handle the load published by other

agents. In simulation, the load agent makes a series of decisions based on the offers received. In general, these decisions consist of using any available PV and supplementing any remaining load requirements from other sources such as the battery or from the grid.

2. PV Agent: This agent is designed to retrieve the amount of power available from the PV array over the same interval periods as the Load agent and is assumed to be constant over that interval. The agent also subscribes to published needs regarding load and battery availability. The PV agent offers to first meet any immediate loads and then offers remaining PV to the battery or to the grid, depending on simulation configurations. Offers to the load agent and battery agent are then published to the IEB.
3. Grid Agent: This agent is designed to retrieve and publish TOU rate data at each interval. In simulation, the grid is assumed to be an infinite source capable of meeting any energy requirement at any time. Consequently, the grid agent does not offer any power to other agents. It is assumed that any remaining or requested energy needs can and will be met by the utility grid.
4. Battery Agent: This agent is designed to represent a simple lithium-ion battery where energy is stored and discharged to meet load requirements. The agent subscribes to information concerning current power demand, rates, and solar PV availability. Based on the SOC of the battery and the specified battery dispatch strategy applied, the battery agent offers stored energy to satisfy energy demands or attempts to reduce peak loads. If an energy offer is

accepted, the battery discharges its energy to meet the demand until the battery SOC reaches its minimum allowable limit or it is constrained by the applied dispatch strategy. The amount of energy dispensed over one time interval is given in Equation 1. The battery is allowed to request energy to restore its SOC according to dispatch constraints and energy availability in accordance with Equation 2. SOC is calculated according to Equation 3. The simulated charge controller is designed to keep the SOC between 20% and 100%.

5. Data Agent: This agent is designed for debugging and analysis purposes and is not required for the other agents to operate correctly. As such, the agent only subscribes to data from other agents and does not publish any messages on the IEB. Rather, the agent collects information regarding the current load, PV power, rates, and the resulting distribution of energy to various agents. At each time interval, it performs a series of calculations to determine data concerning load, overall costs, and rates (see Equations 1-9). Upon performing calculations, data is stored in a .csv file for analysis.

In simulation, these agents read from a file, in an actual physical system, they interface and control physical components. Figure 1 provides a comparison between the simulation architecture and how it would relate to an actual system.

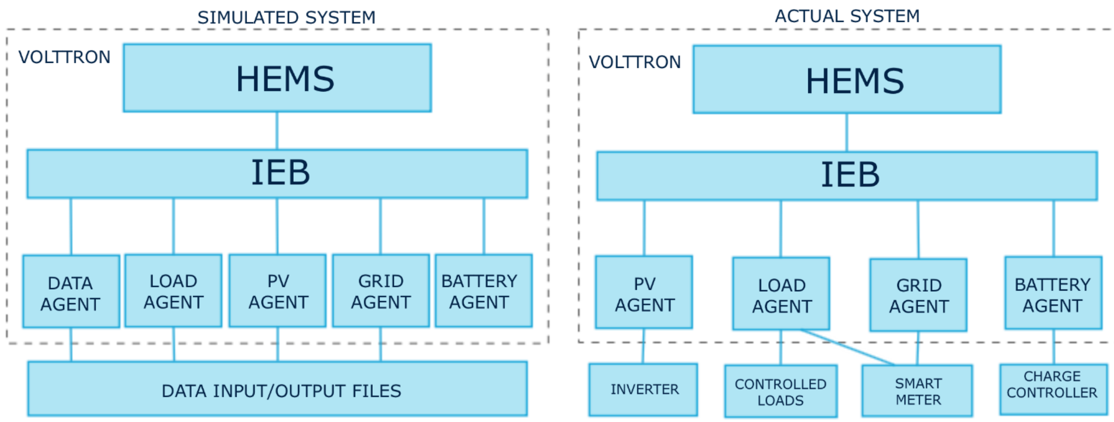

Figure 1. Simulated and Actual System Comparison.

3.4 Simulation Parameters

Several simulations are conducted to examine the efficacy of the agent structure and control logic under different situations and to compare results with those already found in literature. Each agent shares usage of a settings file where case study parameters are specified and dispatch strategies can be altered and implemented.

3.4.1 Static Simulation Parameters

Table 2 provides a summary of the static parameters the agents in VOLTTRON employ throughout all simulation runs. The HEMS is intended to exploit these parameters and maximize their overall effectiveness or, in the case of demand charges, reduce their effects. The size of the PV array is intended to produce a net-zero annual load (e.g. NZEB-site). Demand charges in Austin, TX range between \$5.15/kW in the winter and \$6.15/kW in the summer (Austin Energy). For simplicity in simulation, demand charges remain constant throughout the year at \$6.00/kW.

Table 2: Constant Parameters.

Parameter	PV array size (kW)	Utility Credit ($)	Demand Charge ($/kW)
Value	21	TOU Rate	6.00

3.4.2 Battery Dispatch Strategies

To model different scenarios for how to best implement energy storage, four dispatch strategies are implemented as shown in Table 3. Simulations are ran during first week, starting with the first Sunday, of January, April, July, and October to utilize profiles in all four seasons. During each season, a reference simulation is run that does not implement any kind of battery storage and relies exclusively on solar PV power to reduce energy usage. For comparison, simulations for 3 different battery sizes are ran as well. Battery sizes include a 26 kWh, 13 kWh, and a 6.5 kWh battery capable of meeting 100%, 50% and 25% annual peak load respectively for one hour.

Table 3. Dispatch Strategies Summary.

CASE	**Charging Strategy**	**Discharging Strategy**
BASE	None	None
1A	Grid and Solar PV	TOU Peak time
1B	Grid and Solar PV	Peak Shaving
2A	Solar PV Only	TOU Peak time
2B	Solar PV Only	Peak Shaving

The main objective of these strategies is to optimize allocation of renewable resources using a battery and to reduce overall user cost. Reducing cost is measured in terms of (1) reducing energy usage during peak hours and (2) reducing demand charges. Dispatch strategies are optimized by strategically controlling how a battery is charged and discharged. The strategies implemented in this study are given below:

- Charging Strategies: The battery charge controller is configured to provide two options for charging the battery. These options include charging exclusively from solar PV and charging from both solar PV and the grid. Charging from the grid is constrained to occur between the hours of 7:00 PM and 5:00 AM when solar PV is least likely to be available. The charging rate of the battery when charging from the grid is such that the battery can be charged to 80% of its total capacity in 10 hours (~.056C). The remaining 20% of available capacity is charged via PV power if available.
- Discharging Strategies: the battery is discharged in one of two ways, it is (1) allowed to discharge at any rate during TOU peak hours of the day and (2) only allowed to discharge when power consumption exceeds a certain level. Option (1) is intended to focus mainly on reducing overall cost while option (2) is intended to shave off peak loads and reduce demand charges. Option (2) utilizes a rolling consumption limit based on the cumulative distribution function for each month of the year. The limit is set such that the battery will discharge for the top 25% of peak loads in that month. For reference, cumulative distribution and probability density functions for each month are given in appendix A. When the net energy

usage after solar PV is utilized exceeds this limit, the battery is allowed to discharge at a rate that will bring the energy usage down to that limit.

3.4.3 Evaluation

Control algorithm efficacy is evaluated using several technical and economic merits: energy cost reduction, peak load reduction, load factor increase, and load curtailment, versus the reference case.

- <u>Energy Cost Reduction</u>: Evaluated in terms of the percent savings over the course of one year and during a one week time frame in each season
- <u>Peak Load Reduction:</u> Evaluated in terms of the difference between the reference peak load and the new peak load along with the percent reduction in peak load
- <u>Load Factor Increase:</u> Evaluated as the ratio of the average load over the peak load
- <u>Load Curtailment:</u> Evaluated in terms of the reduction of instantaneous power consumption every minute and total reduction of energy over one week and one year
- <u>Reference Case:</u> Evaluated as the net load when load curtailment only occurs as a result of PV power

Chapter 4. Results and Analysis

4.1 Reference Profiles

Figure 2 shows load and solar PV profiles of the case study household over the course of one year with data resolution of every day. Figure 2 also shows the rate profile over the course of one year using a 50% rate increase during On-Peak hours. In summer months there is significantly more load than during winter months. It can also be observed that there is more available solar PV during the summer than during the winter.

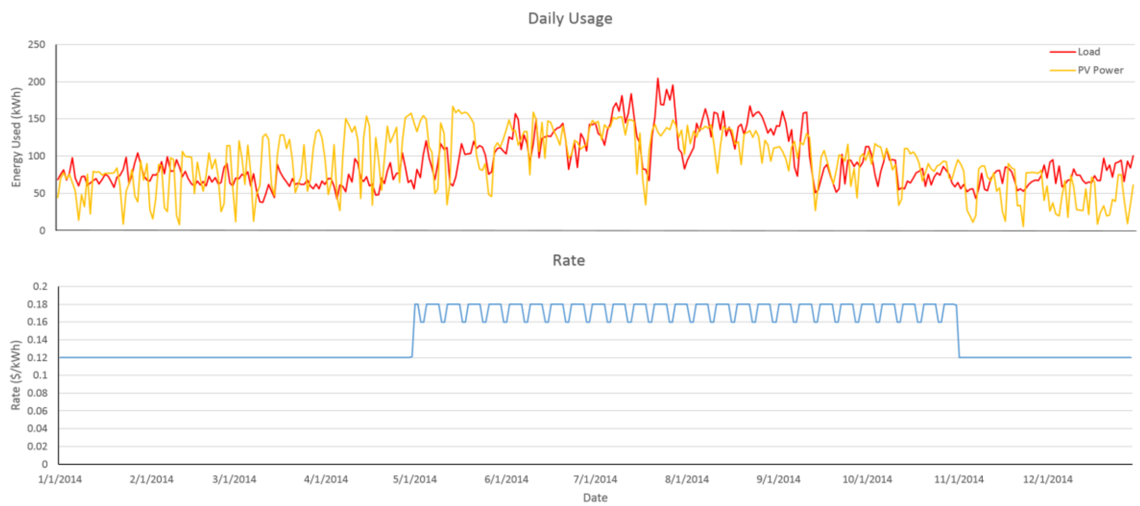

Figure 2. Annual Load and PV (top) and Rate Profile (bottom).

Table 4 gives the total energy used, average load, and total solar PV energy provided over the entire year. Energy use charges ($/kWh) and demand charges ($/kW) are also shown for a reference case without solar PV or batteries. The PV array size is sized to meet the annual energy requirements of the house. In this case, energy usage costs are negative but demand charges are not sufficiently reduced, as expected, because the load and solar profiles do not match exactly.

Table 4. Case Study Annual Load and Cost Summary.

Energy usage (kWh)	**PV Energy (kWh)**	**Average Load (kW)**	**Peak Load (kW)**	**Load Factor**	**Cost ($)**	**Demand Charges ($)**	**Total ($)**
33351.3	33359.48	3.81	26.39	0.14	-256.89	1041.44	610.98

Demand Charges are calculated based on the average energy usage over a 15-minute interval. Figure 3 provides a comparison between the load every minute and the load used for demand charges. In this example, the demand charge would be based off the 12.78 kW average load occurring between 5:00 PM and 5:15 PM.

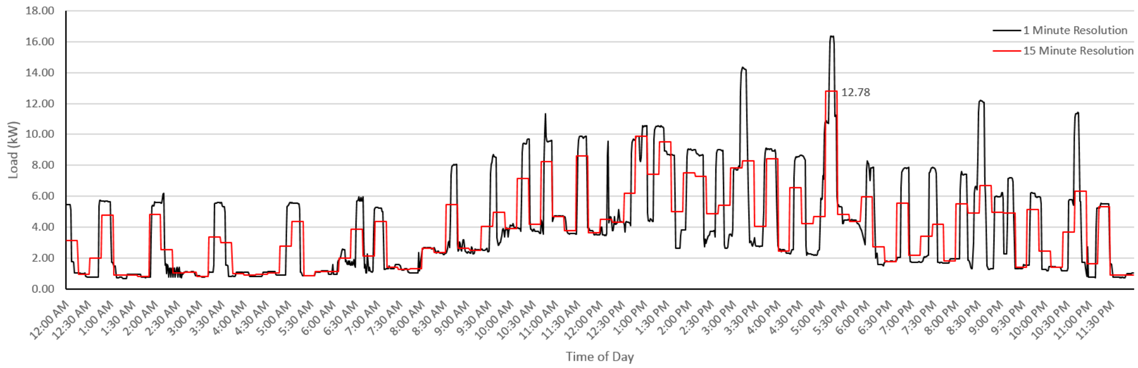

Figure 3. Load Profile at Different Time Resolutions.

4.3 Battery Dispatch Strategy Optimization Analysis

Appendix B provides figures for all dispatch strategies implemented. Table 5 provides a summary of the loads, costs, and demand charges for each season without renewables or battery implementation. Figure 4 provides examples of the load and PV profile for each week in each season. From Table 5, it is apparent that loads, consumption costs, and demand charges are higher during the summer than during other months. Demand charges take up a larger portion of the total cost during non-summer months.

Table 5. Loads and Costs without Renewables or Battery Storage.

Season	Load	Peak Load	Load Factor	Usage Cost	Demand Charge	Total Cost
Winter	510.91	63.80	0.29	61.31	63.80	125.11
Spring	500.41	95.87	0.19	60.05	95.87	155.92
Summer	1122.47	131.30	0.31	206.90	131.30	338.20
Autumn	621.27	72.57	0.26	114.93	87.13	202.06

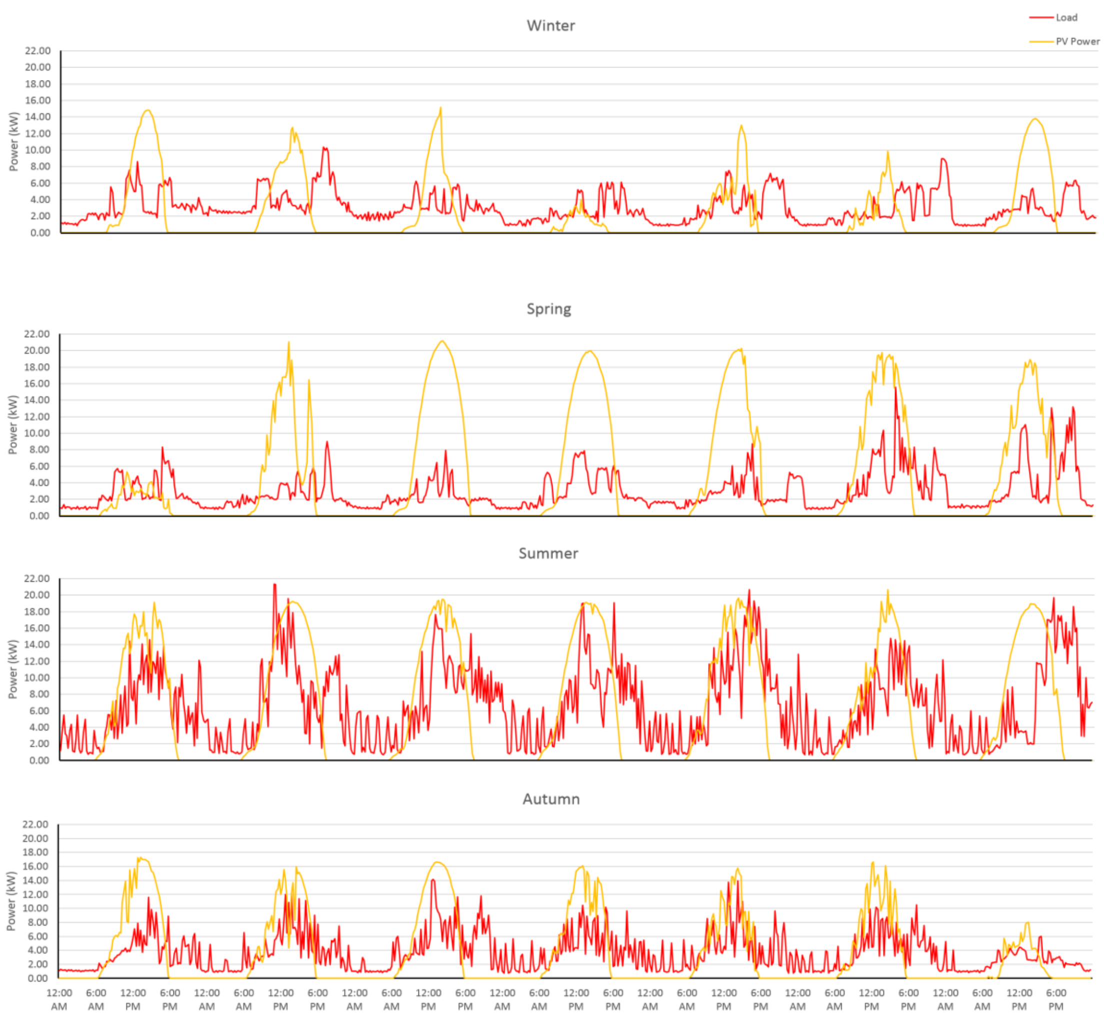

Figure 4. Weekly Profiles at 15-minute Resolution.

Appendix C contains a summary of dispatch strategies implemented in each season for each battery size.

Table 6 provides a summary of the strategies for each season, with the dispatch strategy listed (e.g., 2B) that resulted in the lowest demand charges. In nearly all cases, peak shaving strategies produced the lowest demand charge. The exception occurs during the summer with a battery size of 6.5 kWh. In this instance, there was very little reduction in demand charges for all dispatch strategies because the battery is undersized. Larger storage resulted in increased demand charge reduction and reduced total costs.

Table 6. Cost and Demand Charge Summaries.

Battery Size (kWh)	**Season**	**Dispatch Strategy**	**Peak Load (kW)**	**Load Factor**	**Usage Cost ($)**	**Demand Charge ($)**	**Total Cost ($)**
-	Winter	BASE	10.37	0.09	18.02	63.80	81.82
-	Spring	BASE	13.18	-0.14	-36.99	81.06	44.07
-	Summer	BASE	18.63	0.03	8.74	114.58	123.33
-	Autumn	BASE	11.80	0.00	-5.59	72.57	66.98
26	Winter	1B	4.12	0.22	18.60	25.34	43.94
26	Spring	1B	7.81	-0.24	-37.69	48.03	10.34
26	Summer	1B	11.81	0.05	7.64	72.66	80.30
26	Autumn	1B	9.67	0.01	-4.42	59.46	55.04
13	Winter	2B	7.38	0.12	18.21	45.40	63.60
13	Spring	2B	12.57	-0.15	-37.65	77.33	39.69
13	Summer	1B	18.63	0.03	6.73	114.58	121.31
13	Autumn	2B	6.87	0.01	-3.98	42.27	38.29
6.5	Winter	2B	10.26	0.09	17.94	63.09	81.03
6.5	Spring	2B	13.18	-0.14	-37.21	81.06	43.85
6.5	Summer	1A	18.63	0.03	6.30	114.58	120.88
6.5	Autumn	1B	9.67	0.00	-5.01	59.46	54.44

Figure 5 shows the load, net load, PV energy, and net rates when applying battery dispatch strategies throughout the entire year. The annual simulation uses a 26 kWh battery and dispatch strategy 1B. Net loads and associated net rates are consistently lower throughout the year and rates with energy credit available are consistently lower than rates when energy crediting is unavailable.

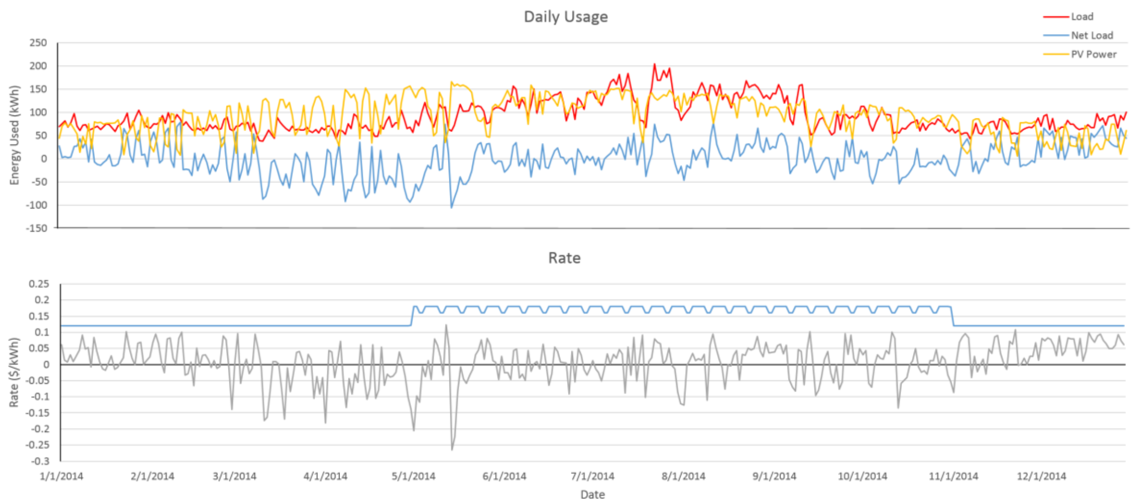

Figure 5. Net Load Profile with Dispatch Strategies.

Table 7 and Table 8 provide summaries of the Load and Cost characteristics for the entire year using dispatch strategy 1B and a 26 kWh Battery. It is observed that there is an increase in overall usage and usage costs but a reduction in peak loads and demand charges. Total cost is $310.36 less when using dispatch strategies.

Table 7. Annual Net Usage Summary.

Dispatch Strategy	Net Usage (kWh)	Net Average Load (kW)	Net Peak Load (kW)	Net Load Factor
BASE	-9.11	0.00	22.06	0.00
1B	163.16	0.02	17.82	0.00

Table 8. Annual Net Cost Summary ($).

Dispatch Strategy	Usage Cost ($)	Bought ($)	Credit ($)	Max Demand Charge ($)	Total Demand Charge ($)	Total Cost ($)
Base	-218.73	2409.09	2627.81	135.64	1067.66	848.94
1B	-197.96	2280.28	2478.24	109.60	736.54	538.58

Chapter 5. Discussion and Conclusion

The analysis performed in this study demonstrated the efficacy of various dispatch strategies at managing household generation, storage, and use to reduce energy charges associated to consumption ($/kWh) and demand ($/kW). VOLTTRON was implemented in a real-time simulation environment to test dispatch strategies for total load reduction and peak shaving. Simulations were performed using VOLTTRON to model four dispatch strategies against a base case (no storage and no intelligent control). These dispatch strategies were run annually with three battery sizes with specific data drawn from a one-week period in each of the four seasons in a year for a case study household in Texas.

The simulations showed that without adequate battery storage, the implementation of advanced dispatch strategies has minimal effect on reducing total energy costs to the user. Stated differently, increased storage capacity supported by algorithms that intelligently charge and discharge storage to reduce TOU net load and shave peak demand periods reduce total energy cost. The optimal size of the PV array and battery storage system is dependent on the electricity rate structure and the costs of installing and operating the solar-storage system; this is planned for future work.

When total installed storage capacity was low, dispatch strategies were found to have only a minor effect on reducing demand charges when compared to the base case. In most dispatch scenarios, particularly those with reoccurring load peaks, the battery reserve was exhausted before all the peak loads were reduced. Since Demand charges are applied to the highest demand period during any singular 15-minute interval in a month, peak shaving efforts are only effective if all intra-day peak loads in a month are similarly reduced below a specified value (e.g., 12 kW). This is a challenging task because peak load values increase (or decrease) during a month and hence require a priori knowledge of potential peaks in the entire month through historical datasets, forecasting, or learning algorithms to adjust demand charge targets (e.g., 12 kW) as loads increase (or decrease). In this study, monthly peak shave targets were set using complete information of upcoming peaks, and battery was dispatched during *any* 15-minute load period that would be in excess of 75% of the monthly peak load, meaning that all loads were, at most, 25% lower than the peak load for the month. This peak shaving target was updated monthly. The demand reduction is more pronounced when larger solar-storage systems are used because the storage is better able to handle all the peak loads that may occur throughout the month.

When evaluated over an entire year, dispatch strategies play a significant role in reducing demand charges. Although some dispatch strategies that charge from the grid during off-peak hours may increase energy usage costs, these costs can be outweighed by effective arbitrage use and demand charge reduction strategies. The benefits of a large storage system are greater if demand charge rates are higher.

Weekly load factors under each battery size and dispatch strategy were found to have a marginal affect when compared to the base case, and this affect varied based upon time of year. To effectively increase load factors, the household energy management system should use solar PV to charge the battery and then discharge the battery in early evenings to reduce peak demand. Power factor will be another performance metric considered in future work with existing results synthesized over the entire year to offer comparison of PV size, battery size, and dispatch strategy across the typical year as seasons change.

Future work will also use other features of VOLTTRON such as load scheduling and device actuation (i.e., demand response). The next phase of work will deploy control technics in the simulated environment to a physical environment in a demonstration home. Eventually, this work will lead to handling loads across multiple homes within a neighborhood or microgrid network. VOLTTRON will manage which loads are on at any given time to ensure more a more even and predictable load profile and collectively reduce user costs.

References

Akyol, B., Haack, J., Ciraci, S., Carpenter, B., Vlachopolou, M., & Tews, C. (2012). VOLTTRON: An Agent Execution Platform for the Electric Power System. *ATES*.

Austin Energy. (n.d.). *Commercial Electric Rates and Line Items.* Retrieved April 24, 2015, from www.austinenergy.com: http://www.austinenergy.com/wps/portal/ae/commercial/rates/

Bauzid, A. M., Guerrero, J. M., Cheriti, A., Bouhamida, M., Sicard, P., & Benghanem, M. (2015). A survey on control of electric power distributed generation systems for microgrid applications. *Renewable and Sustainable Energy Reviews*, 751-756.

Beaudin, M., Zareipour, H., Schellenberg, A., & Rosehart, W. (2015). Energy Storage for Mitigating the Variability of Renewable Electricity Sources. In *Energy Storage for Smart Grids* (pp. 1-33). Calgary: Elsevier.

Cawley, D., Pless, S., & Torcellini, P. (2009). Getting to Net Zero. *ASHRAE Journal*, 18-25.

Cazelet, E. G. (2014). Transactive Energy: Interoperable Transactive Retail Tariffs. In F. P. Sioshansi (Ed.), *Distributed Generation and its Implications for the Utility Industry* (pp. 205-229). San Diego, CA: Academic Press.

Cox, W., & Considine, T. (2013). Structured energy: Microgrids and autonomous transactive operation. *2013 IEEE PES Innovative Smart Grid Technologies Conference.*

Deng, S., Wang, R. Z., & Dai, Y. J. (2014). How to evaluate performance of net zero energy building - A literature research. *Energy*, 1-16.

Ellabban, O., Abu-Rub, H., & Blaabjerg, F. (2014). Renewable energy resources: Current status, future prospects and their enabling technology. *Renewable and Sustainable Energy Reviews*, 748-764.

European Union. (2010). Directive 2010/31/EU of the European Parliament and of the Council of 19 May 2010 on the energy performance of buildings. *Official Journal of the European Union*, 13-35.

Figueiredo, J., & Sa da Costa, J. (2012). A SCADA system for energy management in intelligent buildings. *Energy and Buildings*, *49*, 85-98.

GTM Research/SEIA U.S. Solar Market Insight. (2014). *U.S. Solar Market Insight Report: 2014 Year in Review*. GTM Research and SEIA.

Haack, J., Akyol, B., Tenney, N., Carpenter, B., Pratt, R., & Carroll, T. (2013). VOLTTRON: An Agent Platform for the Smart Grid. *International Conference of Connected Vehicles and Expo* (pp. 1367-1368). IEEE.

Hledik, R. (2014). Rediscovering Residential Demand Charges. *The Electricity Journal*, 82-96.

IEA. (2014). *2014 Key World Energy Statistics.*

Johnson, N., Lilienthal, P., & Shoechle, T. (2011). Modeling distributed premises-based renewables integration using HOMER. *Proceedings of 2011 Grid-Interop Conference.* Phoenix, AZ.

Koohi-Kamali, S., Tyagi, V. V., Rahim, N. A., Panwar, N. L., & Mokhlis, H. (2013). Emergence of energy storage technologies as the solution for reliable operation of smart power systems: A review. *Renewable and Sustainable Energy Reviews*, 135-165.

Kylili, A., & Fokaides, P. A. (2015). European Smart Cities: The role of zero energy buildings. *Sustainable Cities and Society*, 86-95.

Lagorse, J., Paire, D., & Miraoui, A. (2010). A mulit-agent system for energy management of distributed power sources. *Renewable Energy, 35*(1), 174-182.

Lockemann, P. C. (2006). Agents. In S. Kirn, O. Herzog, P. Lockemann, & O. Spaniol (Eds.), *Multiagent Engineering, Theories and Applications* (pp. 17-33). Berlin: Springer.

Lockemann, P. C., Kirn, S., & Herzog, O. (2006). Management Summary. In S. Kirn, O. Herzog, P. Lockemann, & O. Spaniol (Eds.), *Multiagent Engineering, Theory and Applications in Enterprises* (pp. 1-13). Berlin: Springer.

Mehta, B., & Reddy, Y. (2015). SCADA Systems. In *Industrial Process Automation Systems* (pp. 237-300). Elsevier.

Nan, C., Eusgeld, I., & Kroger, W. (2013). Analyzing vulnerabilities between SCADA system and SUC due to interdependencies. *Reliability Engineering & System Safety*, 76-93.

Nottrott, A., Kleissl, J., & Washom, B. (2013). Energy dispactch schedule optimization and cost benefit analysis for grid-connected, photovoltaic-battery storage systems. *Renewable energy, 55*, 230-240.

Olivares, D., Canizares, C., & Kazerani, M. (2011). A Centralized Optimal energy Management System for Microgrids. *IEEE Power and Energy Society General Meeting.*

Pacific Northwest National Laboratory. (2014). VOLTTRON 2.0: User Guide. Springfield, VA: U.S. Department of Commerce.

Pecan Street Inc. (2014). *Pecan Street*. Retrieved from www.pecanstreet.org: http://www.pecanstreet.org

Pepermans, G., Driesen, J., Haeseldonckx, D., Belmans, R., & D'haeseleer, W. (2005). Distributed generation: definition, benefits and issues. *Energy Policy*, 787-798.

Rahimi, F. A., & Ipakchi, A. (2012). Transactive Energy Techniques: Closing the Gap between Wholesale and Retail Markets. *The Electricity Journal*, 29-35.

Ratnam, E. L., Weller, S. R., & Kellett, C. M. (2015). An optimization-based approach to scheduling residential battery storage with solar PV: Assessing customer benefit. *Renewable Energy, 75*, 123-134.

Schoenung, S. M. (2001). *Characteristics and Technologies for Long-vs. Short-Term Energy Storage.* Albuquerque: Sandia National Laboratories.

Torcellini, P., Pless, S., Deru, M., & Crawley, D. (2006). Zero Energy Buildings: A Critical Look at the Definition. *ACEEE Summer Study*, (p. 15). Pacific Grove, CA.

U.S. Energy Information Association. (2015). *Annual Energy Outlook 2015.* Washington D.C.: U.S. Energy Information Association.

Yalcintas, M., & Kaya, A. (2009). Conservation vs. renewable energy: Cases studies from Hawaii. *Energy Policy*, 3268-3273.

Yoo, C.-H., Chung, I.-Y., Lee, H.-J., & Hong, S.-S. (2013). Intelligent Control of Battery energy Storage for Multi-Agent Based Microgrid Energy Management. *energies*, *6*, 4956-4979.

Yoshino, A. (2014). Development of the Lithium-Ion Battery and Recent Technological Trends. In G. Pistoia (Ed.), *Lithium-Ion Batteries Advances and Applications* (pp. 1-20). Amsterdam: Elsevier.

APPENDIX A

MONTHLY NORMAL AND CUMULATIVE DISTRIBUTION PLOTS

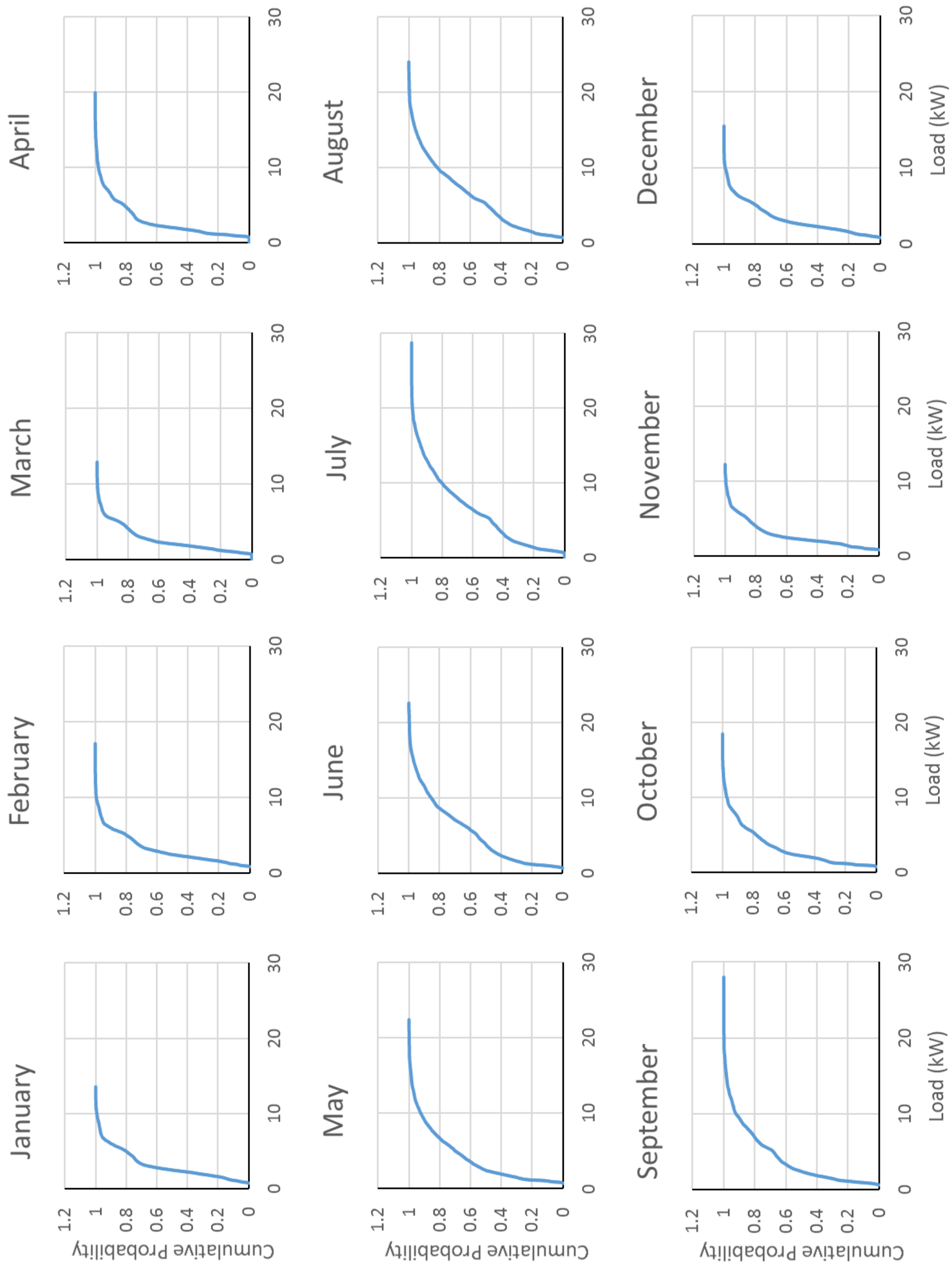

Figure A. Monthly Cumulative Distribution Functions

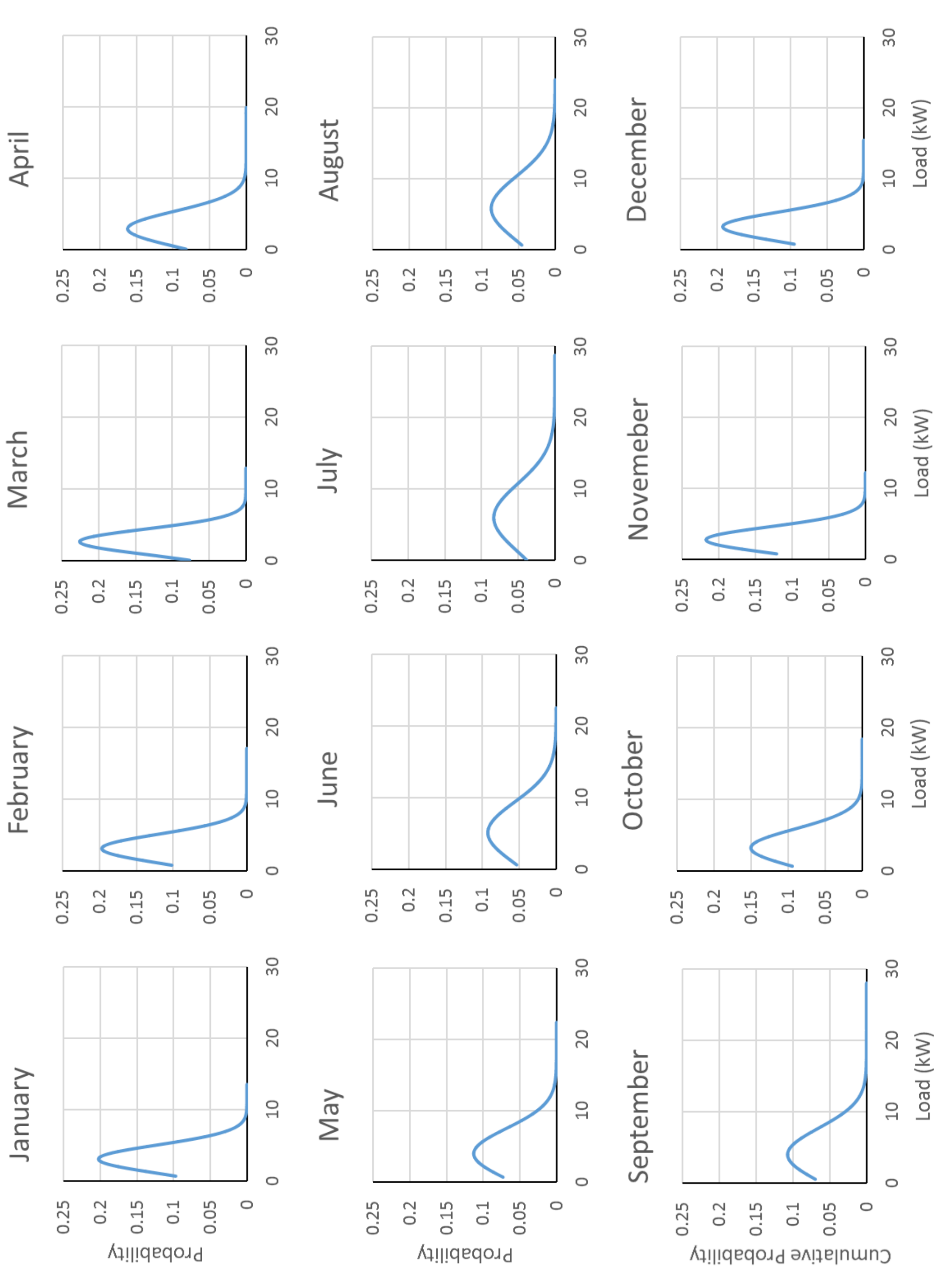

Figure B. Monthly Probability Density Functions

APPENDIX B

OUTPUT FROM WEEK-LONG DISPATCH STRATEGY SIMULATIONS

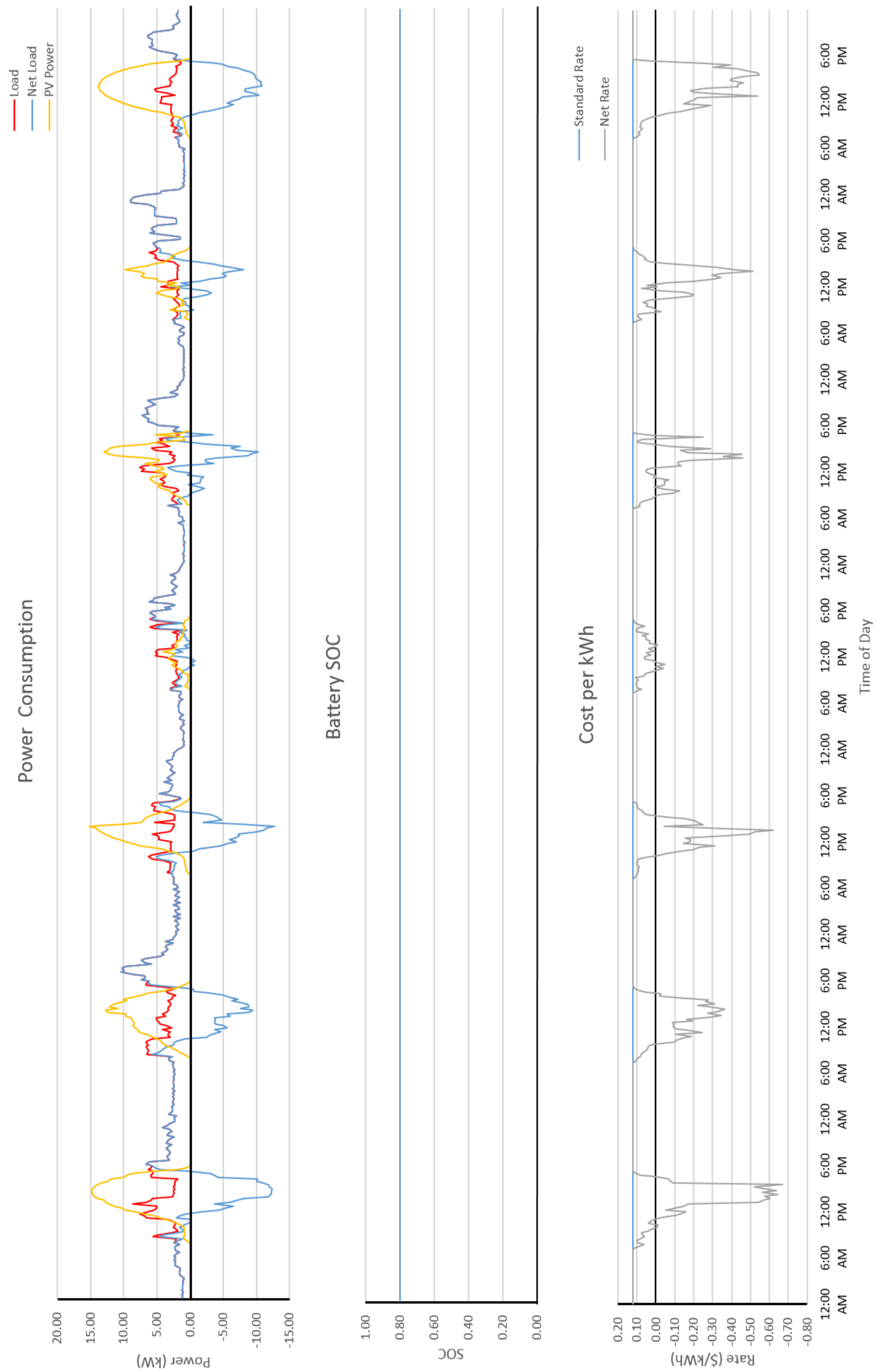

Figure B.1. Winter – Base

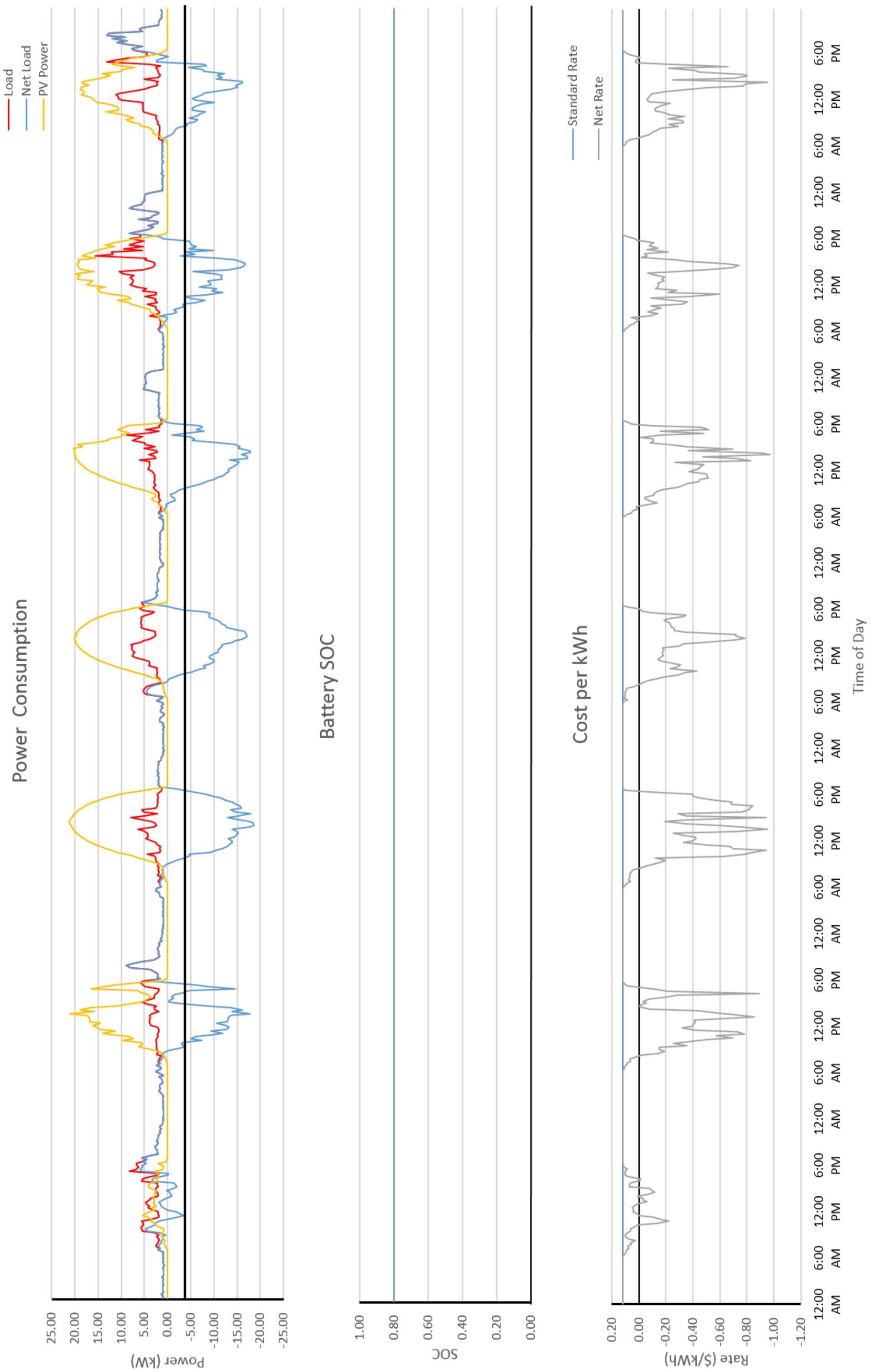

Figure B.2. Spring – Base

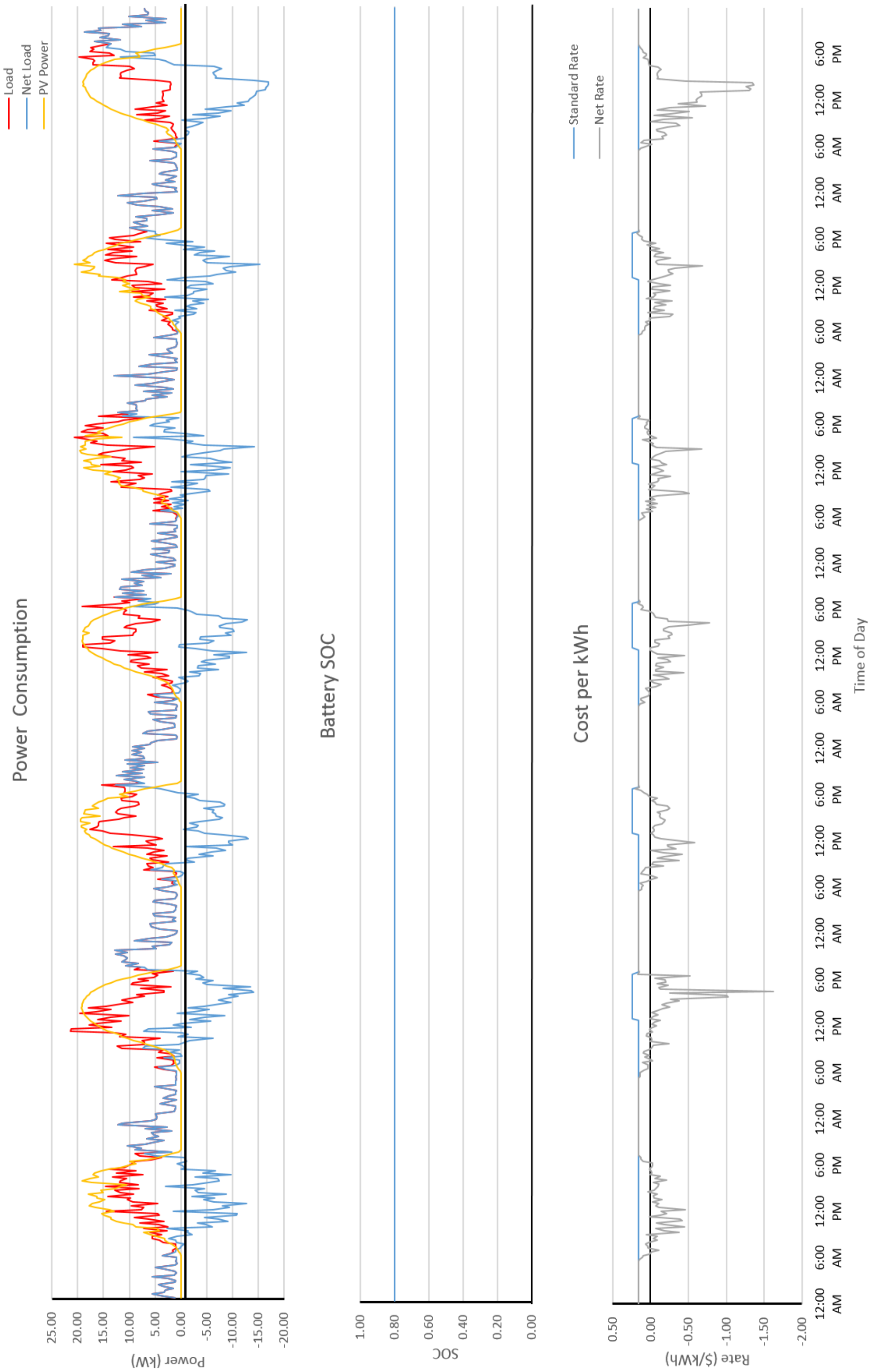

Figure B.3. Summer – Base

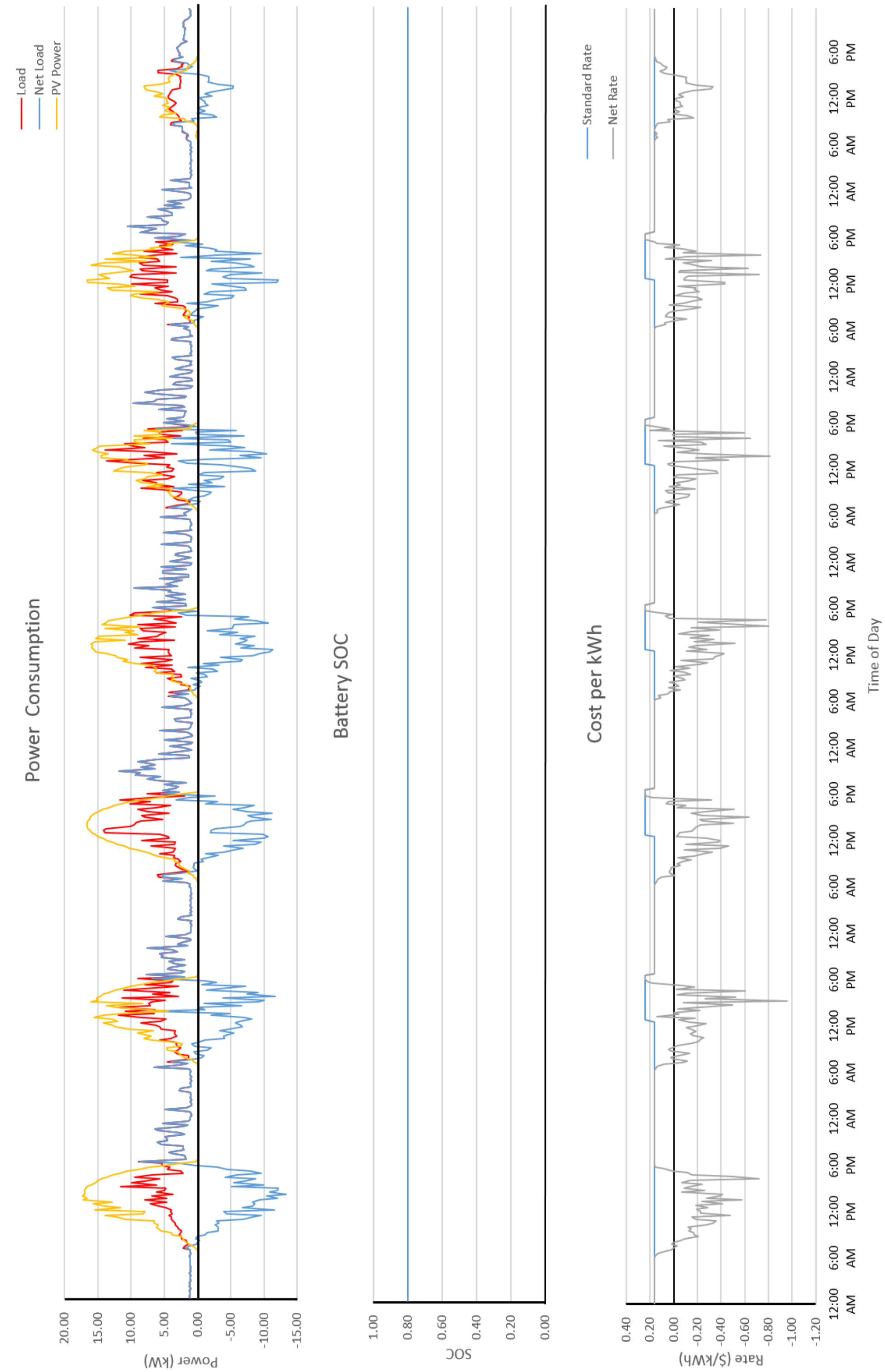

Figure B.4 Autumn – Base

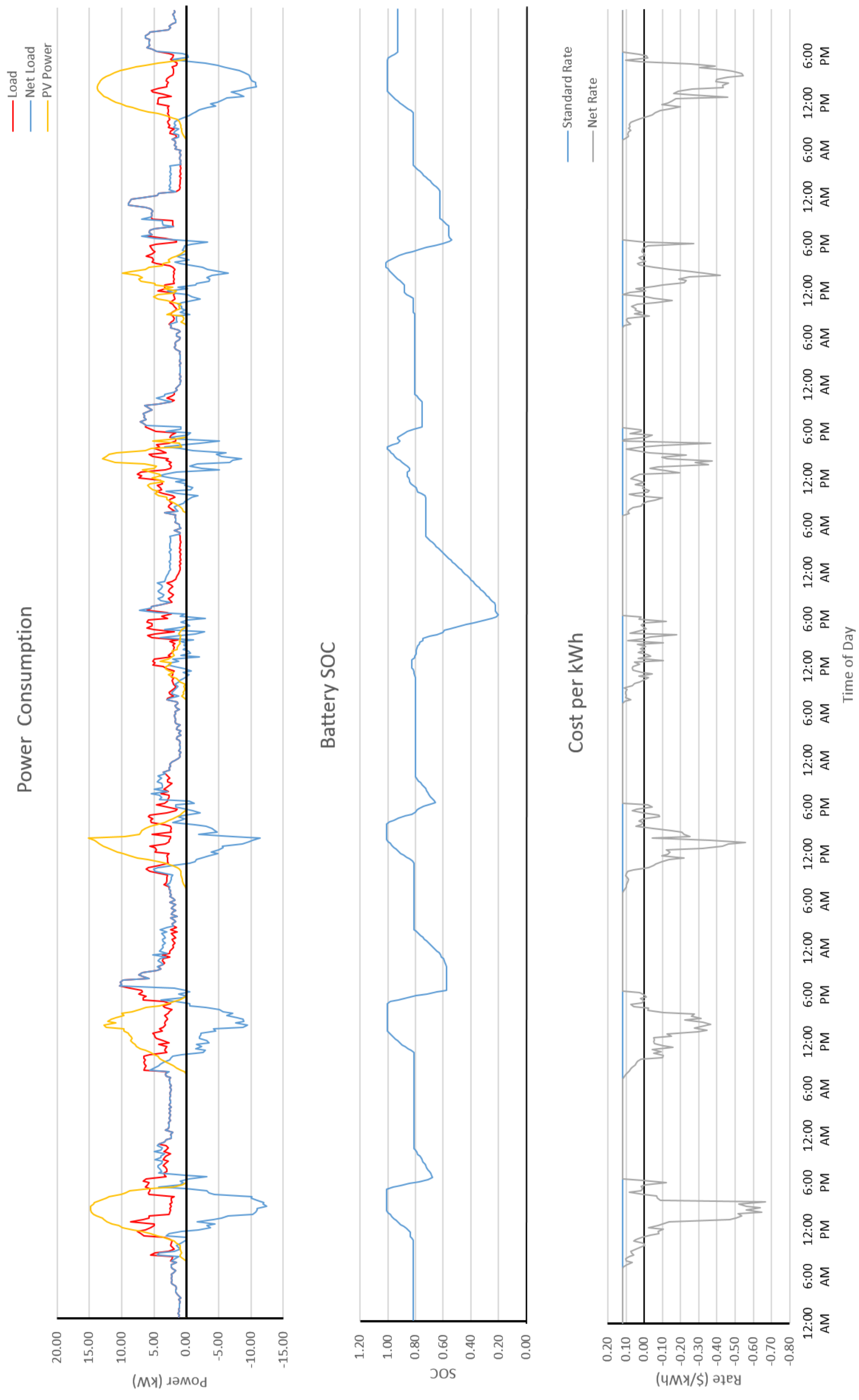

Figure B.5. Winter – 1A – 26 kWh Battery

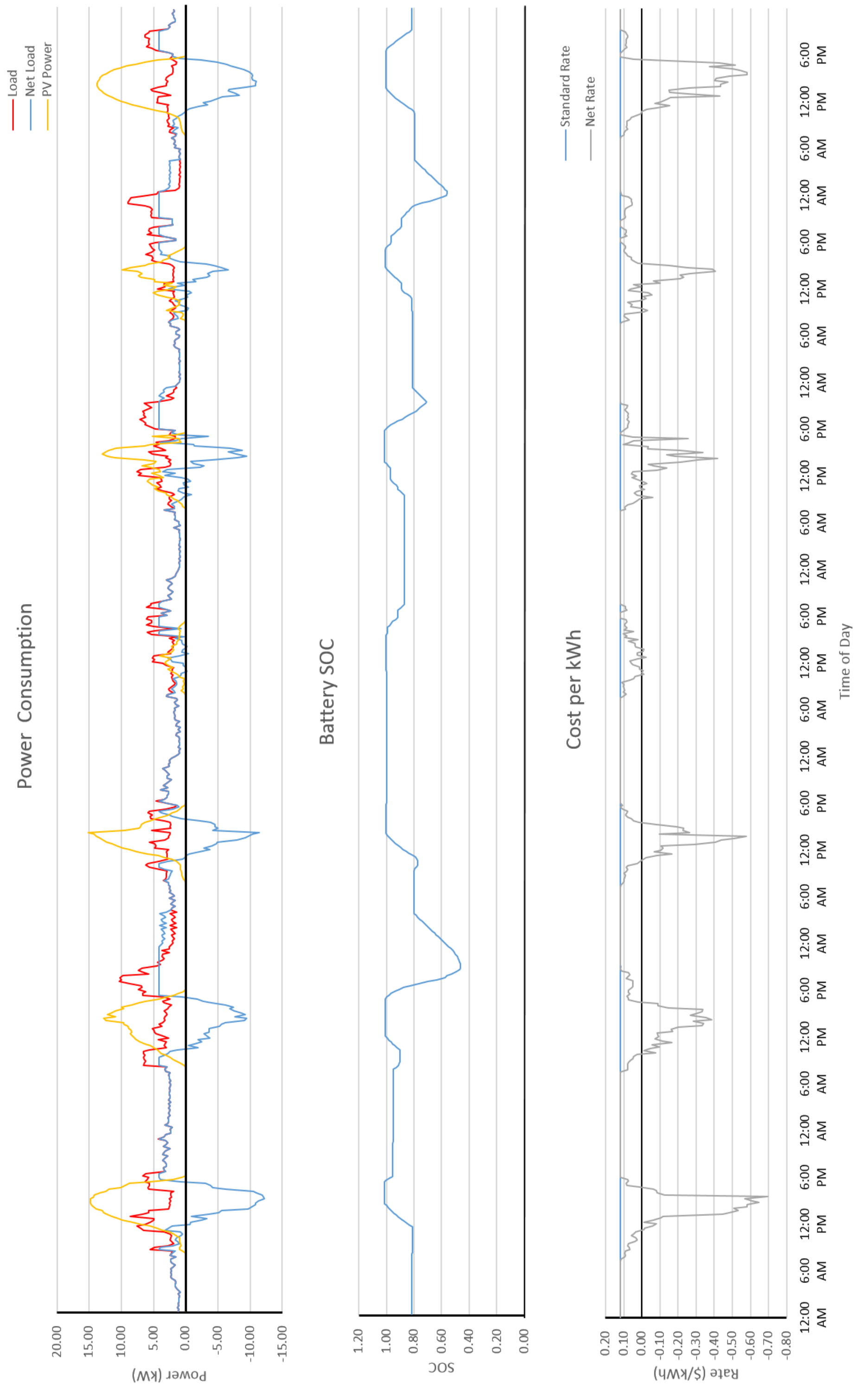

Figure B.6. Winter – 1B – 26 kWh Battery

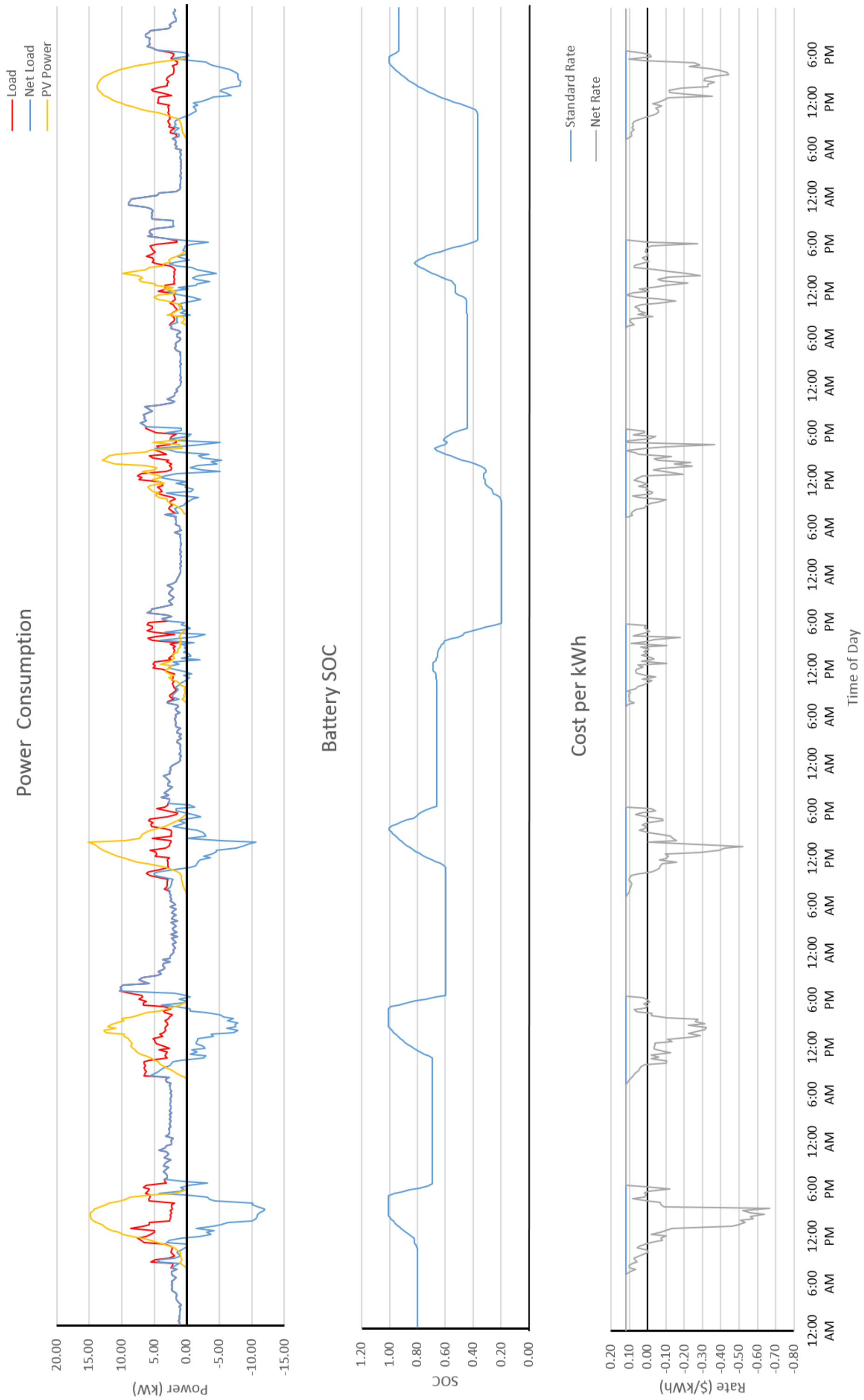

Figure B.7. Winter – 2A – 26 kWh Battery

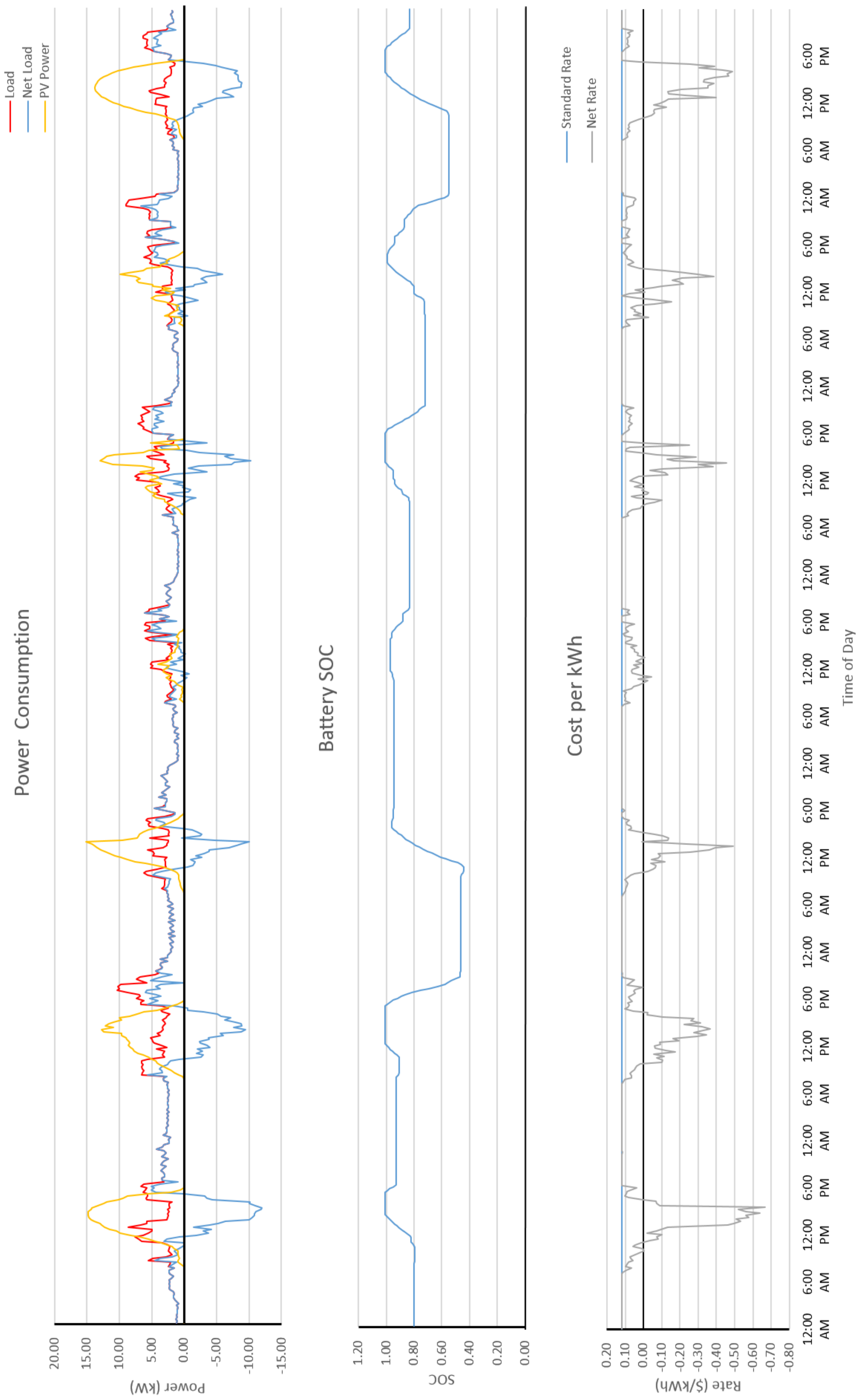

Figure B.8. Winter – 2B – 26 kWh Battery

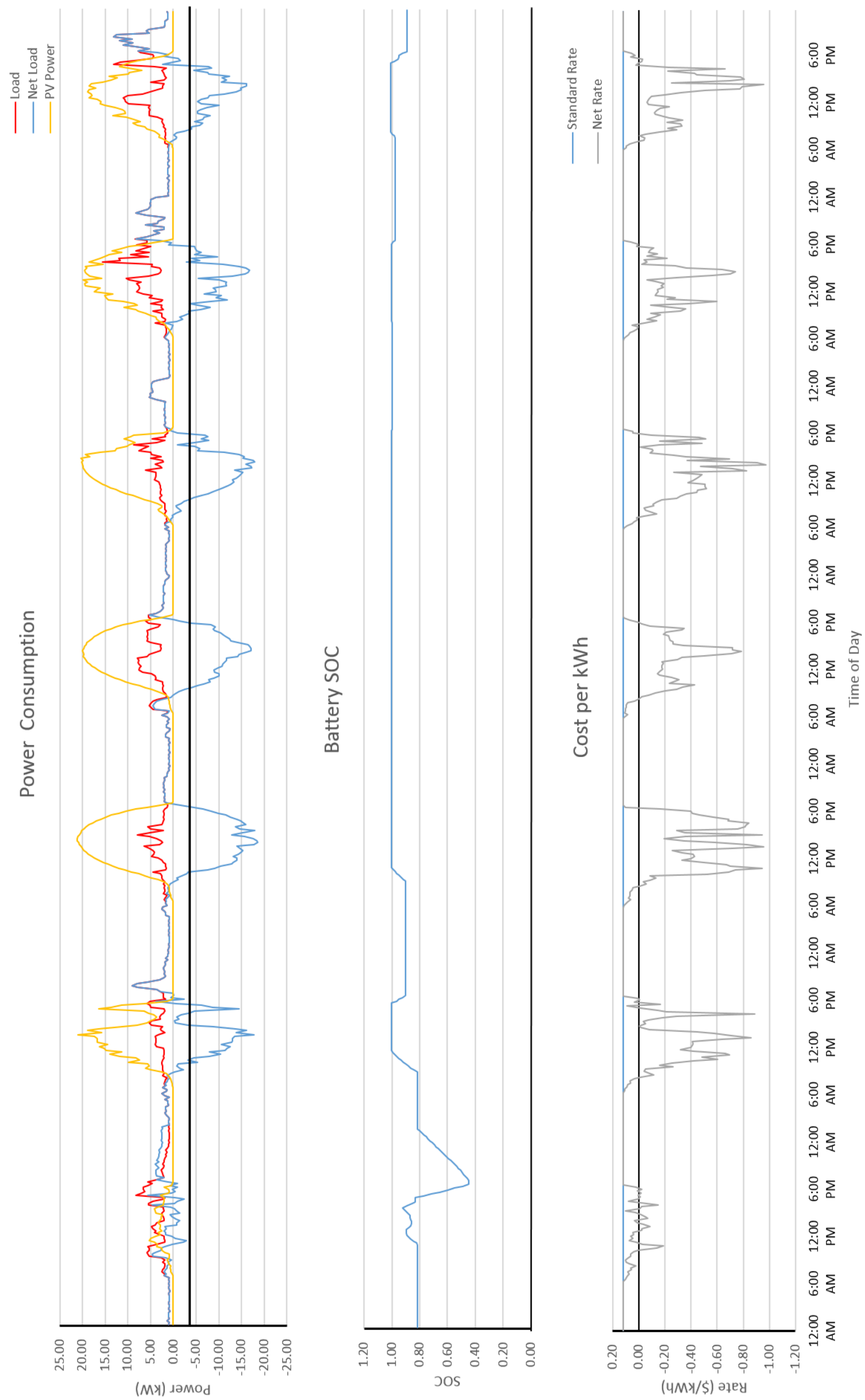

Figure B.9. Spring – 1A – 26 kWh Battery

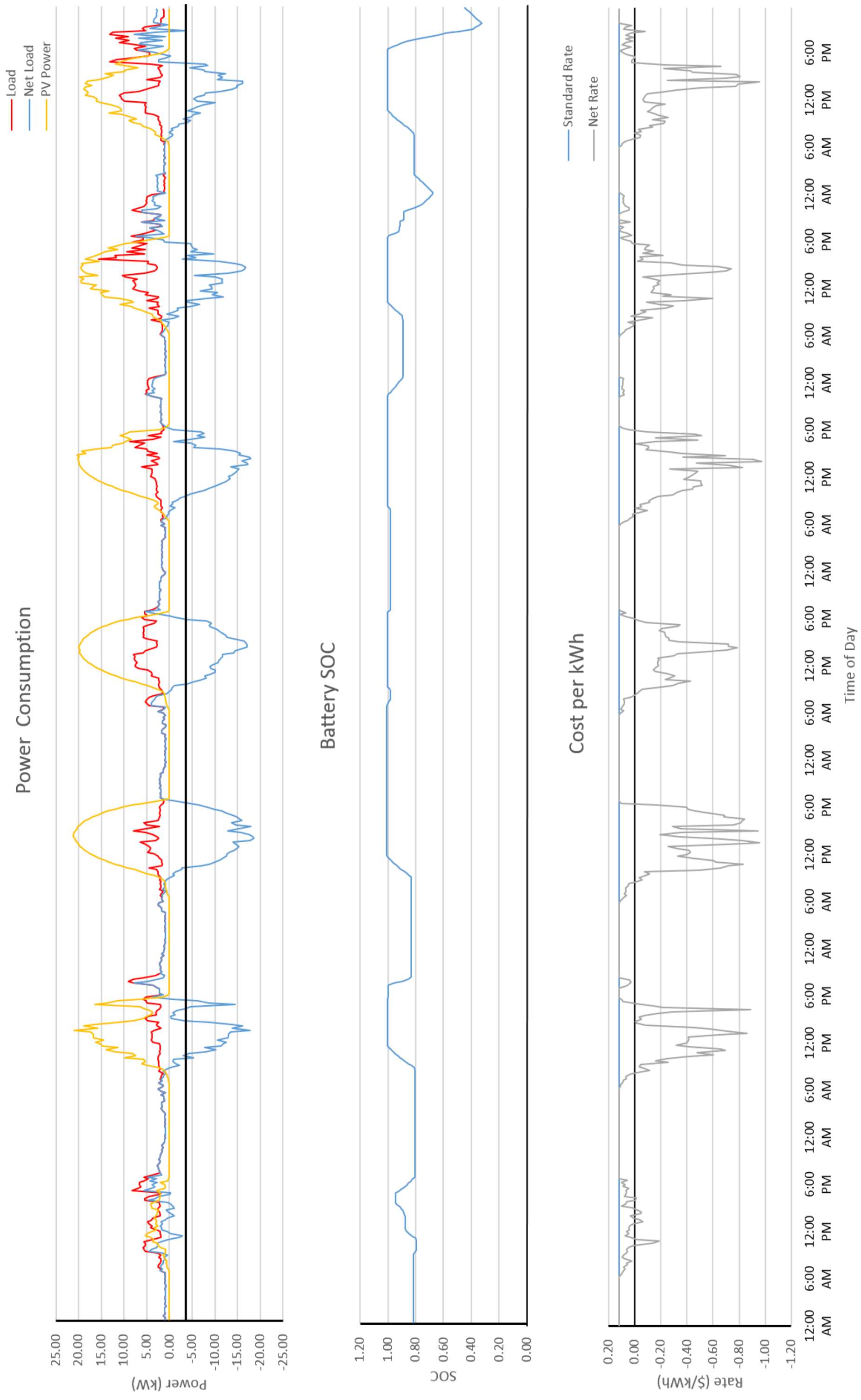

Figure B.10. Spring – 1B – 26 kWh Battery

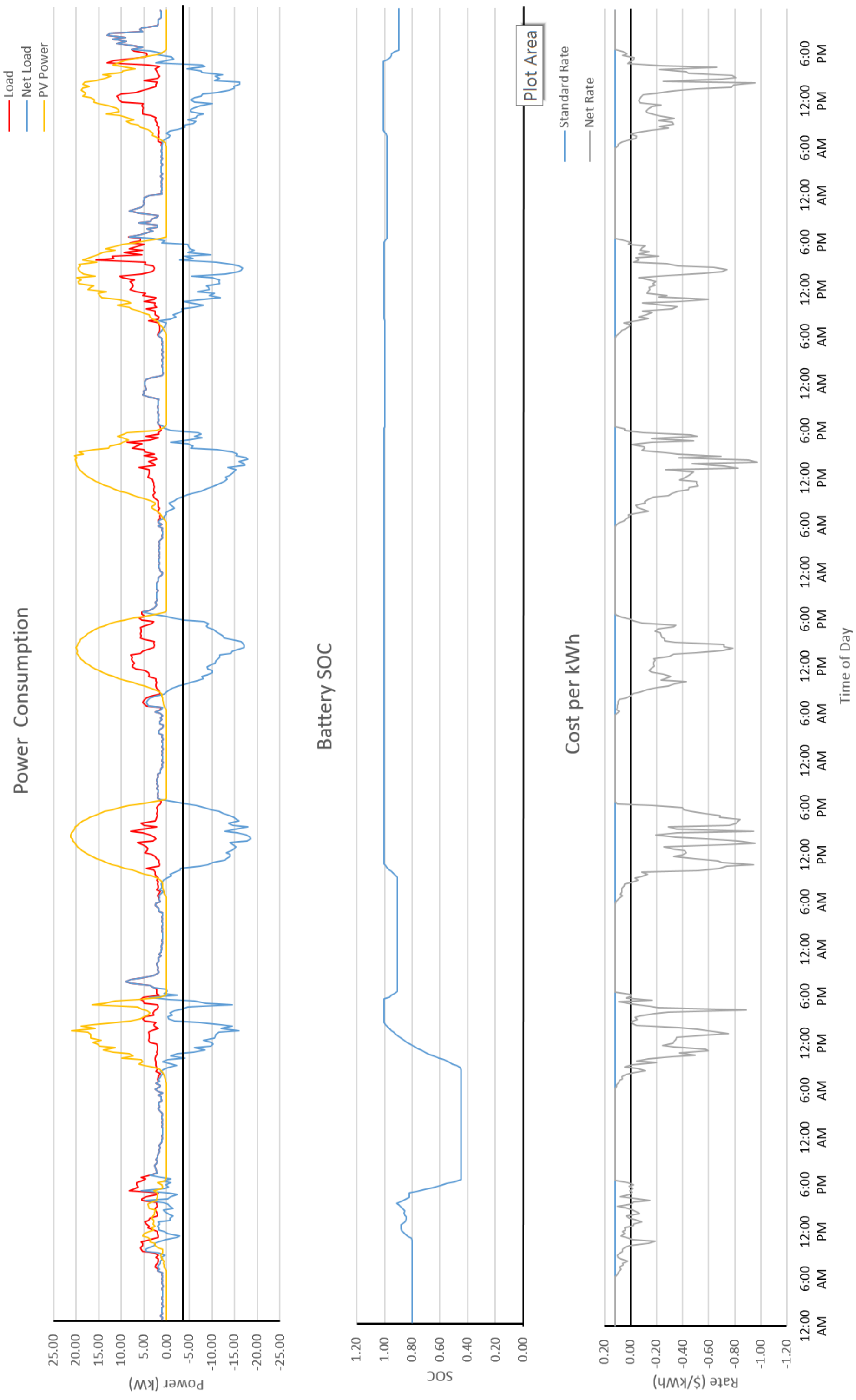

Figure B.11. Spring – 2A – 26 kWh Battery

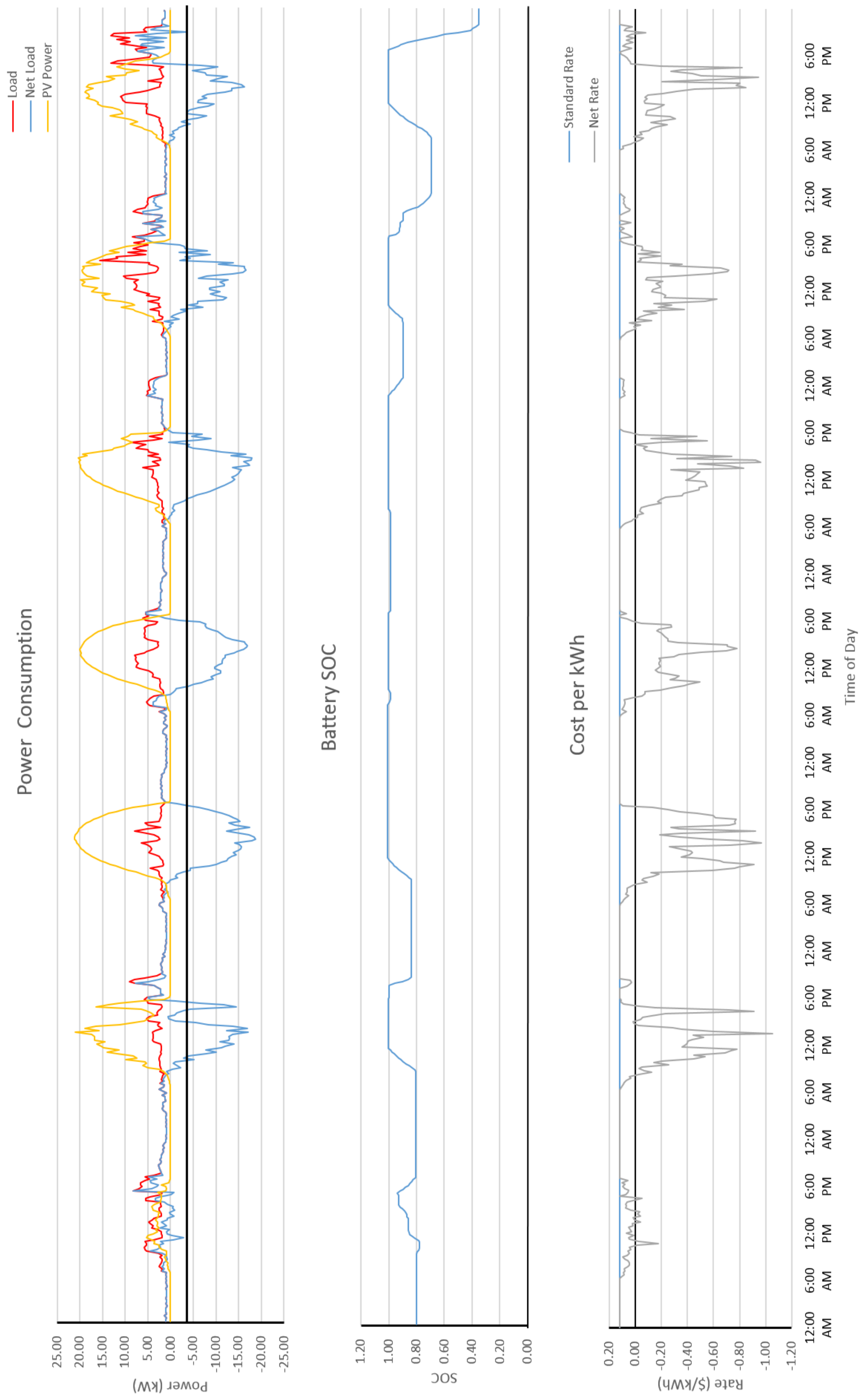

Figure B.12. Spring – 2B – 26 kWh Battery

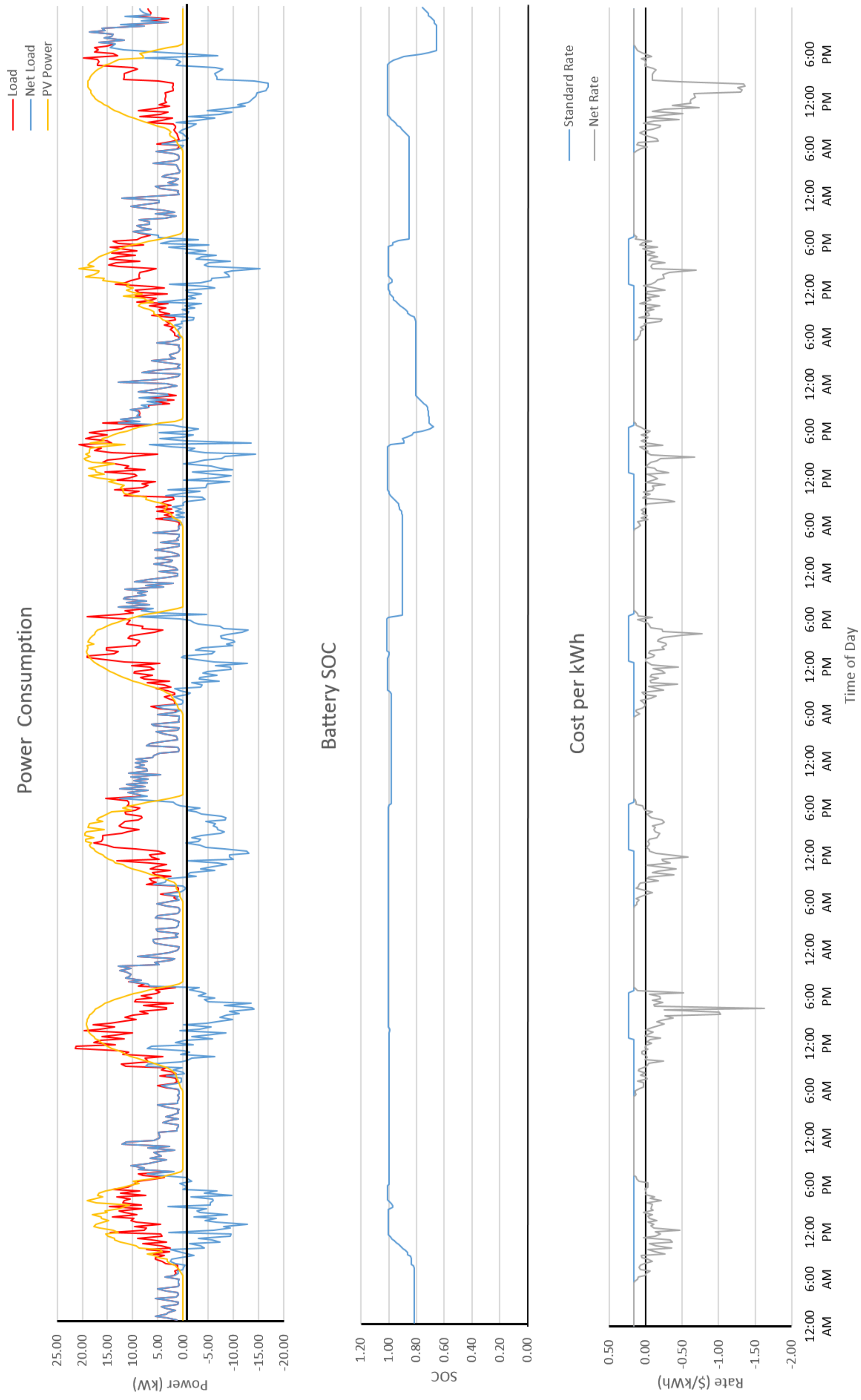

Figure B.13. Summer – 1A – 26 kWh Battery

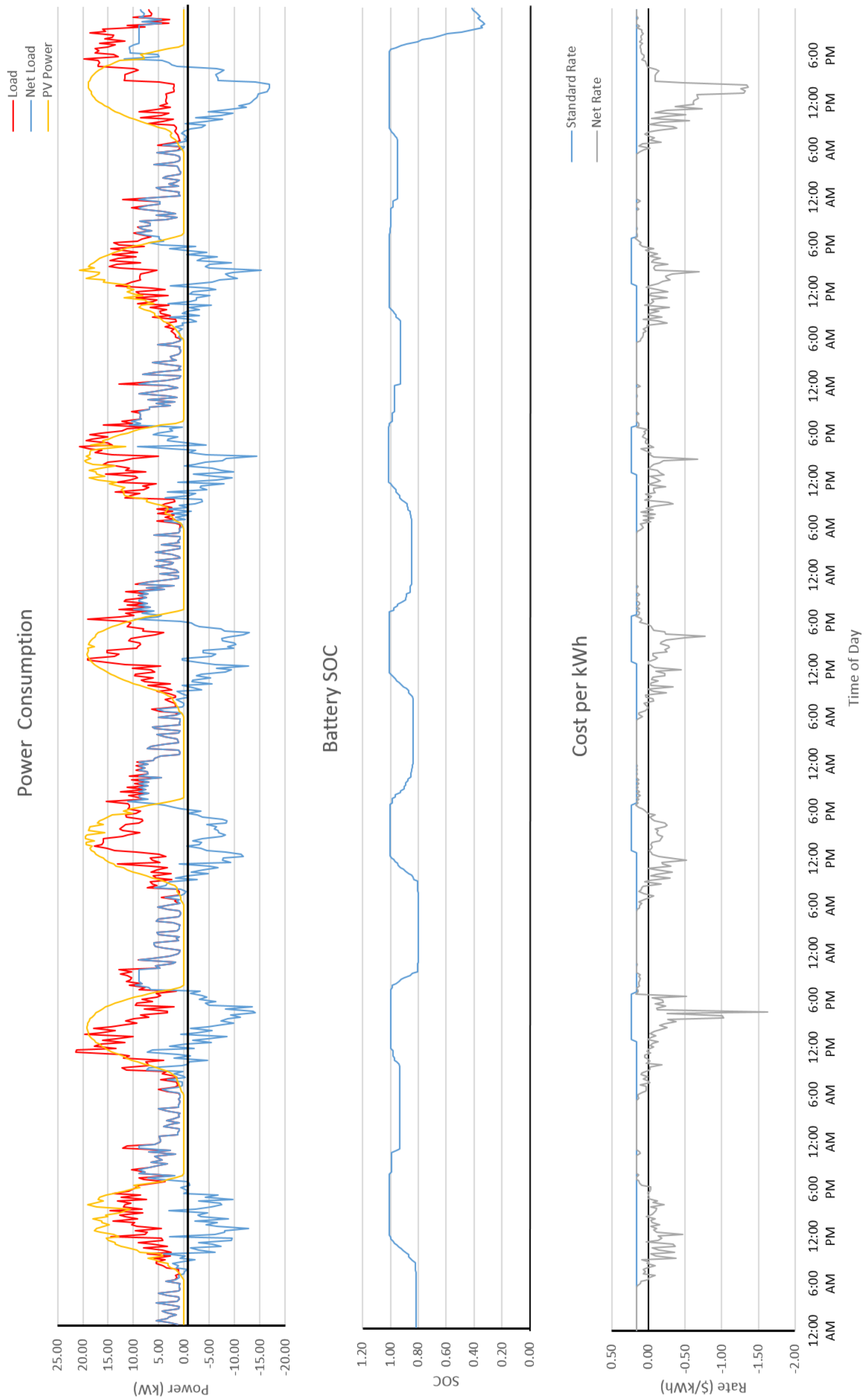

Figure B.14. Summer – 1B – 26 kWh Battery

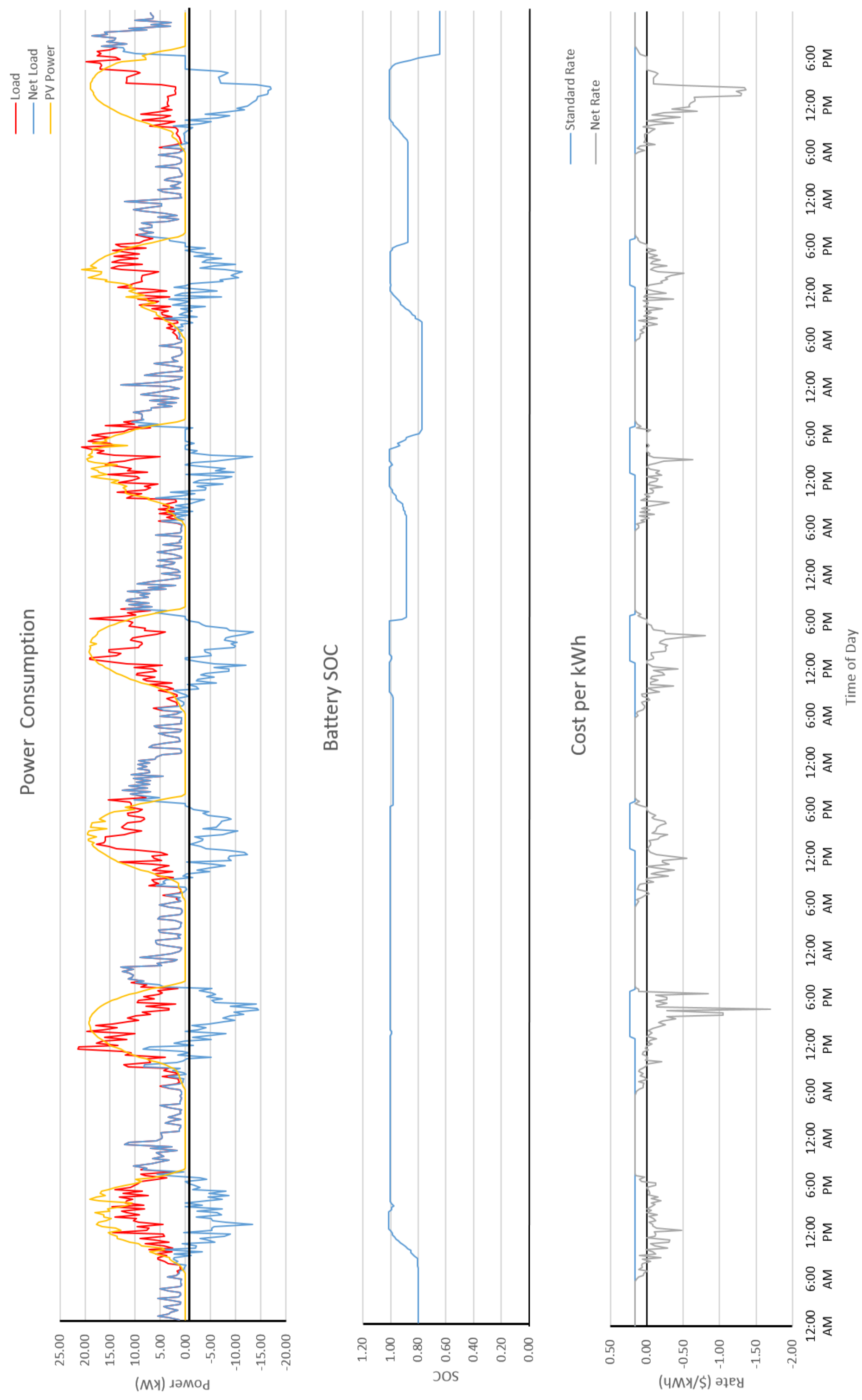

Figure B.15. Summer – 2A – 26 kWh Battery

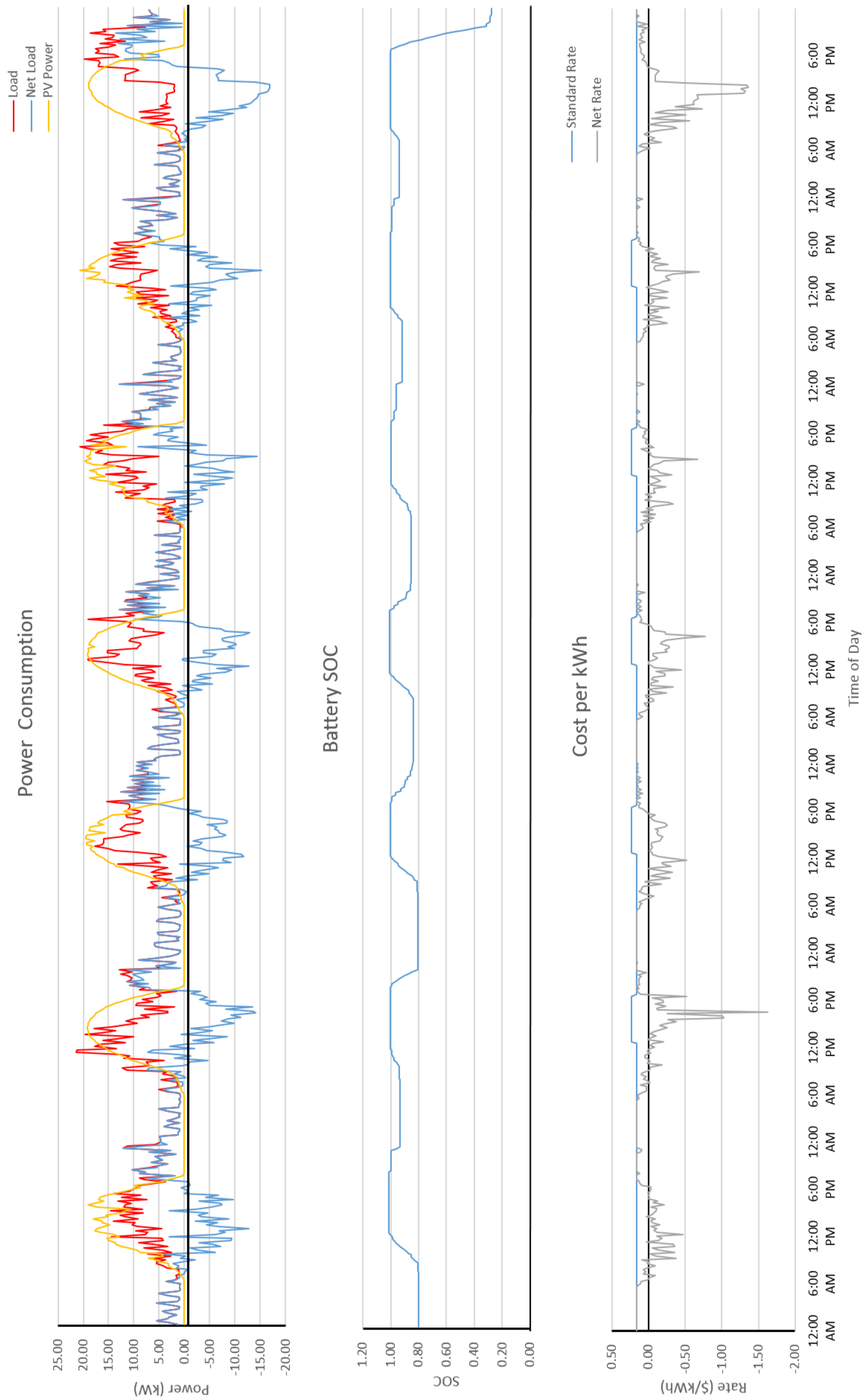

Figure B.16. Summer – 2B – 26 kWh Battery

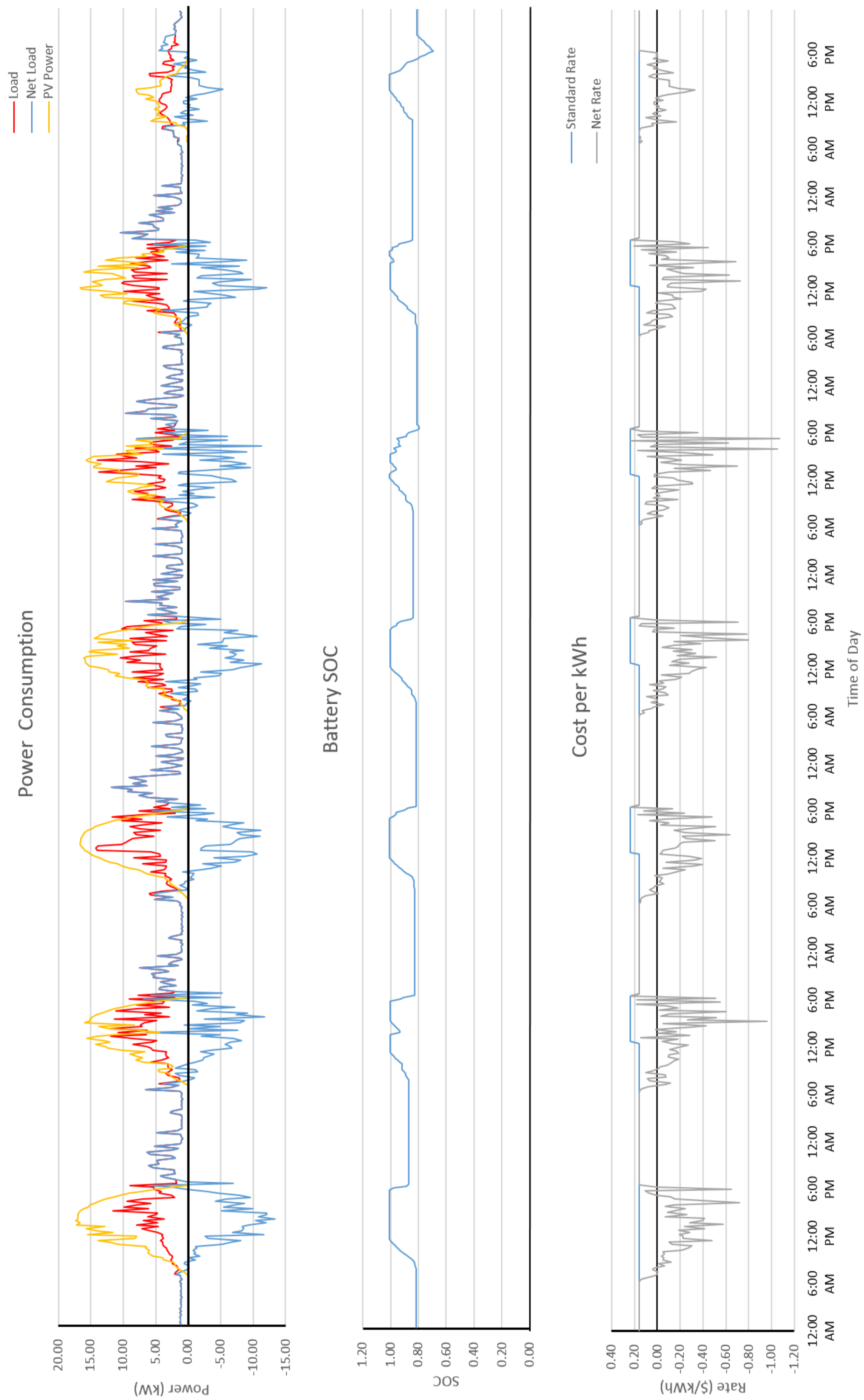

Figure B.17. Autumn – 1A – 26 kWh Battery

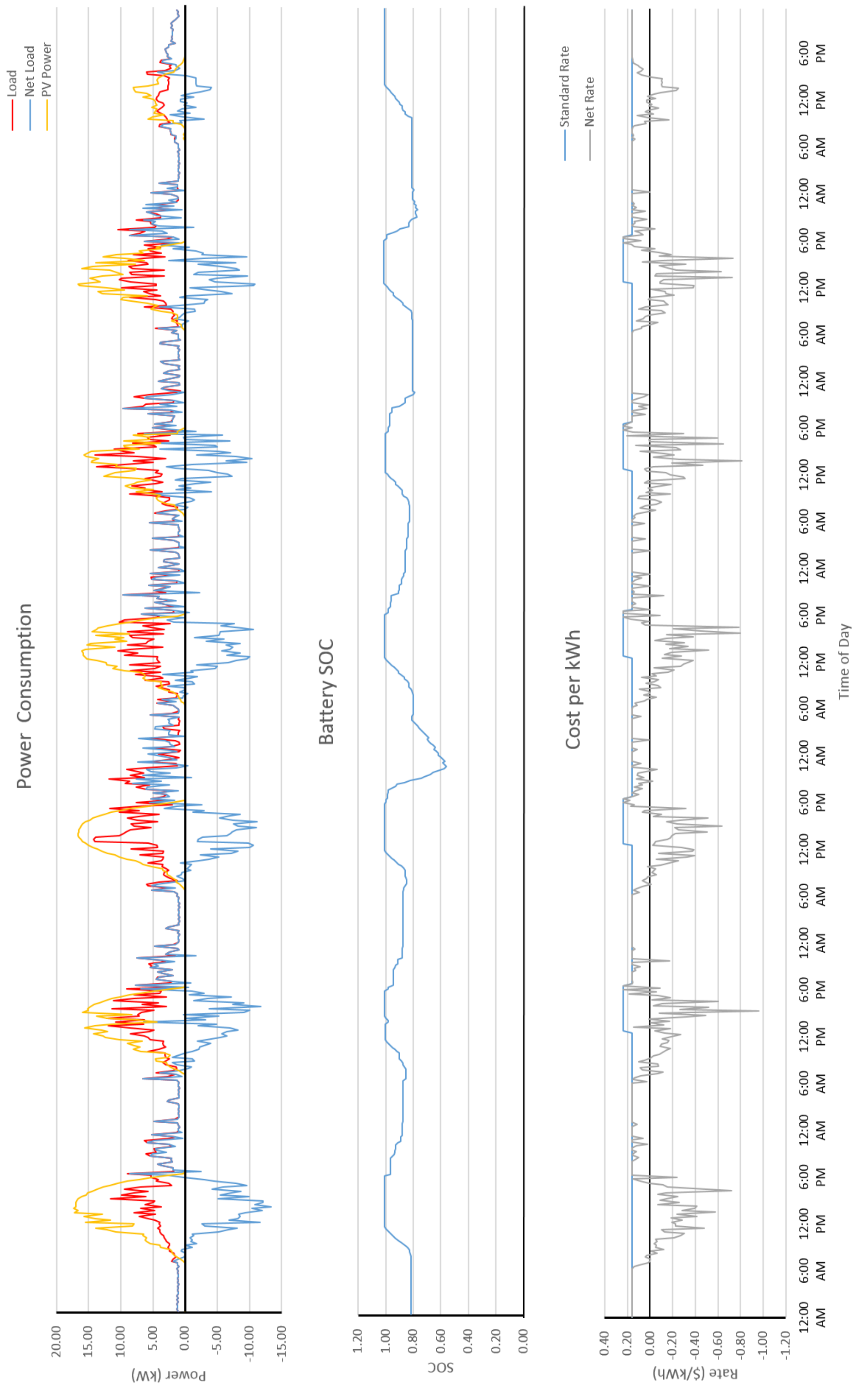

Figure B.18. Autumn – 1B – 26 kWh Battery

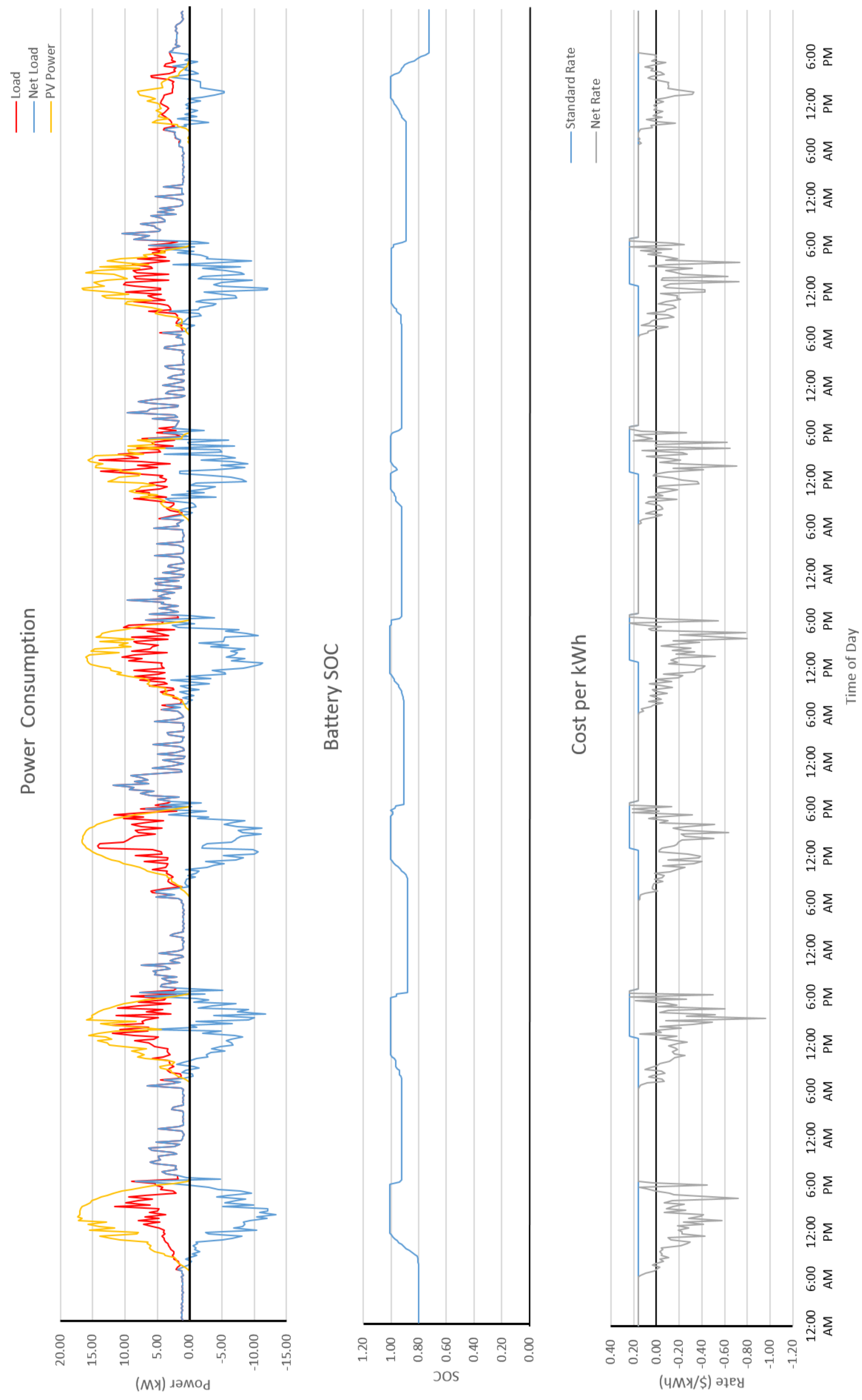

Figure B.19. Autumn – 2A – 26 kWh Battery

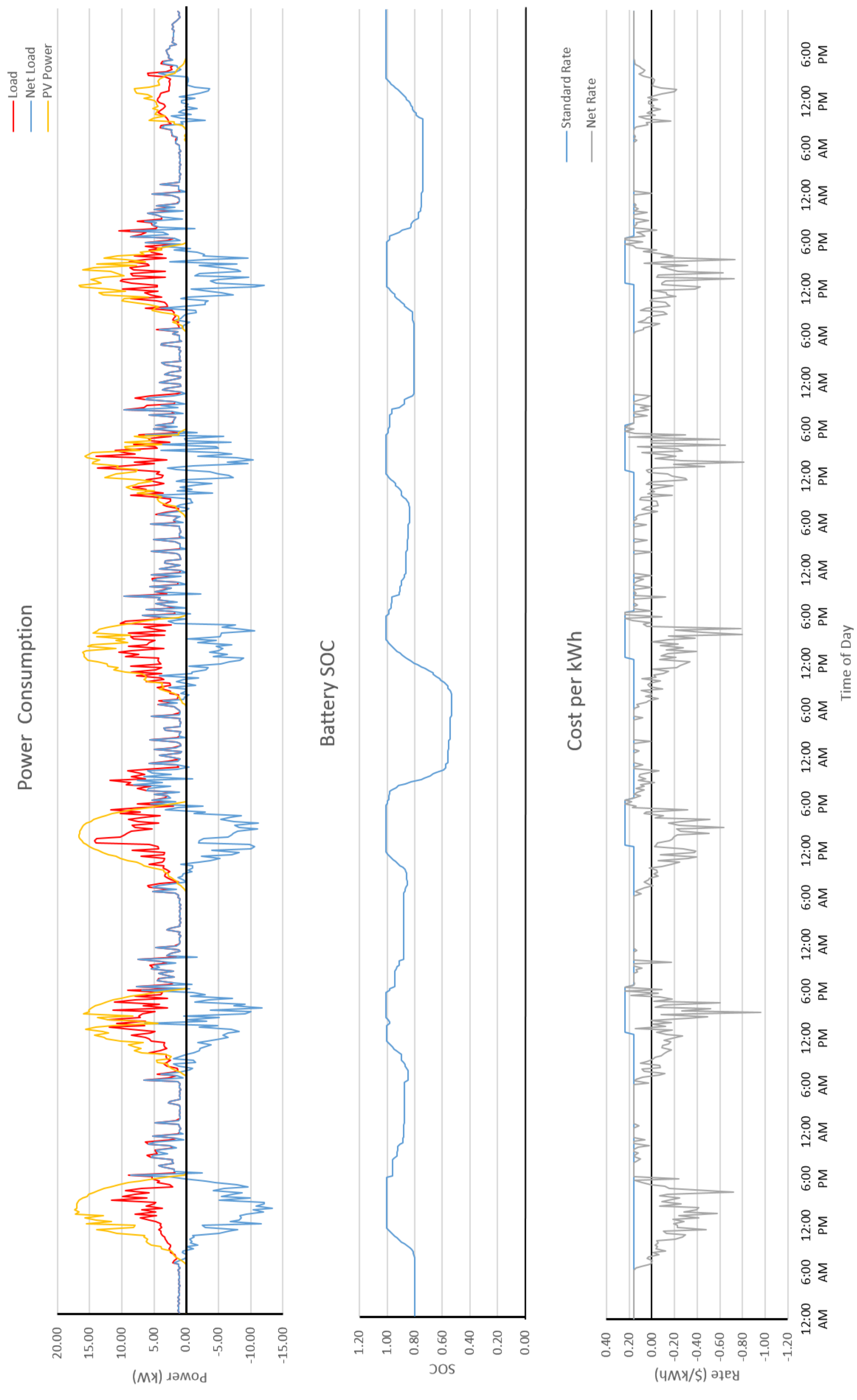

Figure B.20. Autumn – 2B – 26 kWh Battery

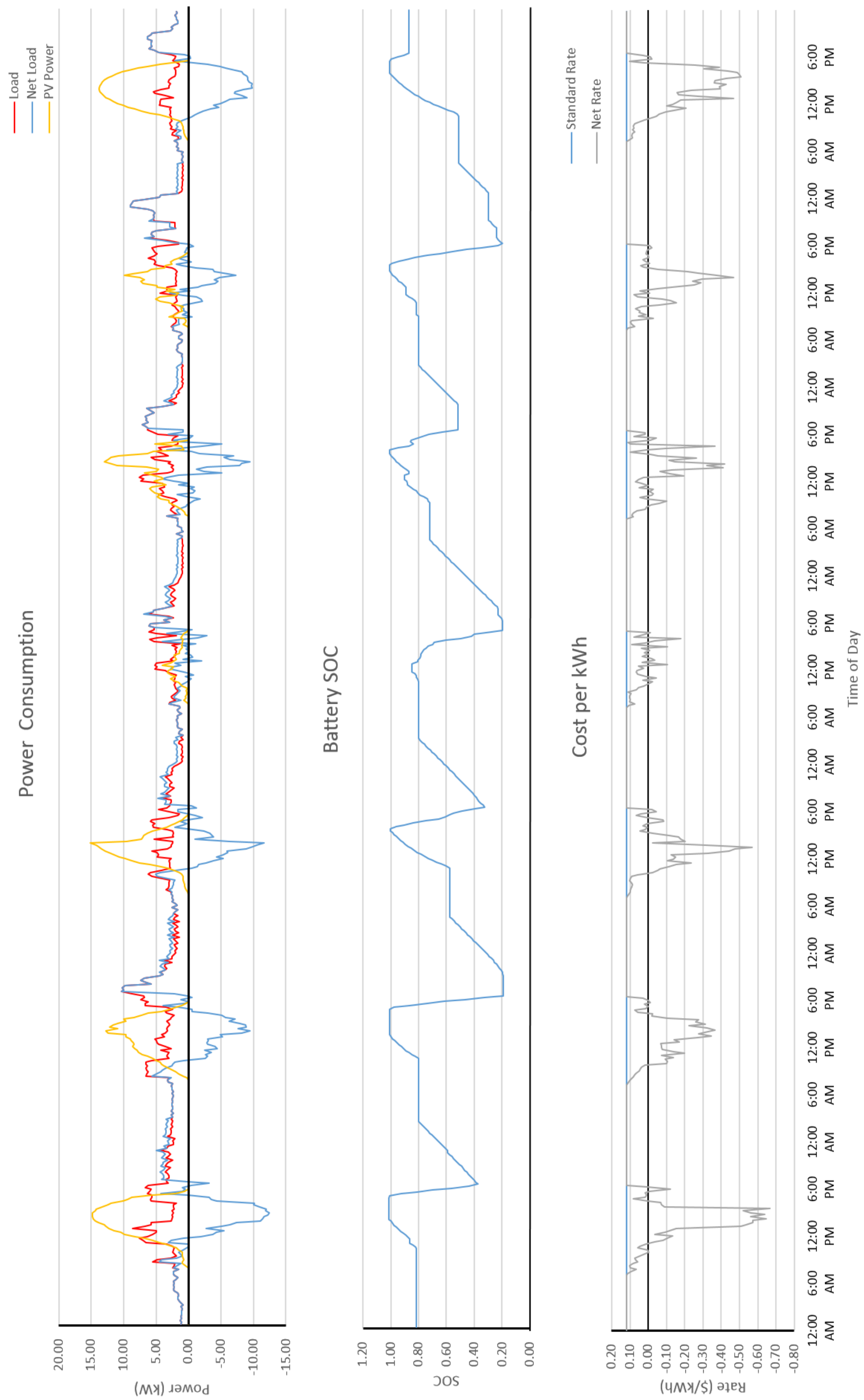

Figure B.21. Winter – 1A – 13 kWh Battery

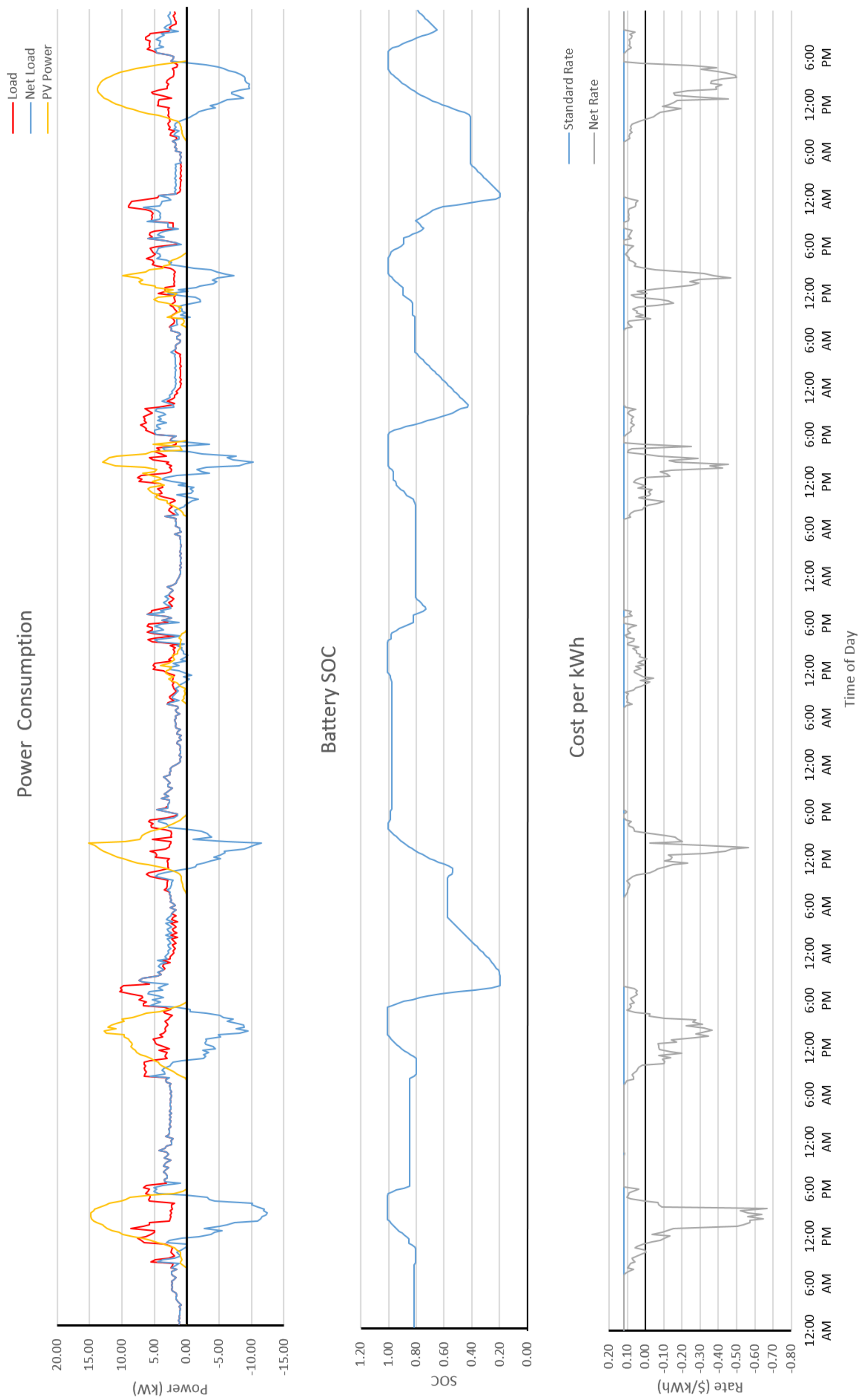

Figure B.22. Winter – 1B – 13 kWh Battery

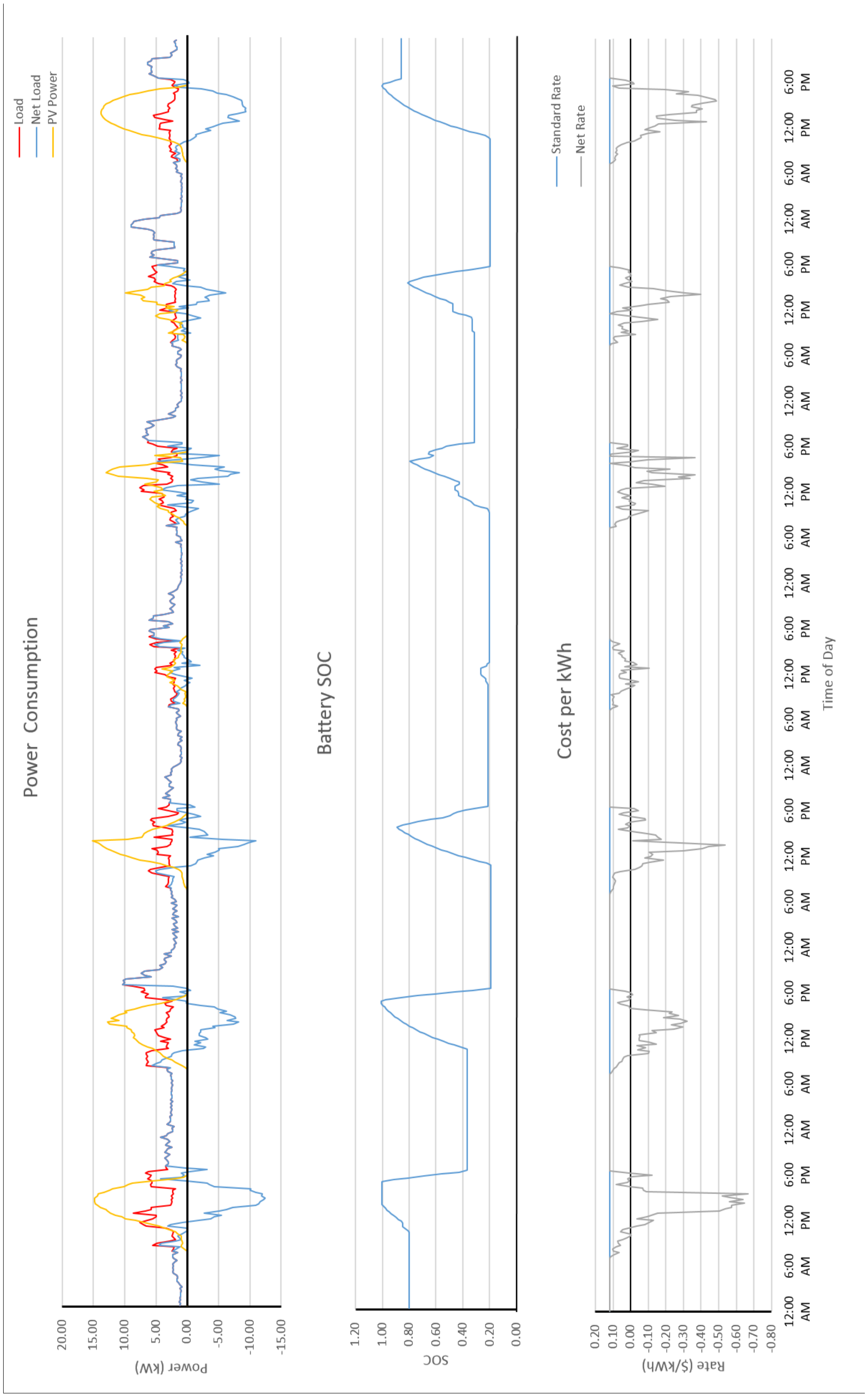

Figure B.23. Winter – 2A – 13 kWh Battery

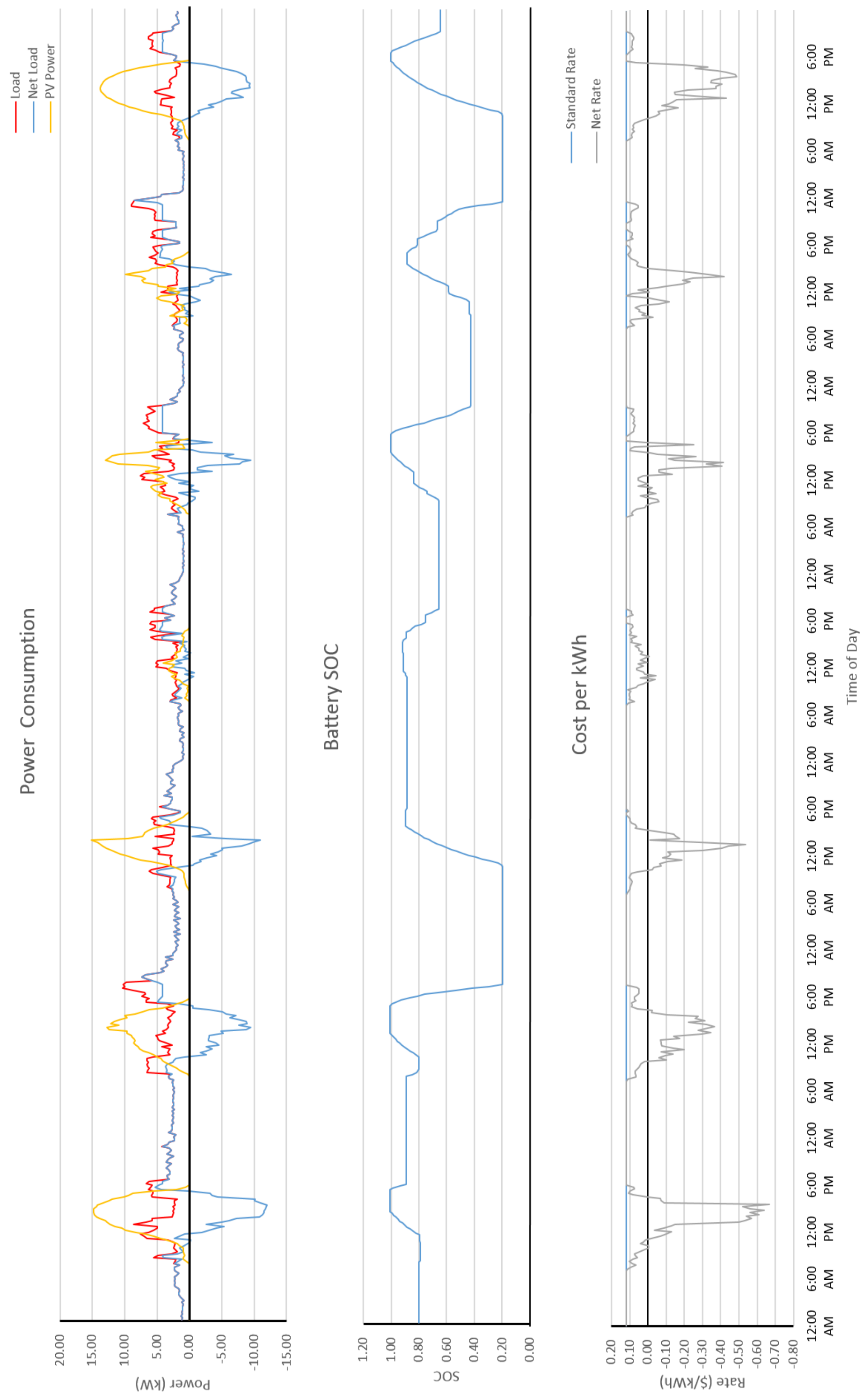

Figure B.24. Winter – 2B – 13 kWh Battery

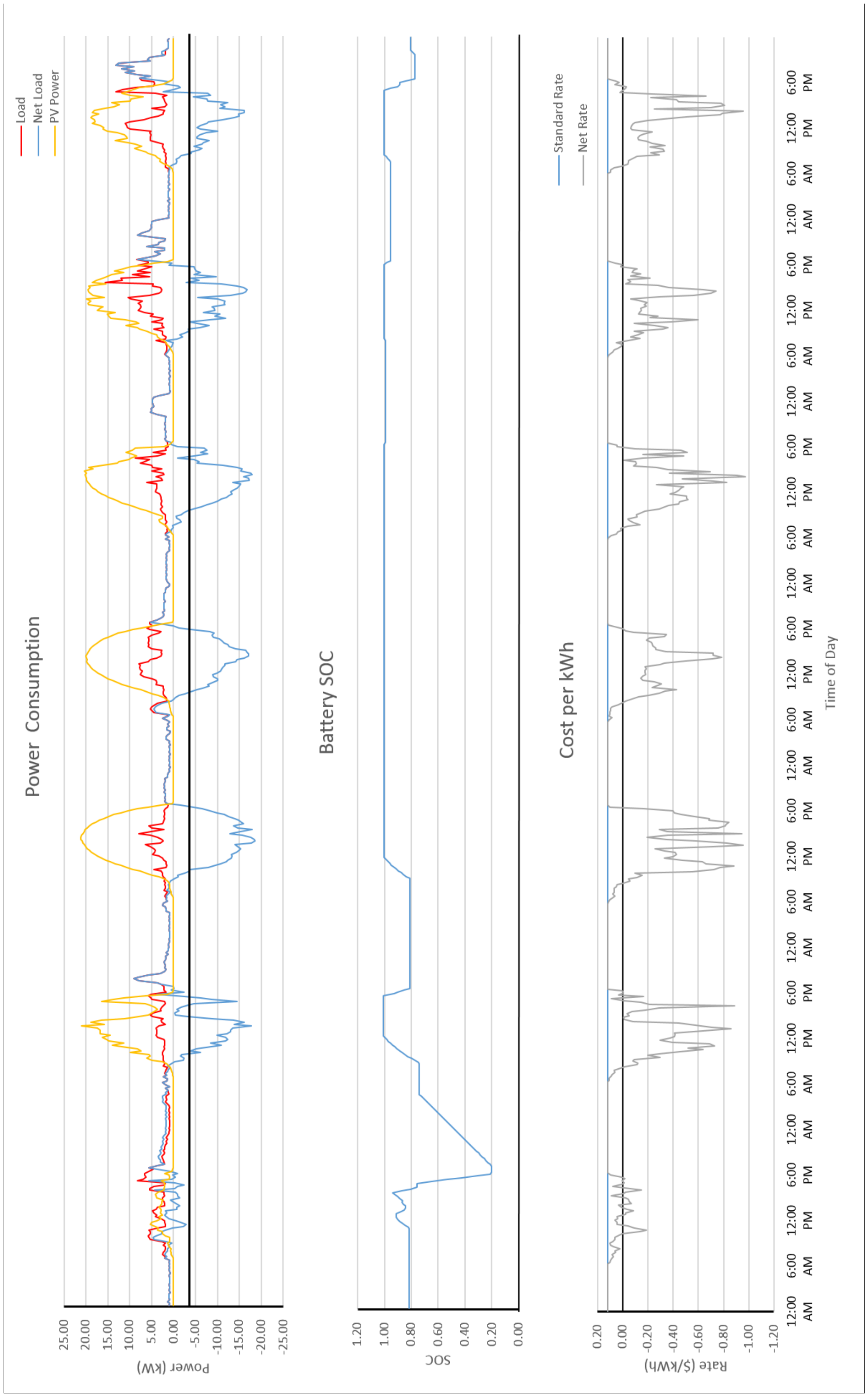

Figure B.25. Spring – 1A – 13 kWh Battery

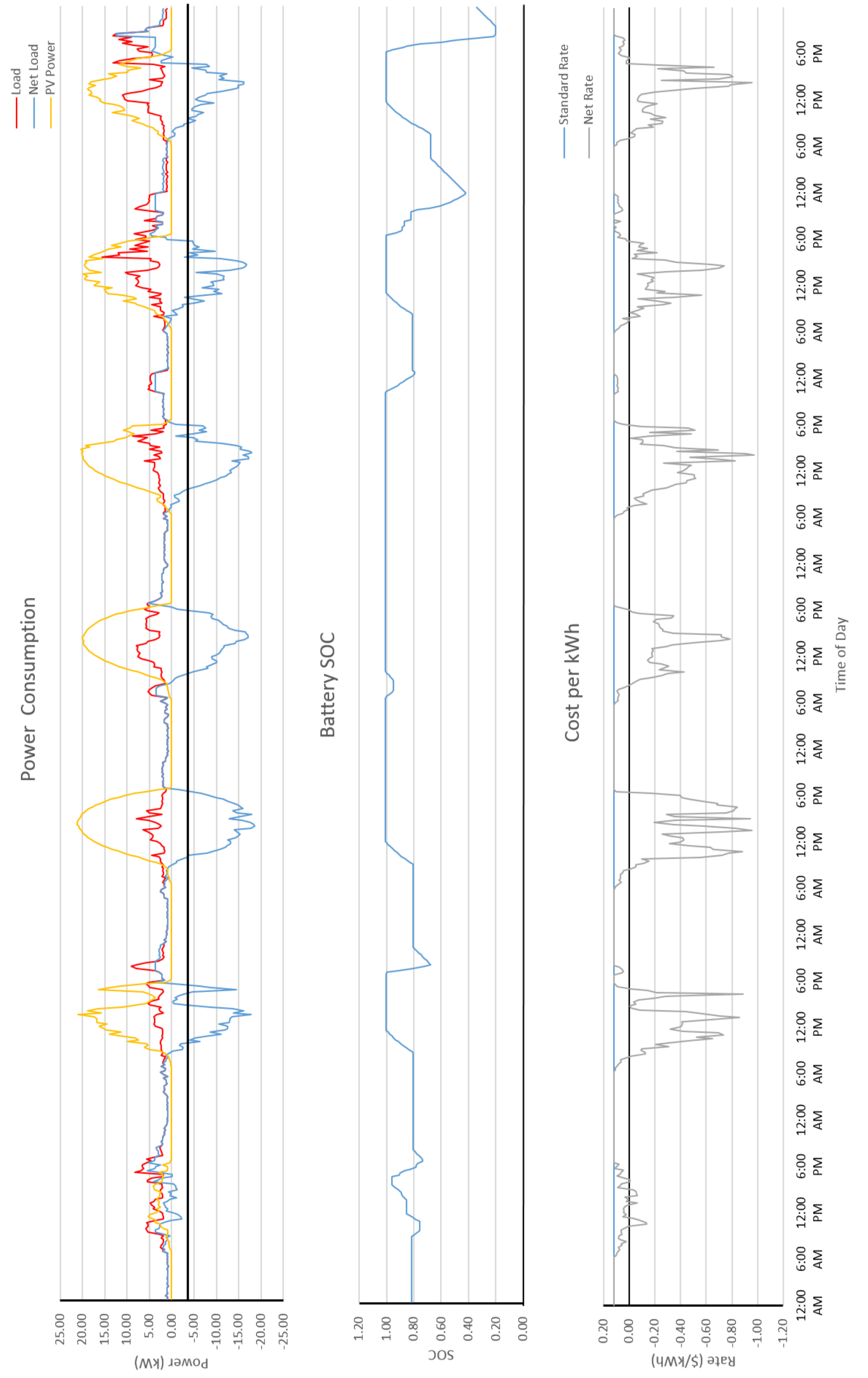

Figure B.26. Spring – 1B – 13 kWh Battery

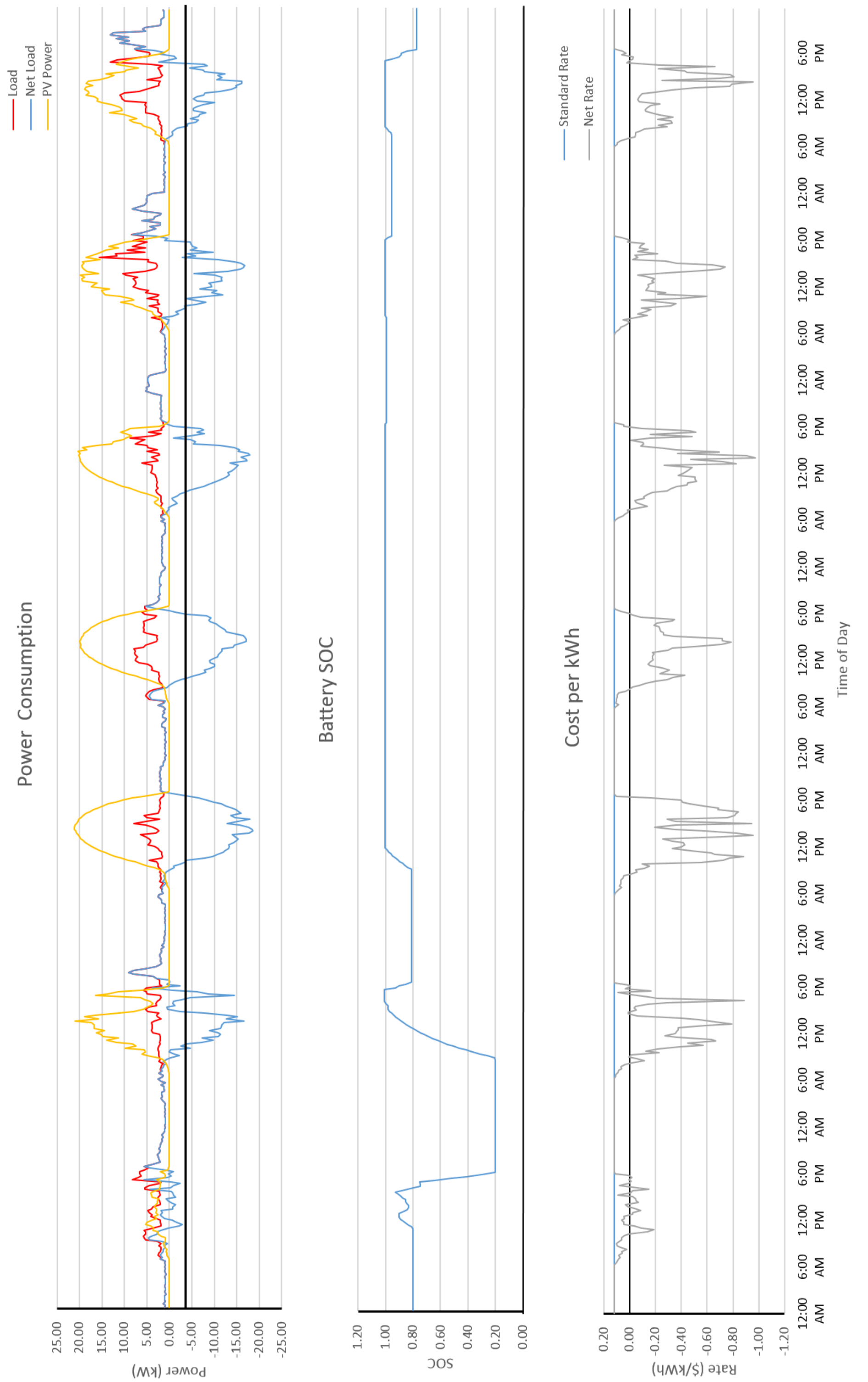

Figure B.27. Spring – 2A – 13 kWh Battery

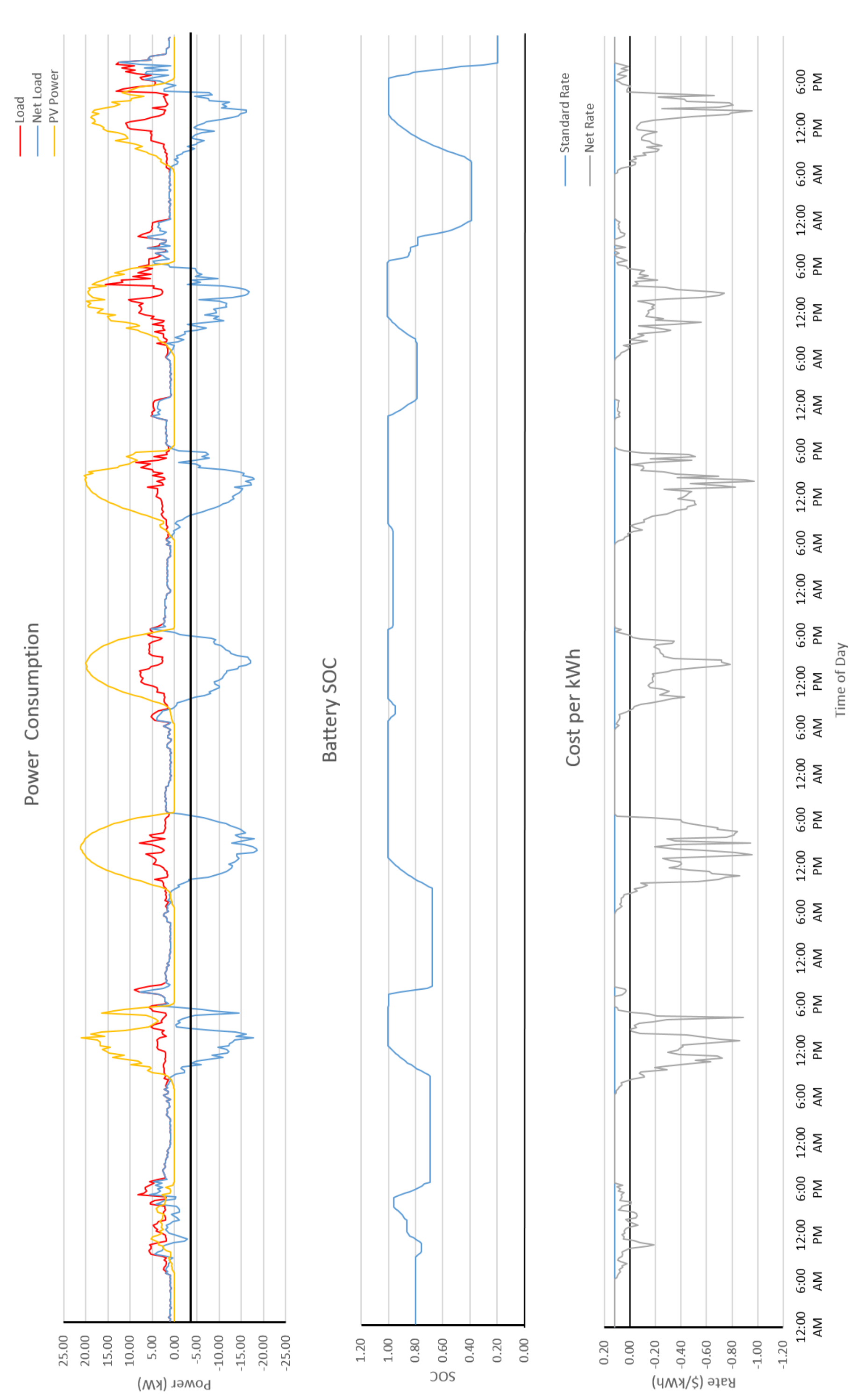

Figure B.28. Spring– 2B – 13 kWh Battery

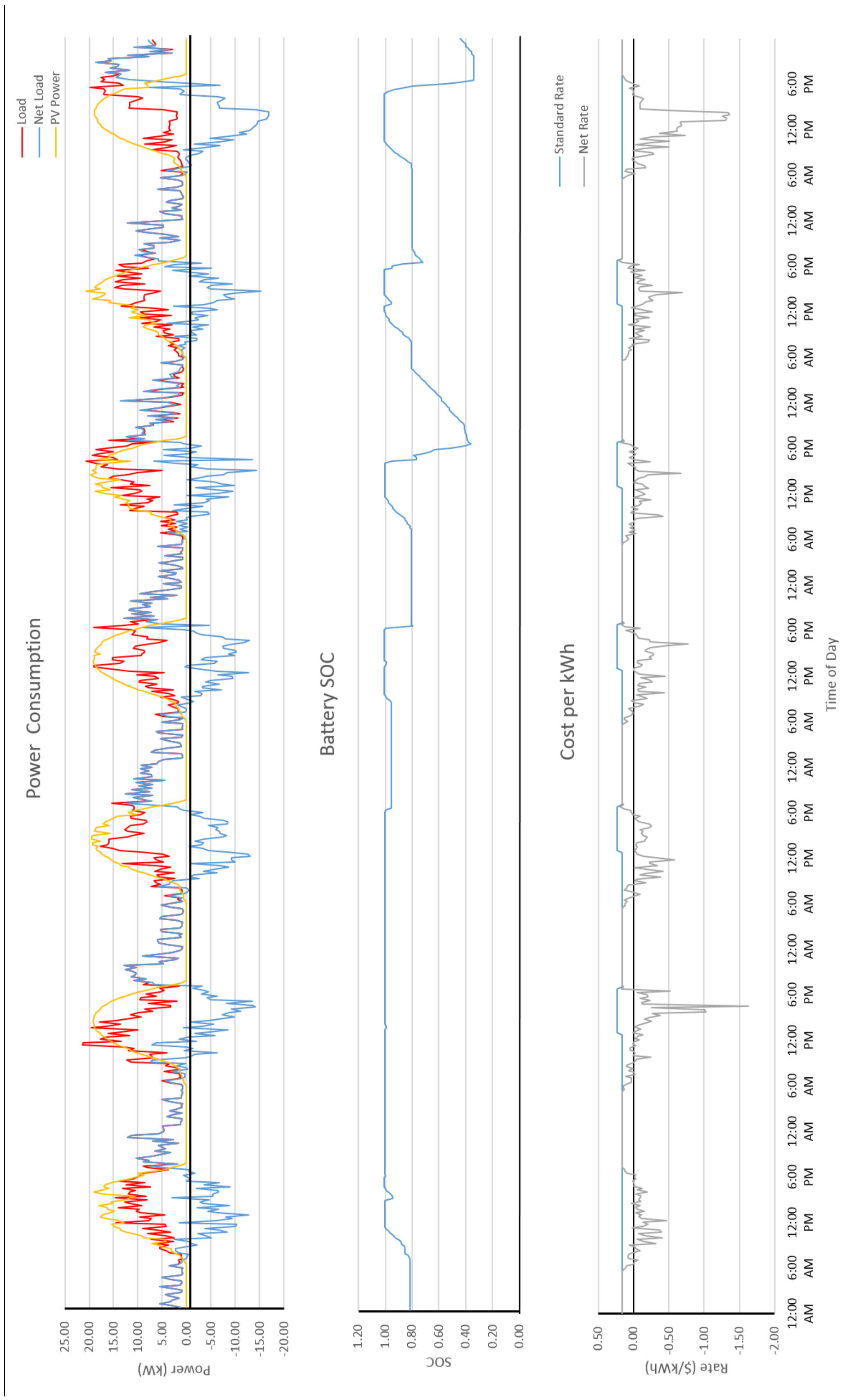

Figure B.29. Summer – 1A – 13 kWh Battery

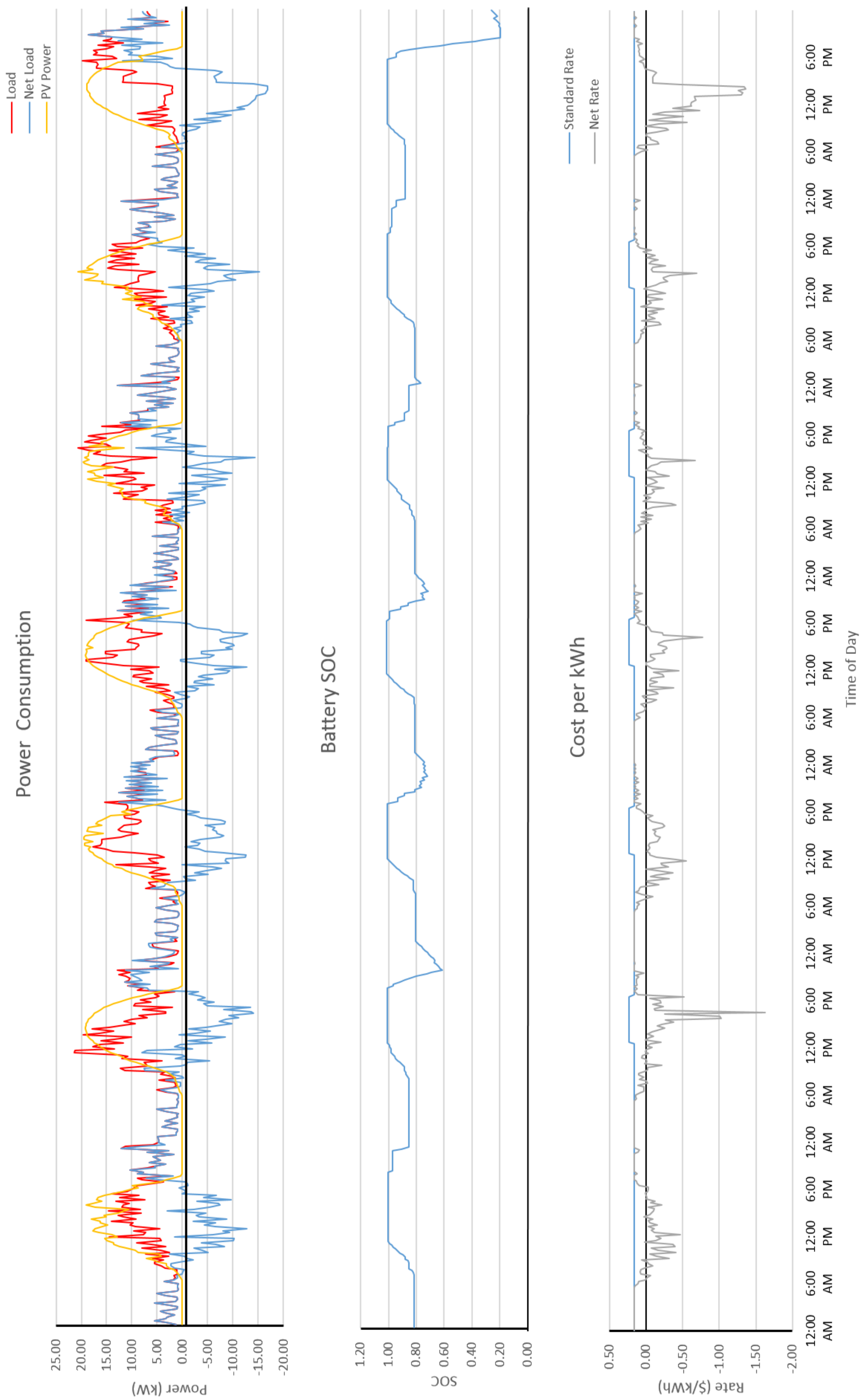

Figure B.30. Summer – 1B – 13 kWh Battery

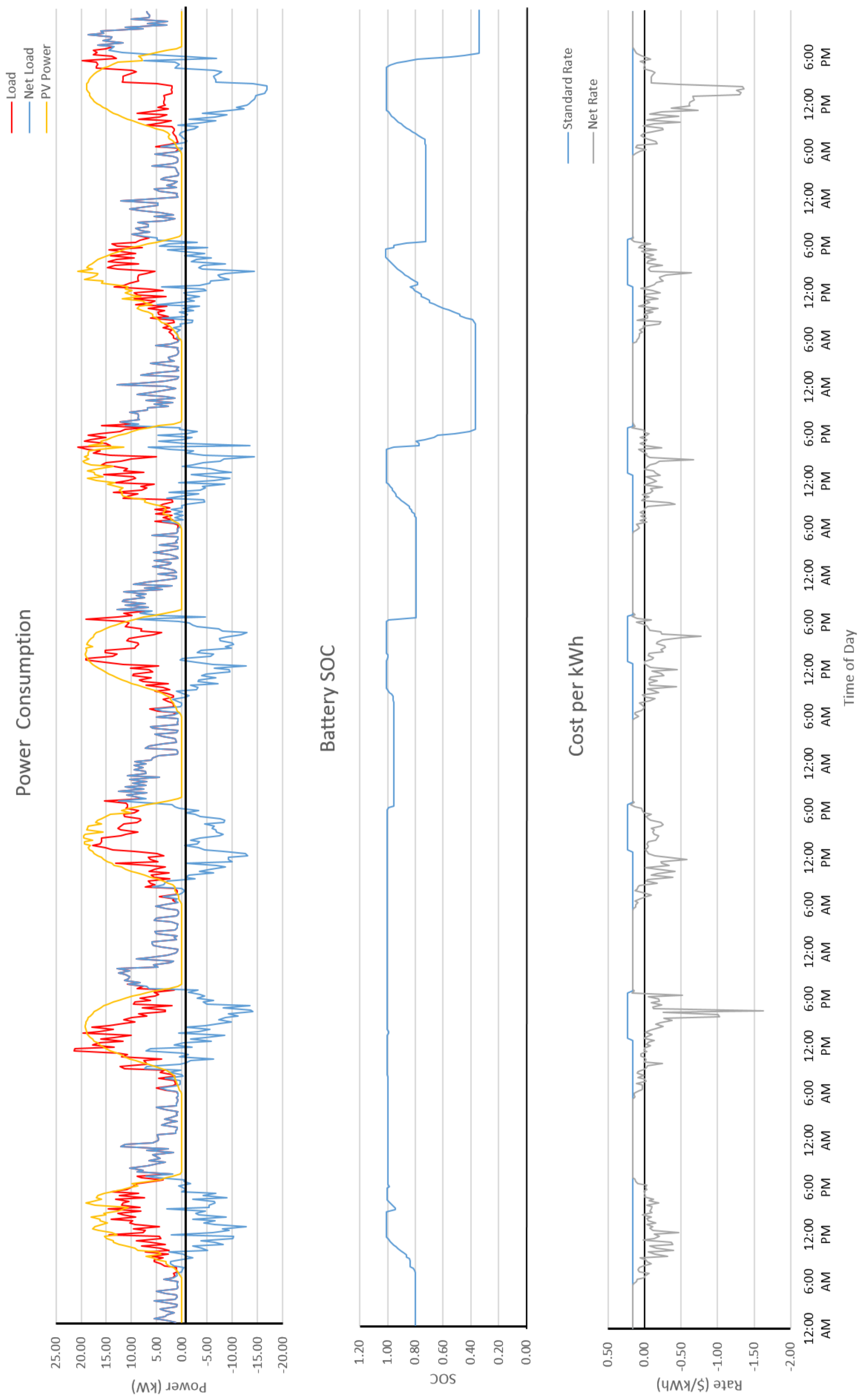

Figure B.31. Summer – 2A – 13 kWh Battery

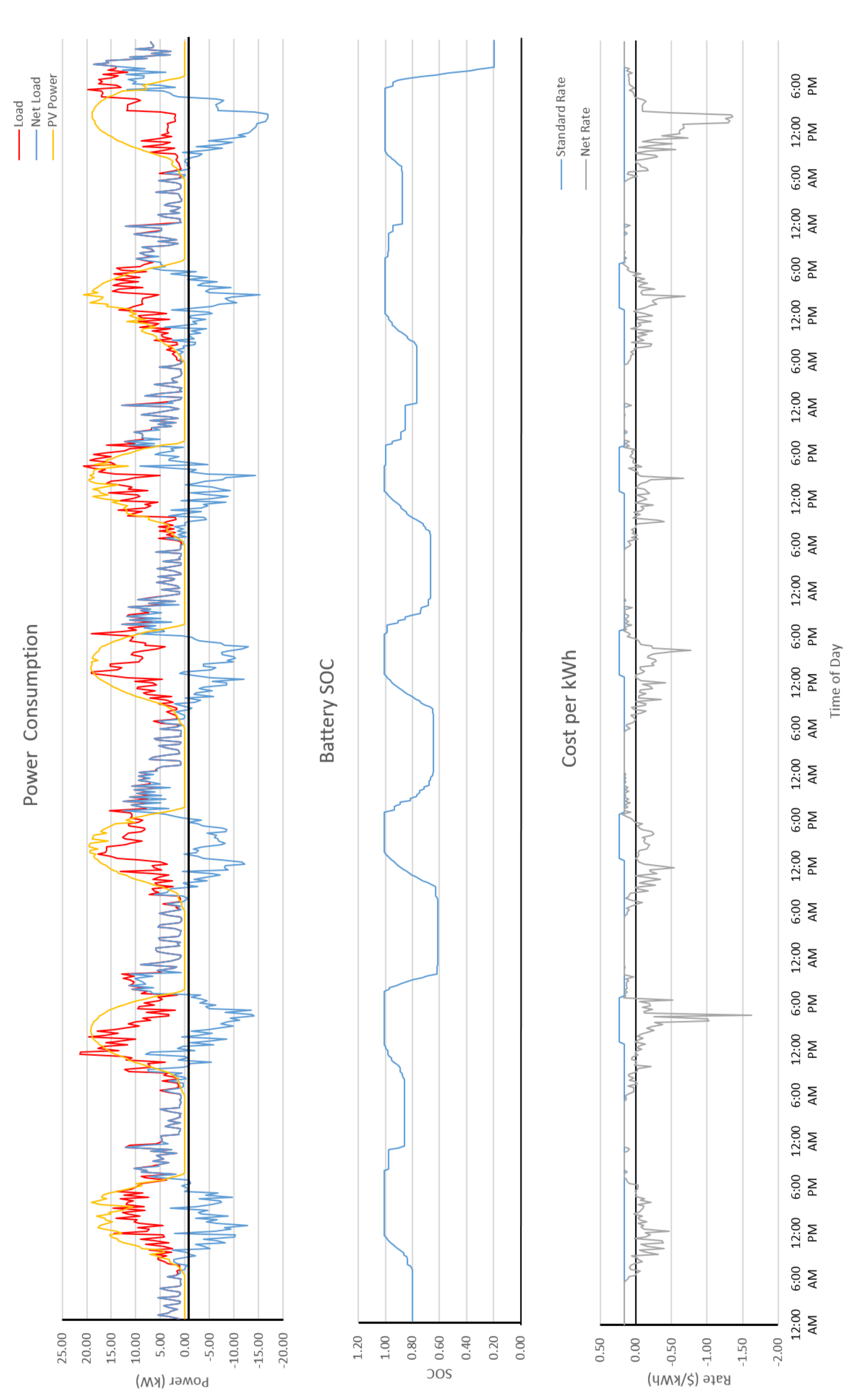

Figure B.32. Summer – 2B – 13 kWh Battery

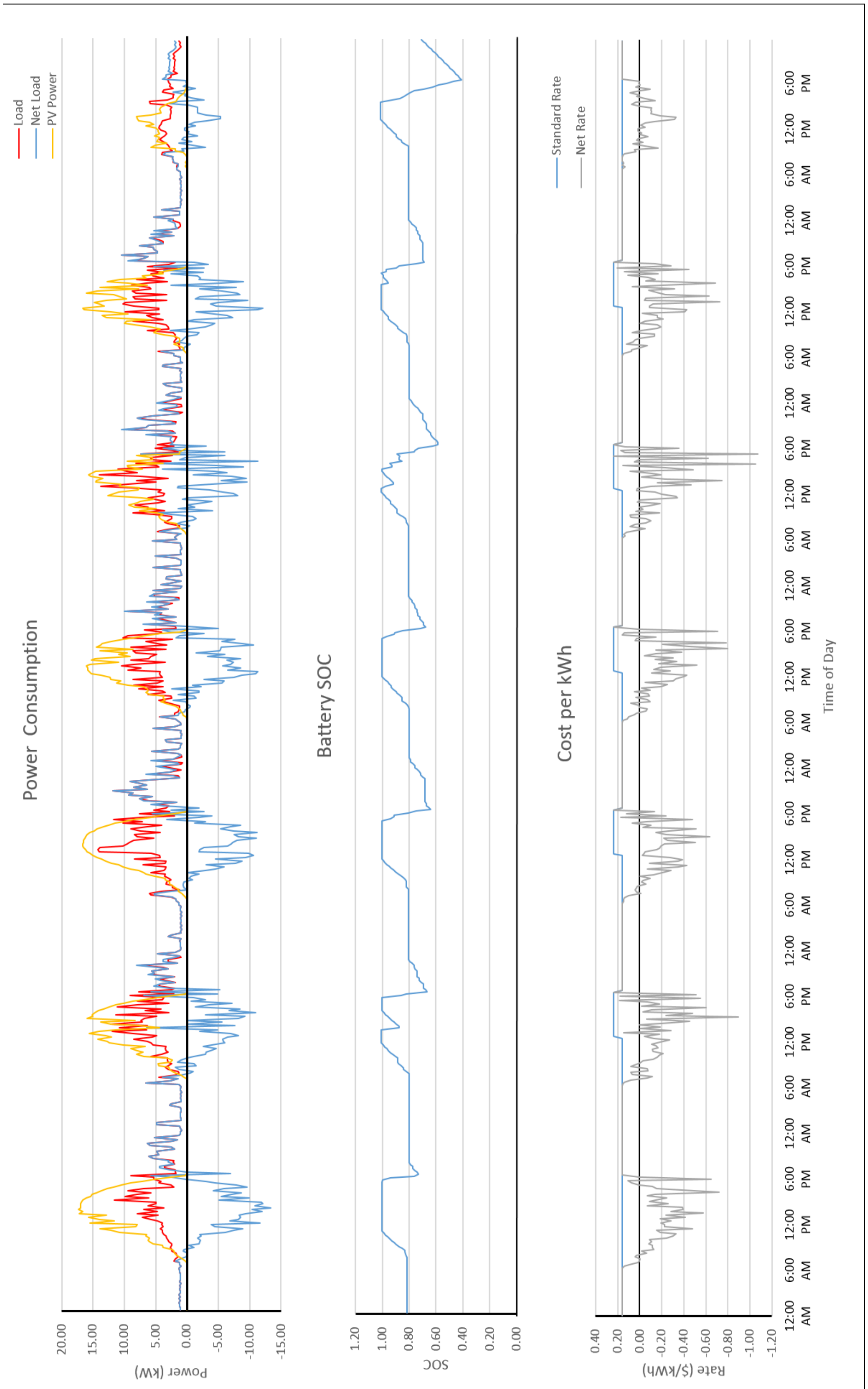

Figure B.33. Autumn – 1A – 13 kWh Battery

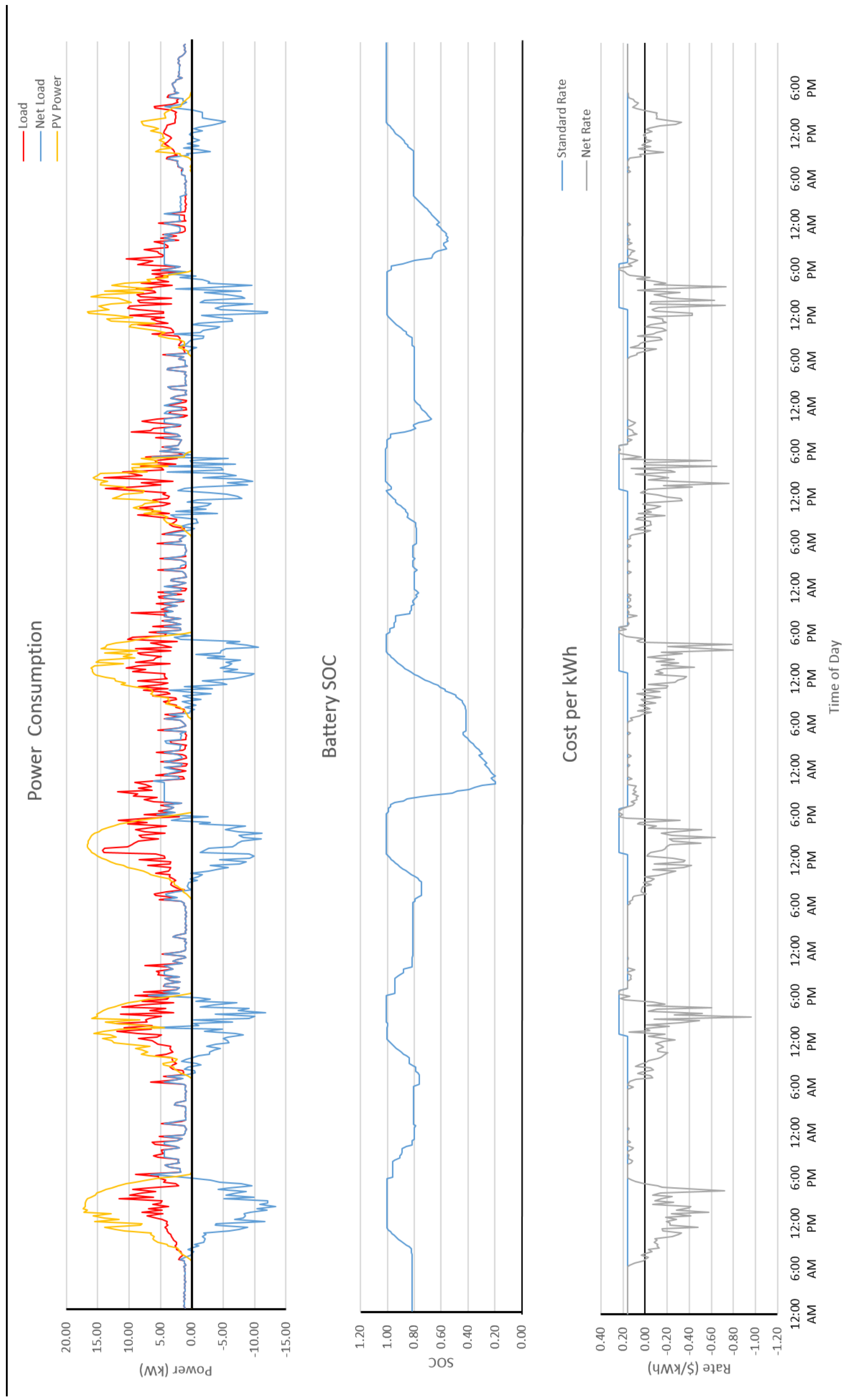

Figure B.34. Summer – 1B – 13 kWh Battery

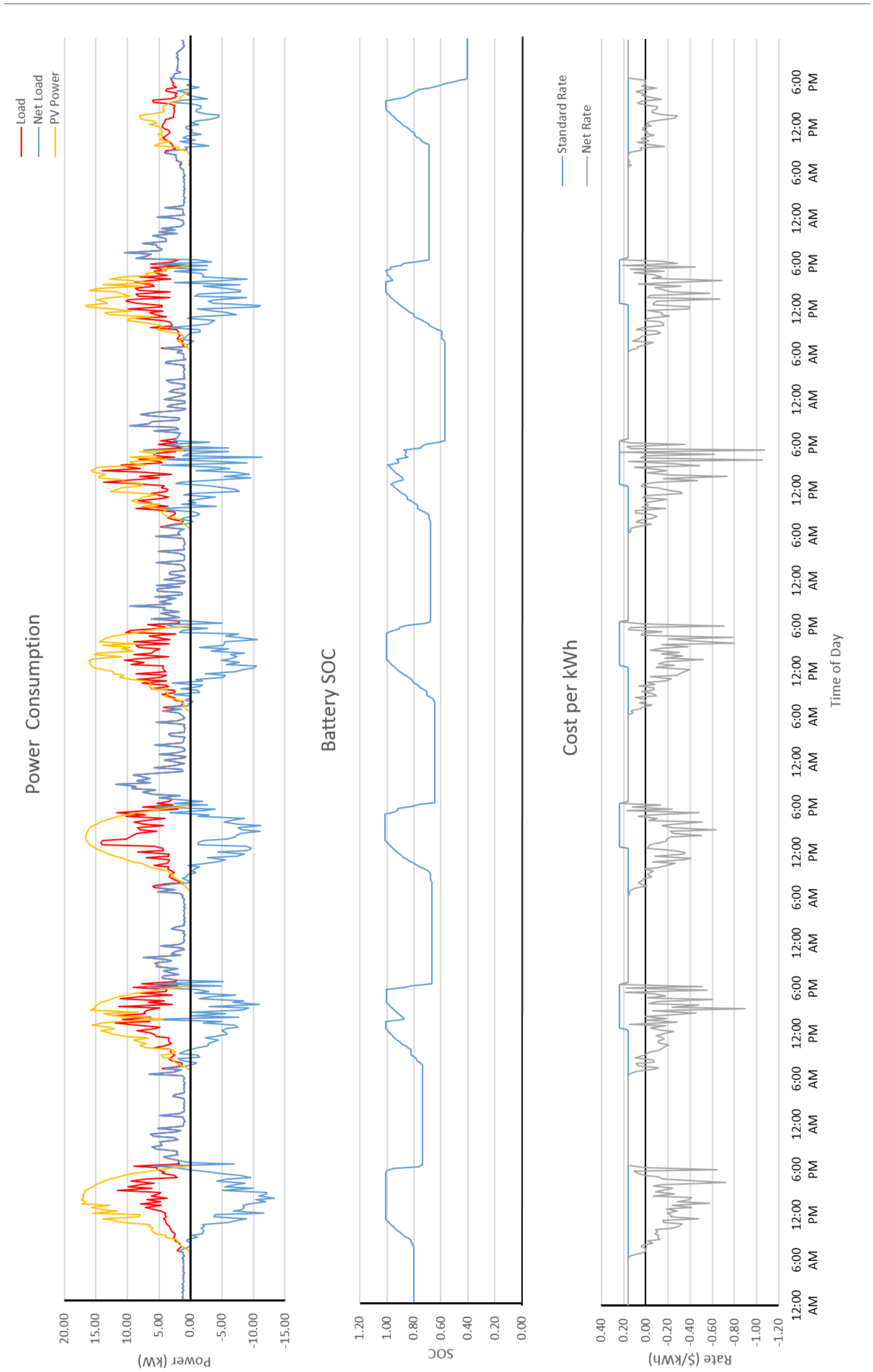

Figure B.35. Summer – 2A – 13 kWh Battery

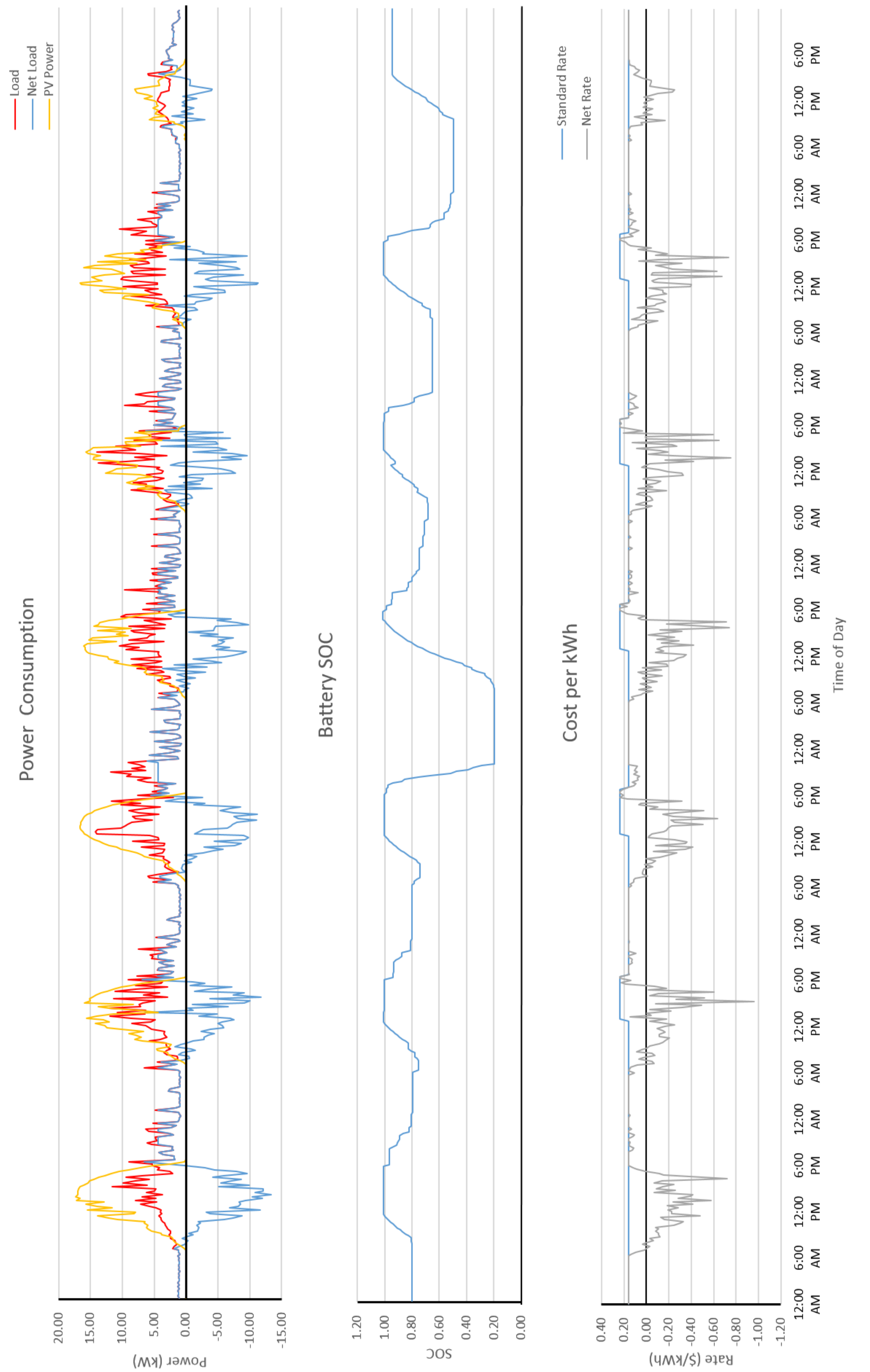

Figure B.36. Summer – 2B – 13 kWh Battery

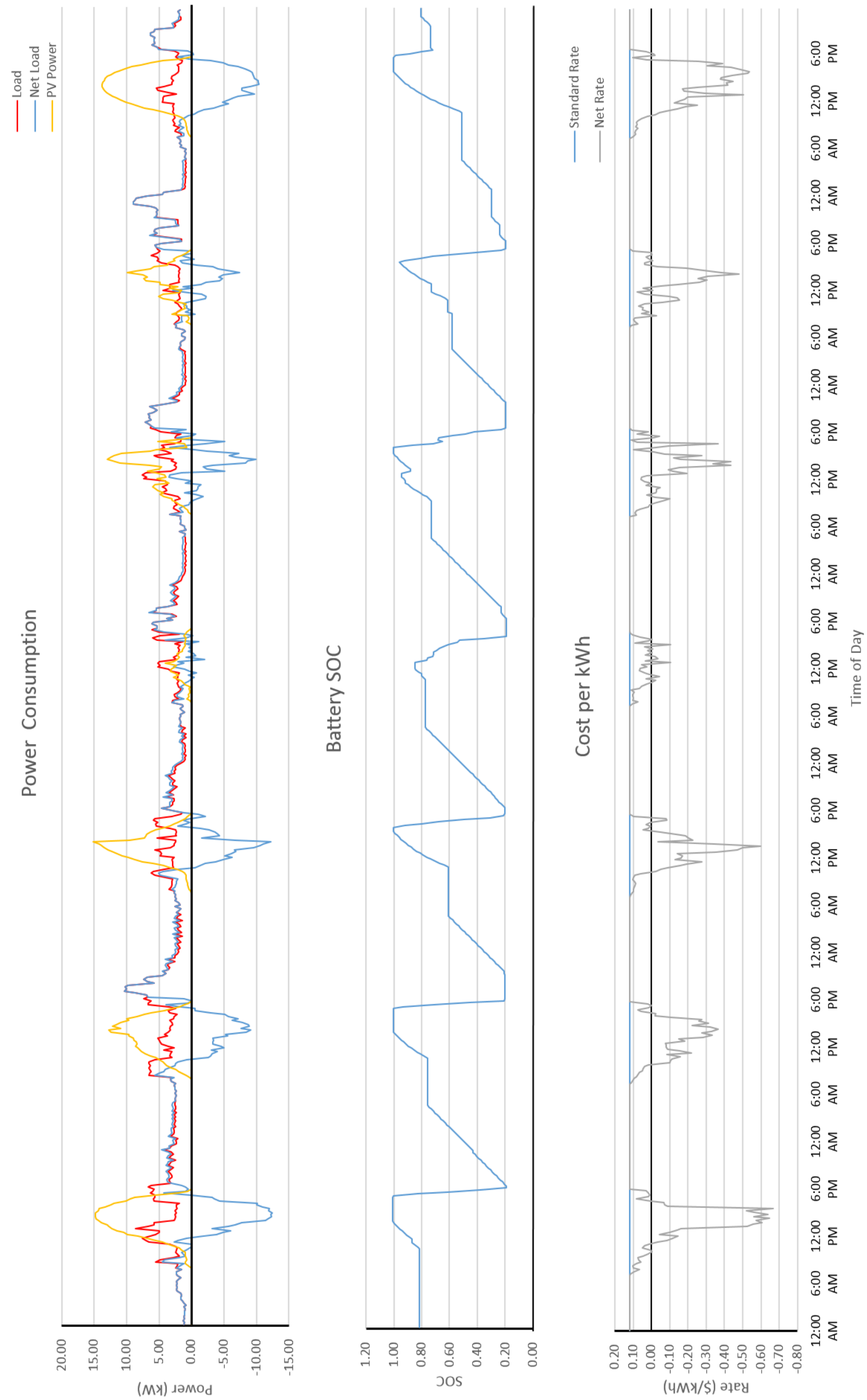

Figure B.37 – Winter – 1A 6.5 kWh Battery

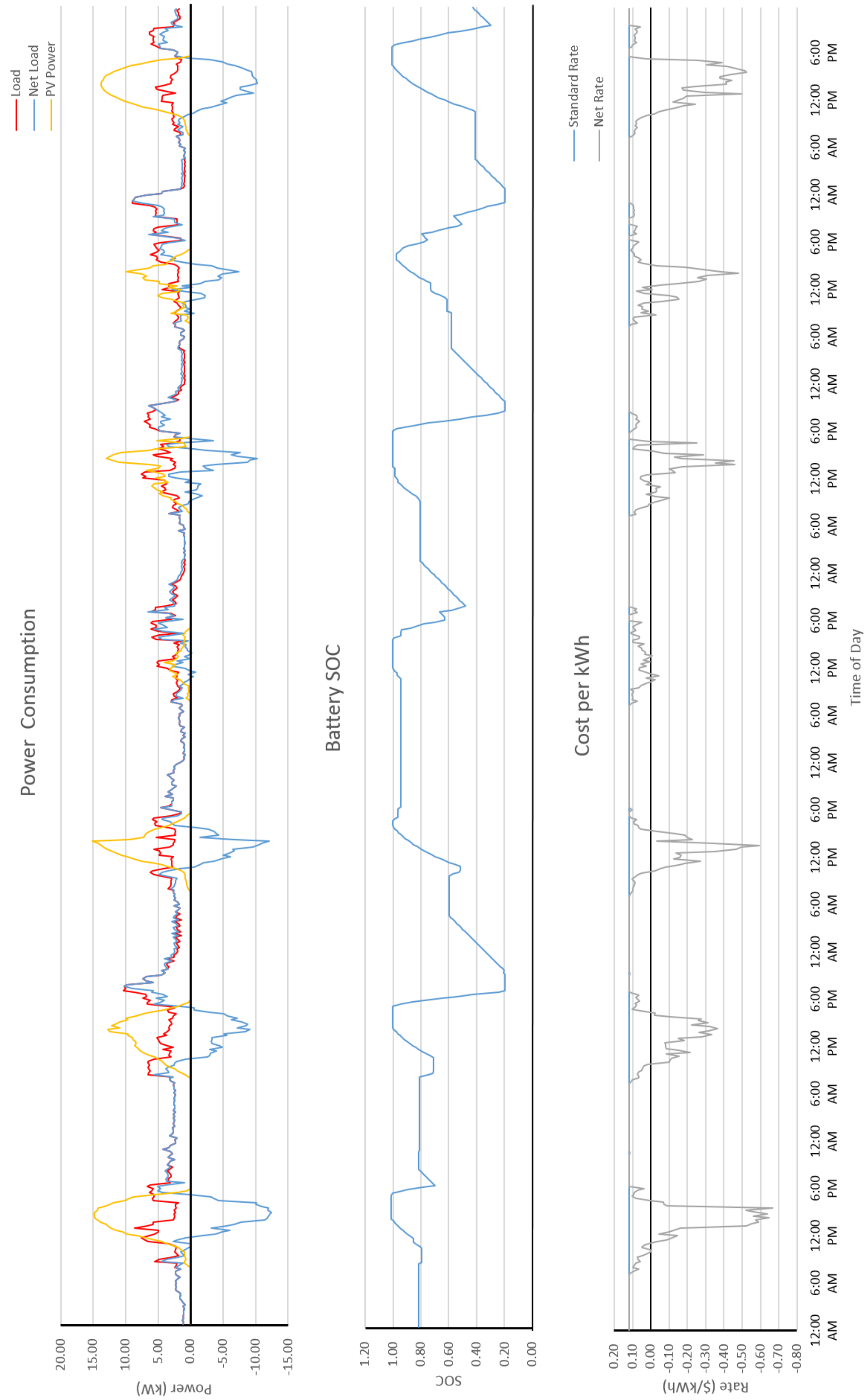

Figure B.38 – Winter – 1B 6.5 kWh Battery

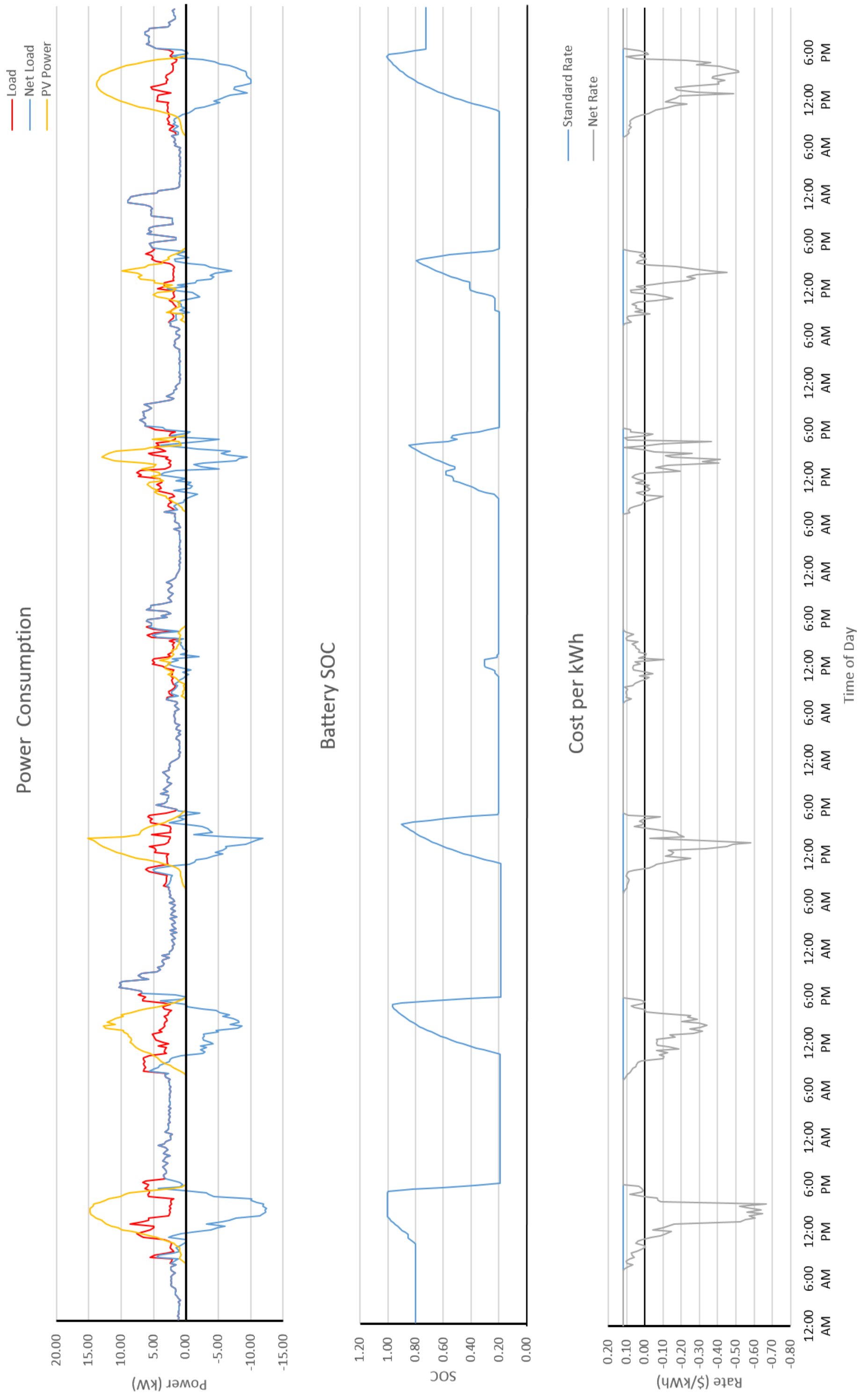

Figure B.39 – Winter – 2A 6.5 kWh Battery

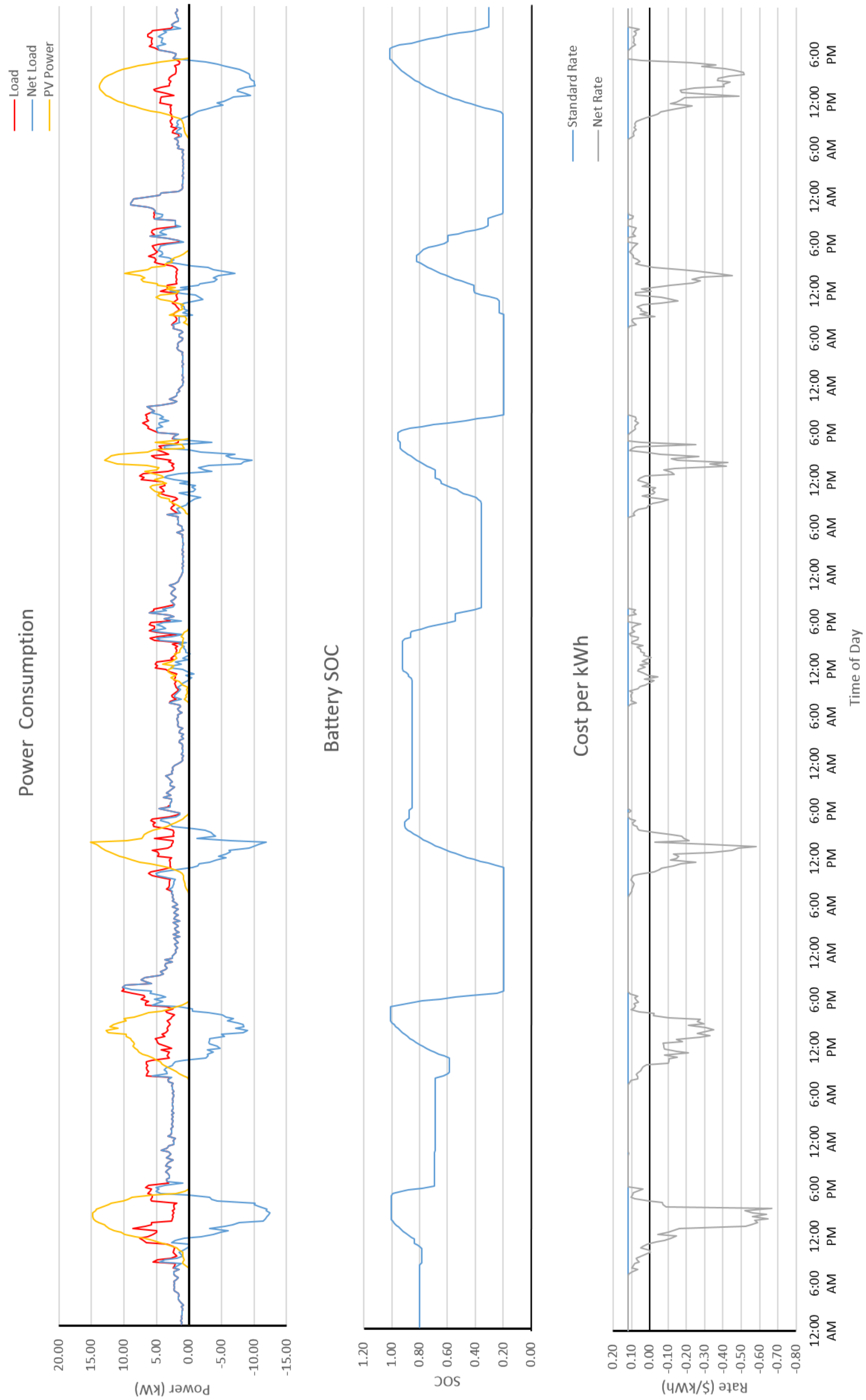

Figure B.40 – Winter – 2B 6.5 kWh Battery

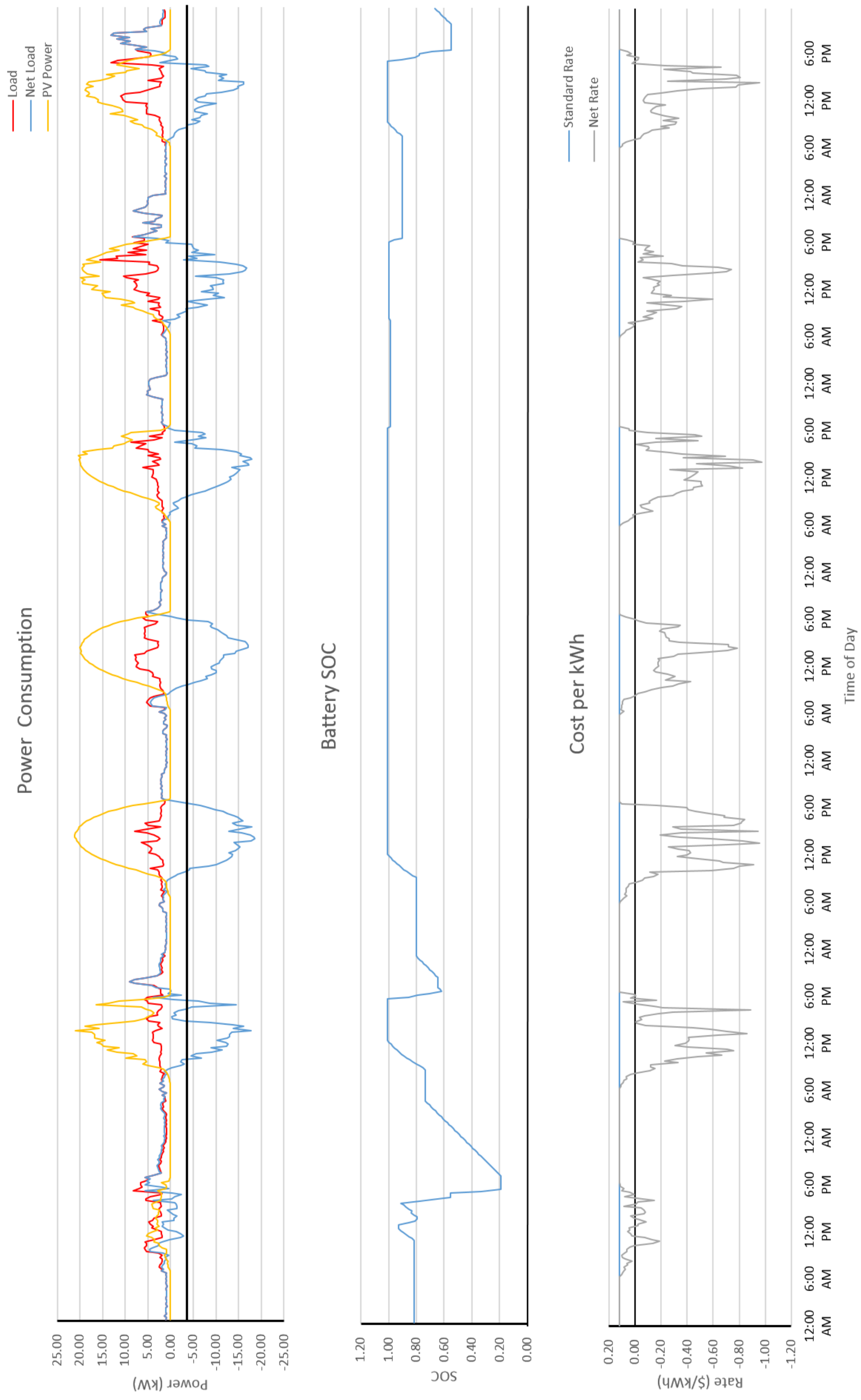

Figure B.41 – Spring – 1A 6.5 kWh Battery

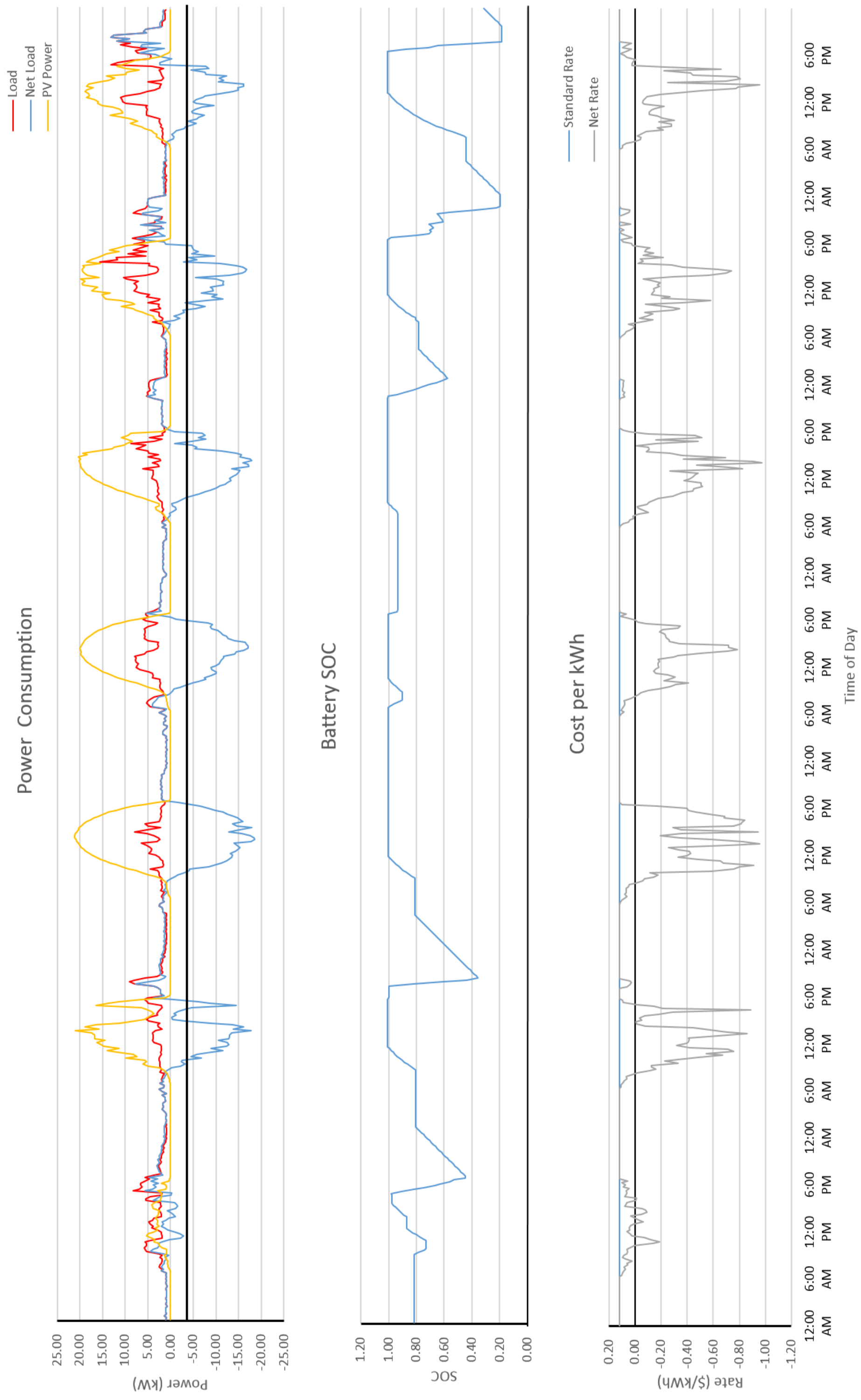

Figure B.42 – Spring – 1B 6.5 kWh Battery

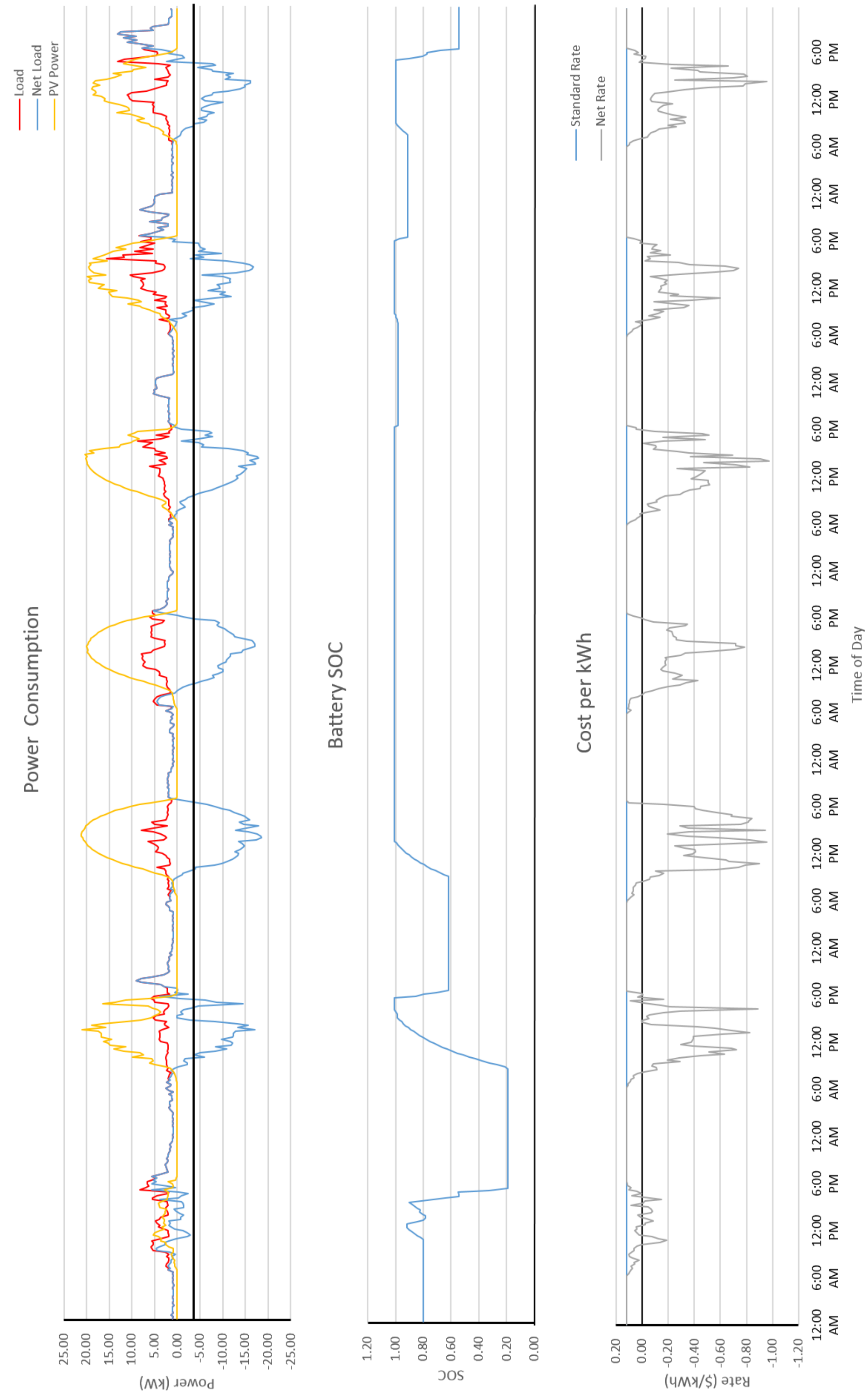

Figure B.43 – Spring – 2A 6.5 kWh Battery

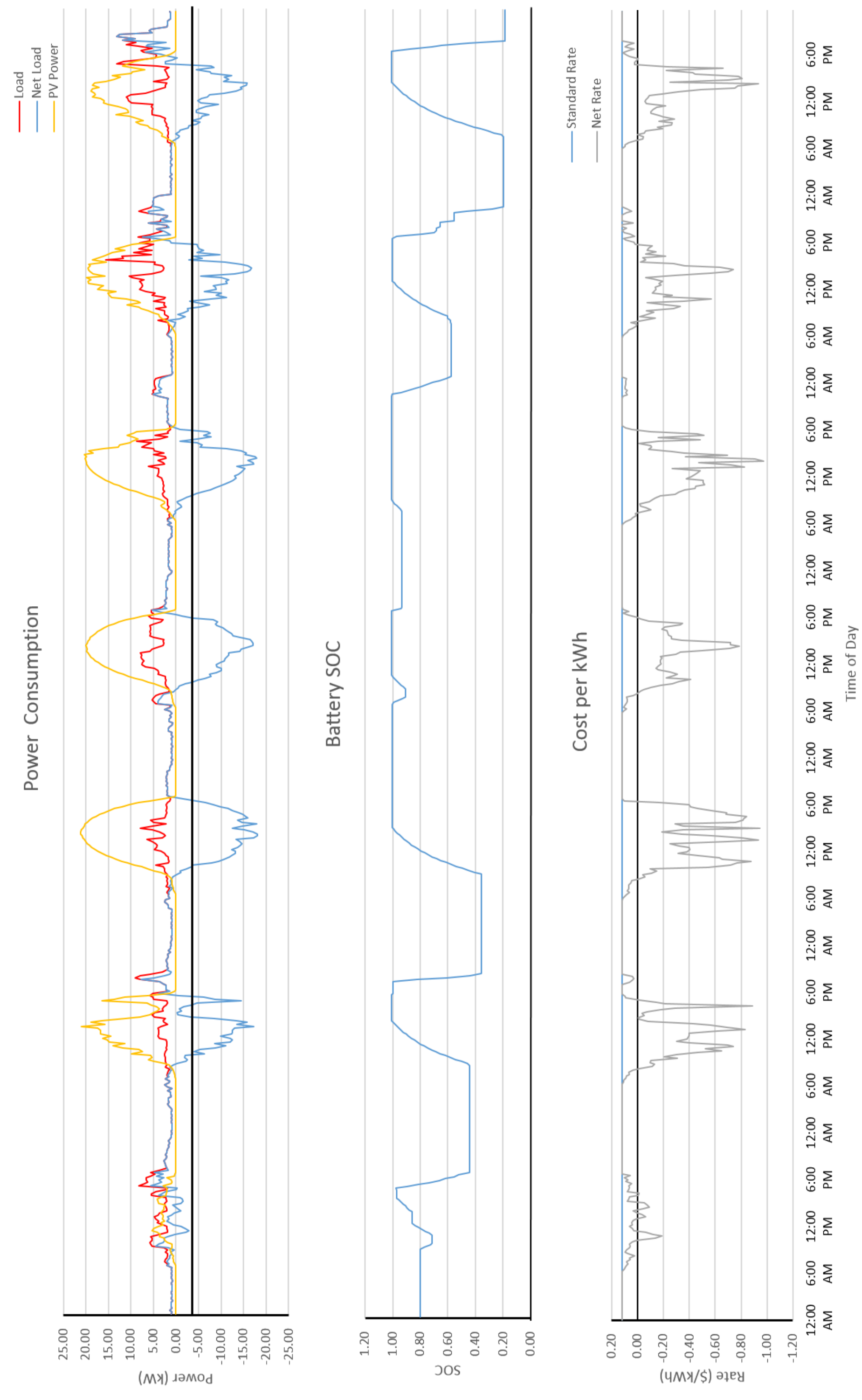

Figure B.44 – Spring – 2B 6.5 kWh Battery

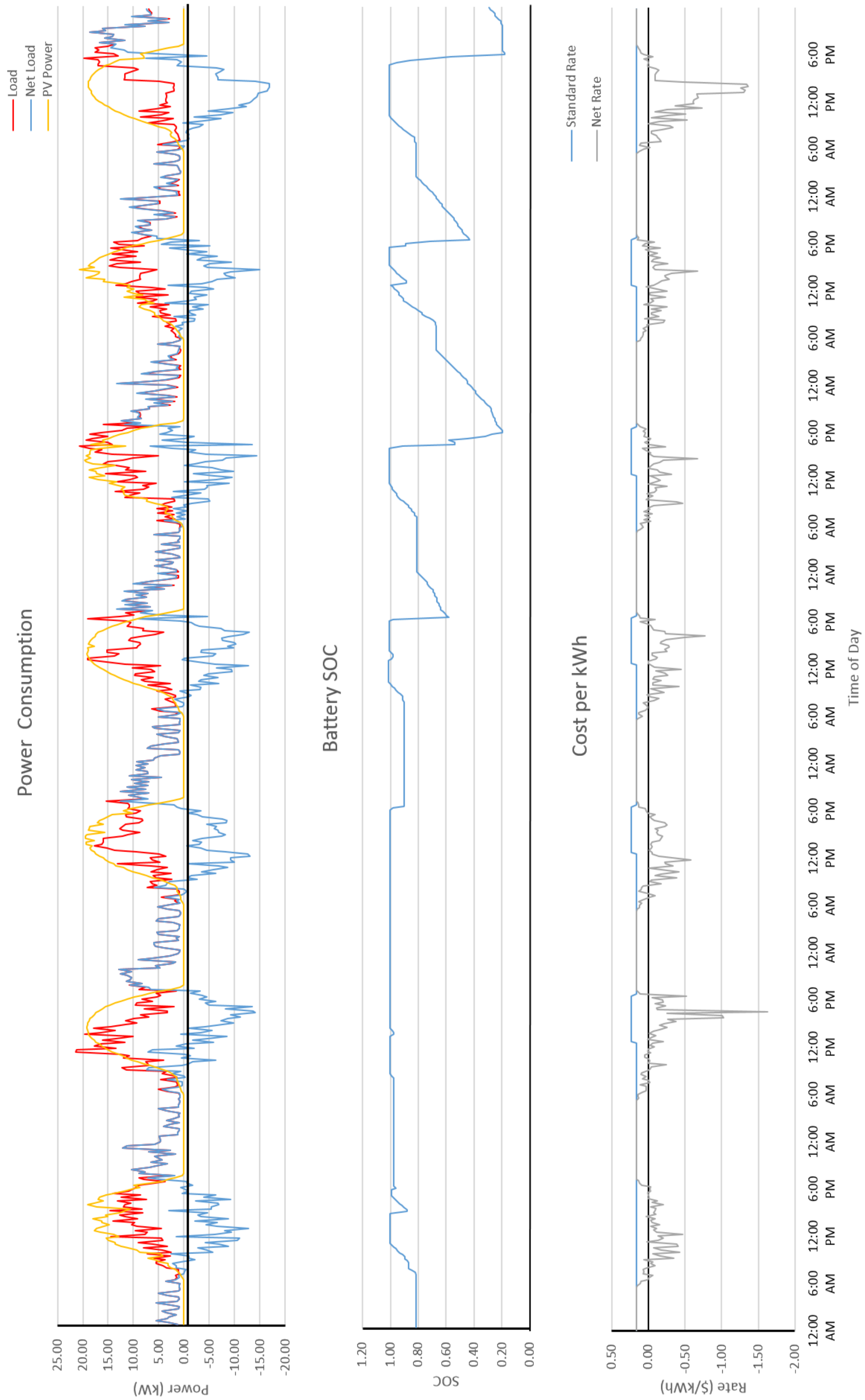

Figure B.45 – Summer – 1A 6.5 kWh Battery

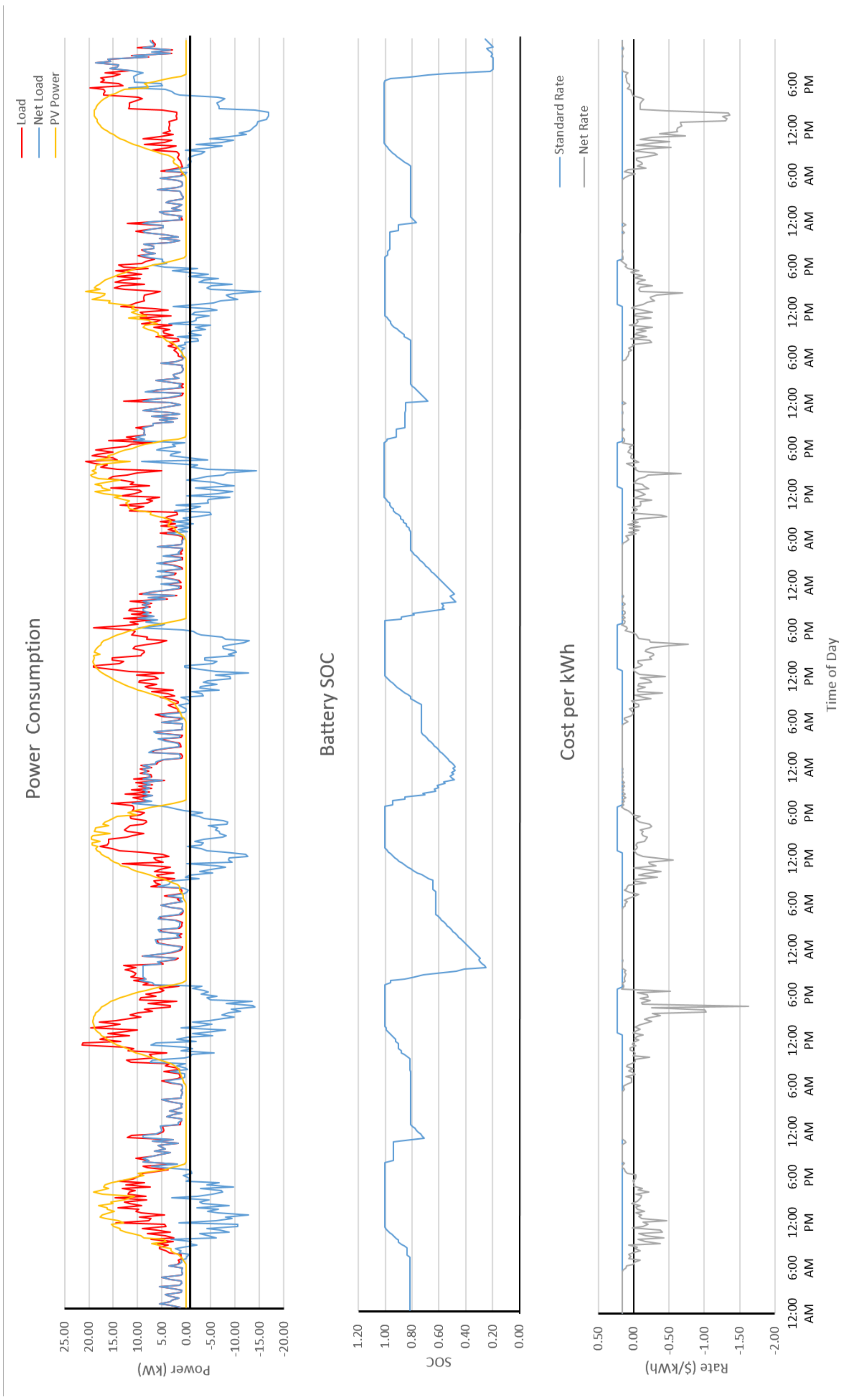

Figure B.46 – Summer – 1B 6.5 kWh Battery

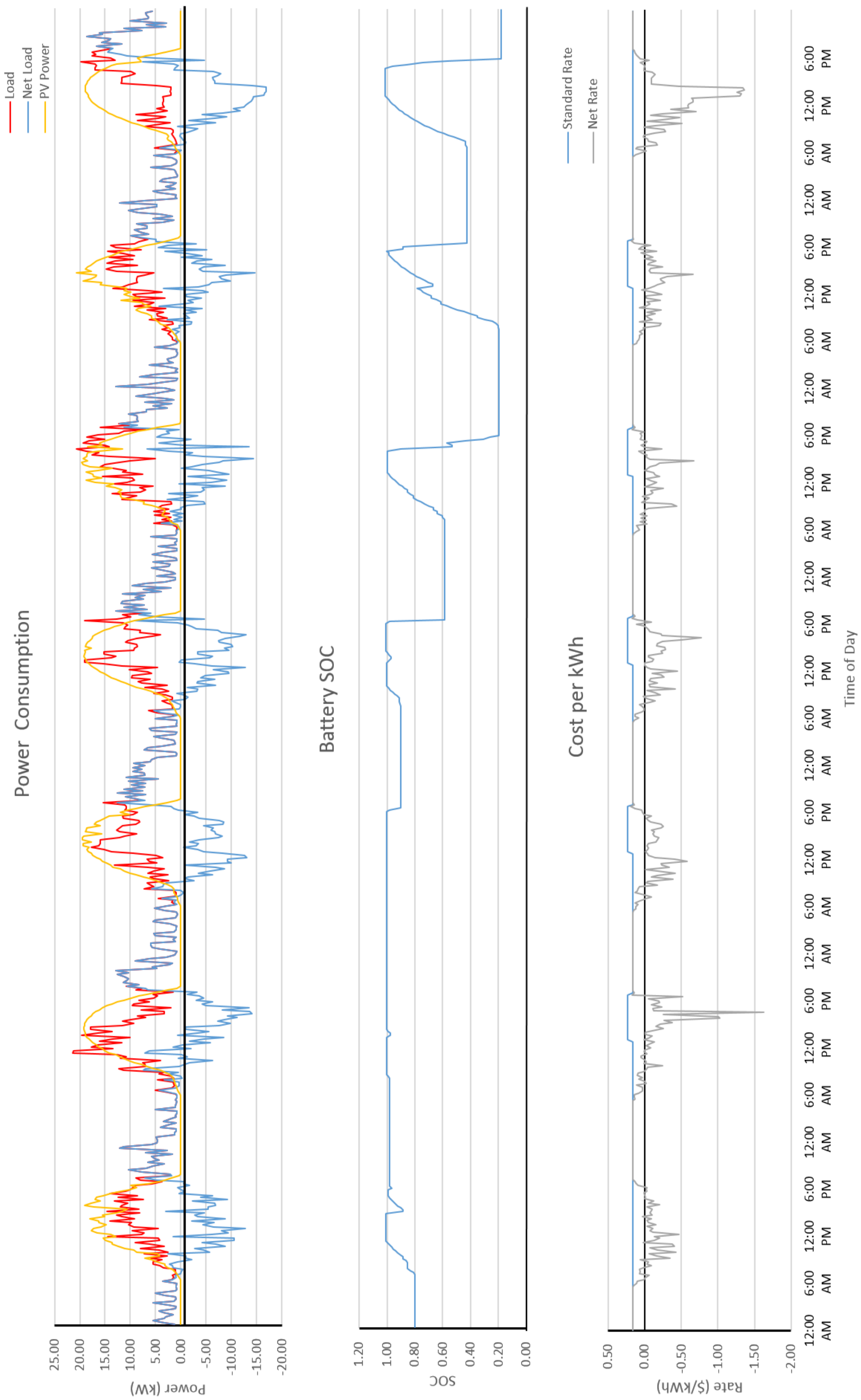

Figure B.47 – Summer – 2A 6.5 kWh Battery

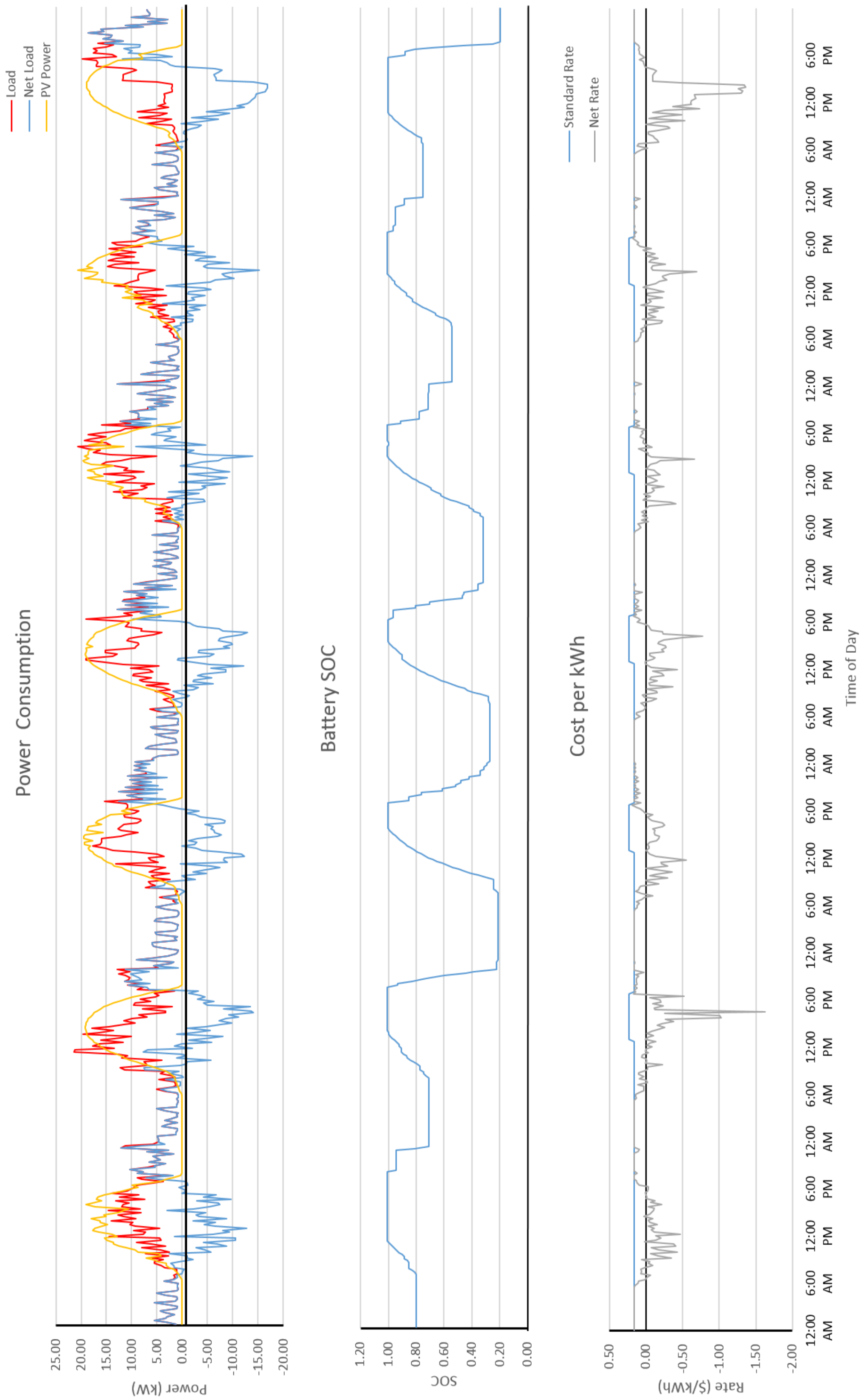

Figure B.48 – Summer – 2B 6.5 kWh Battery

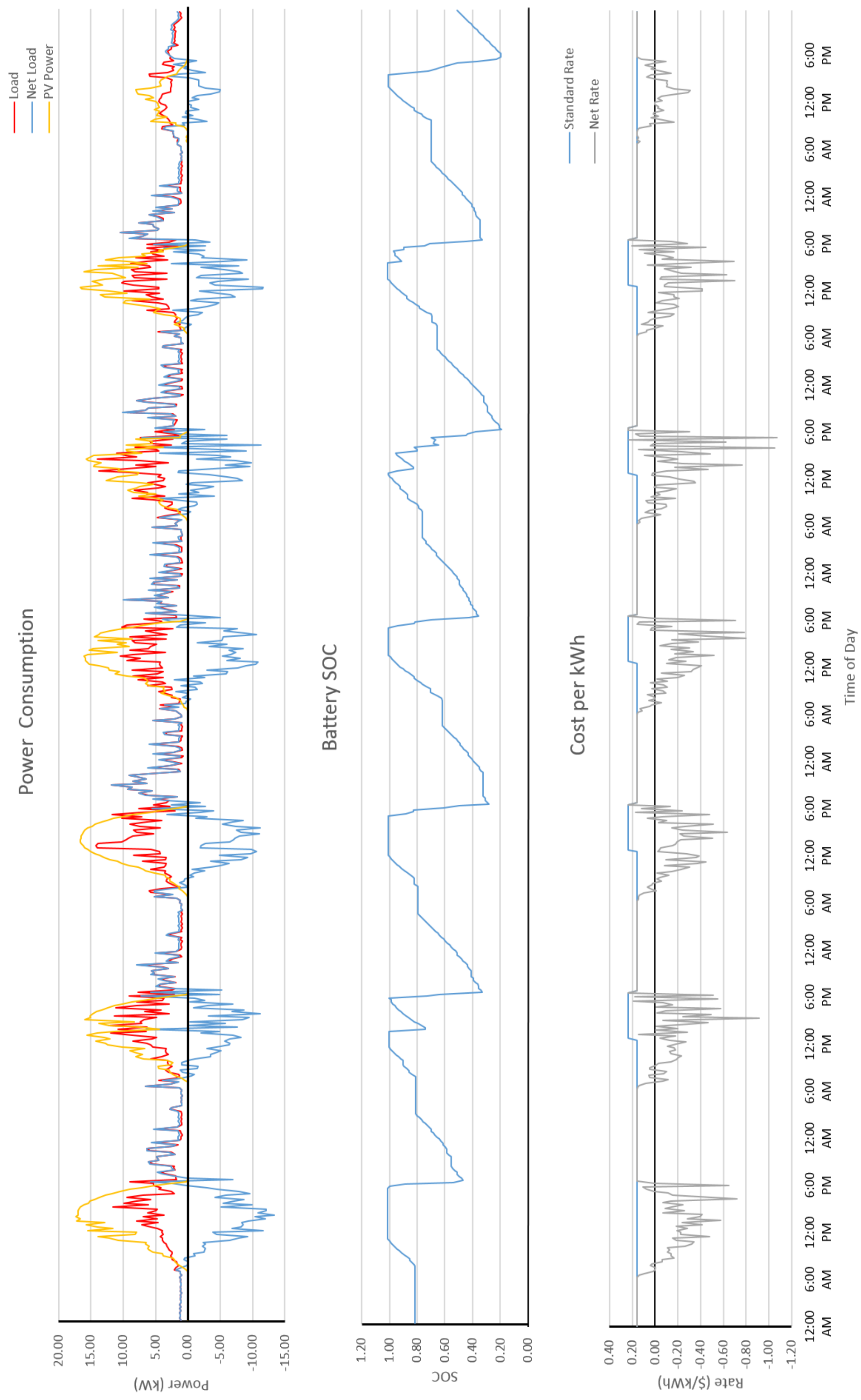

Figure B.49 – Autumn – 1A 6.5 kWh Battery

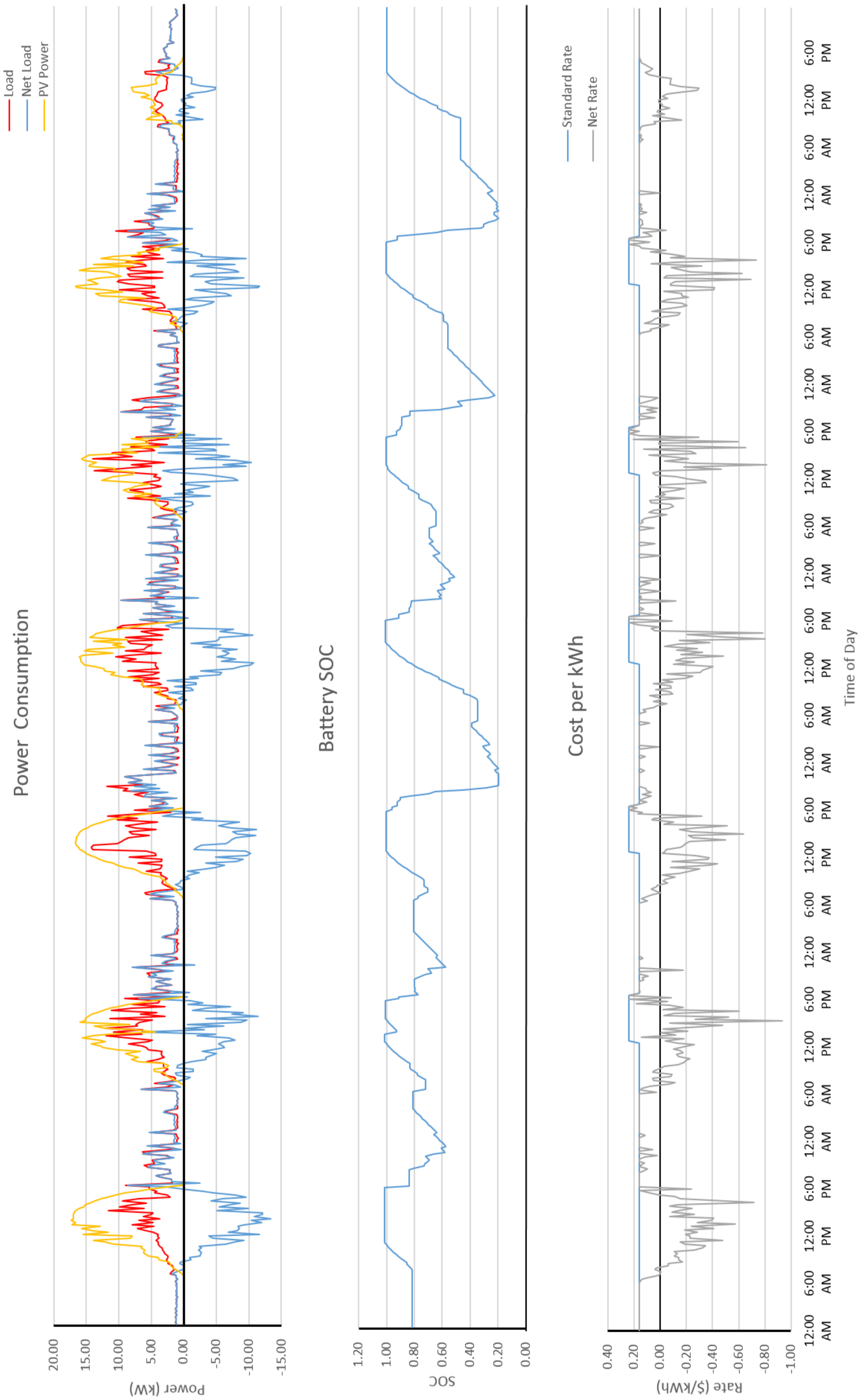

Figure B.50 – Autumn – 1B 6.5 kWh Battery

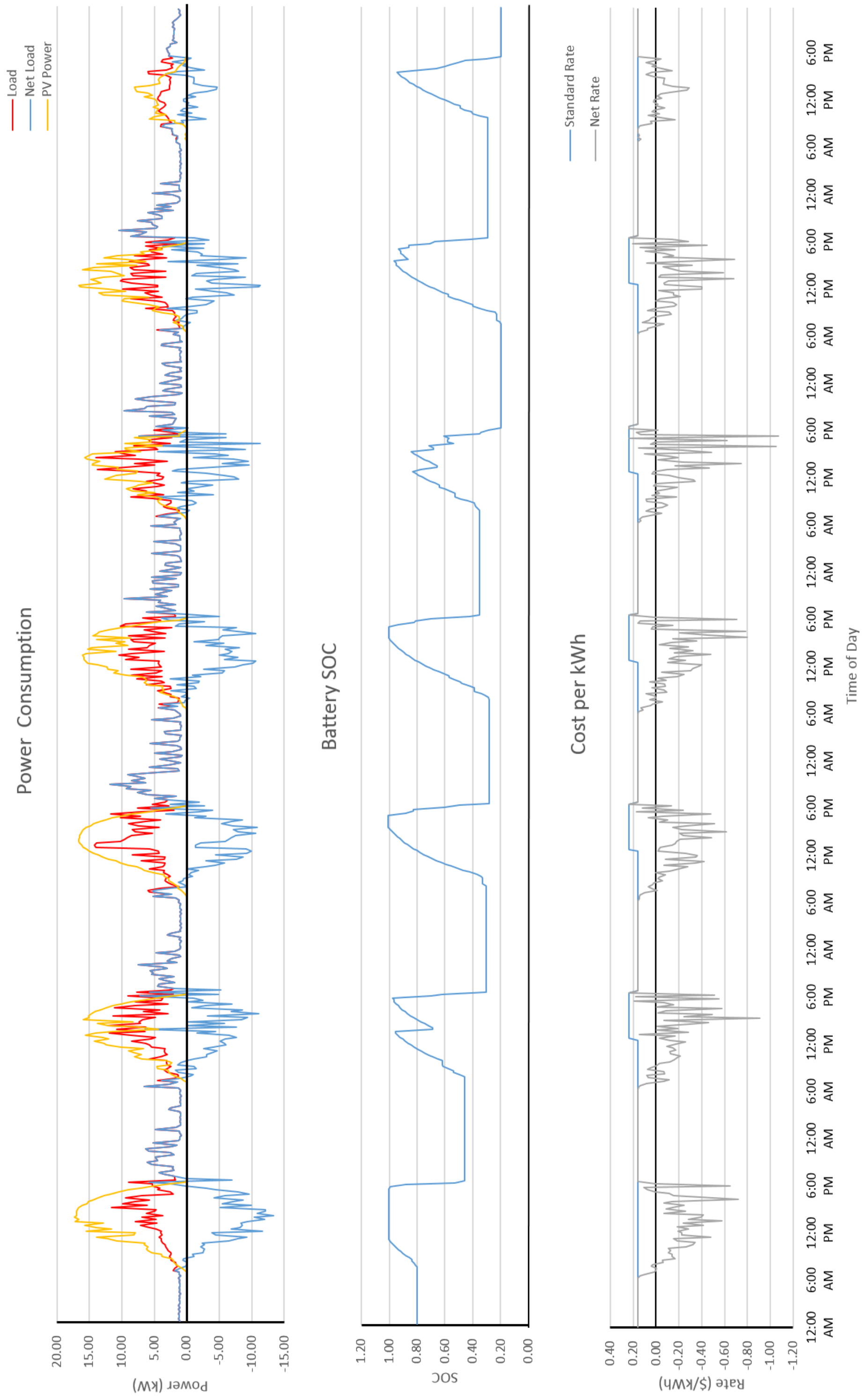

Figure B.51 – Autumn – 2A 6.5 kWh Battery

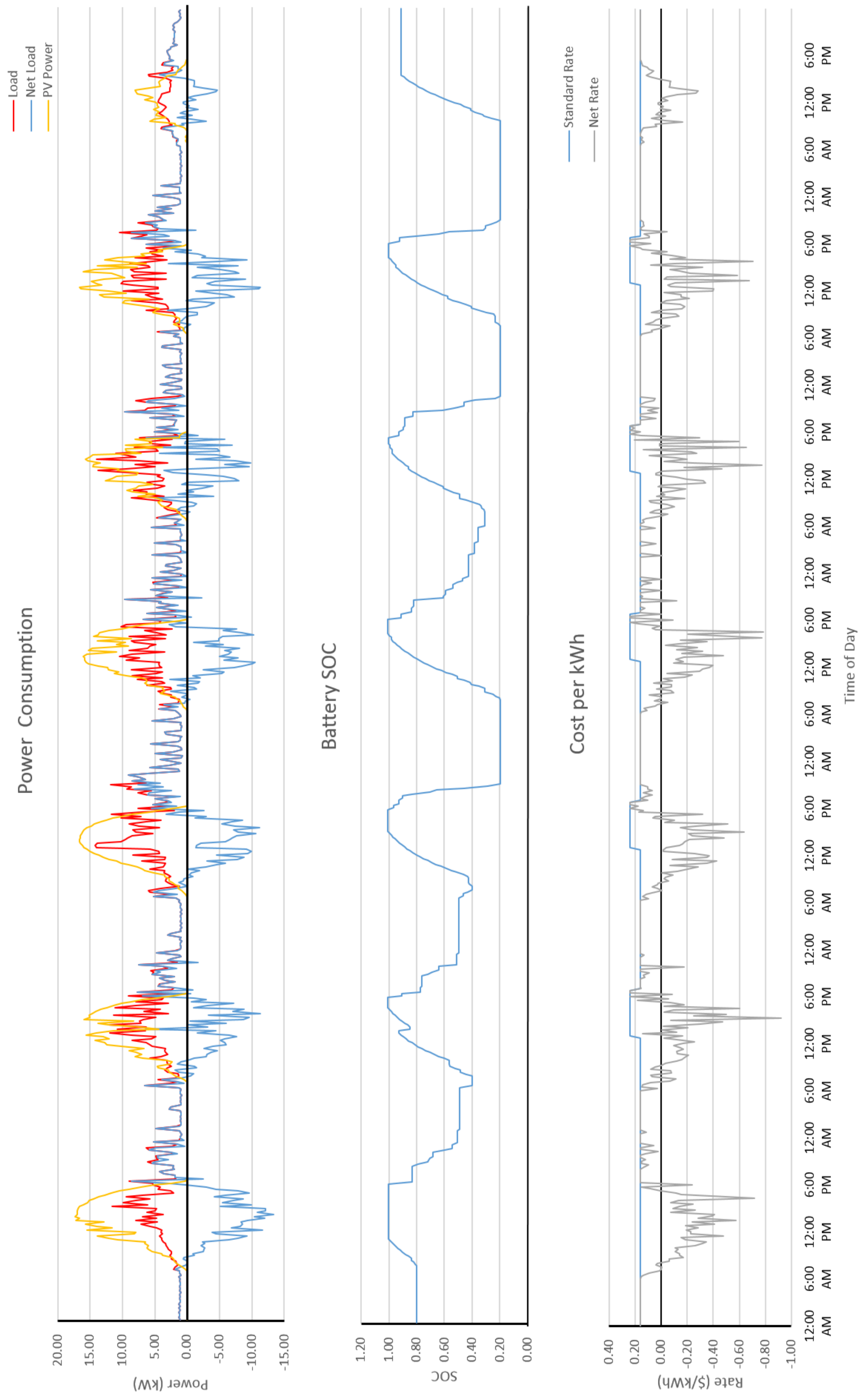

Figure B.52 – Autumn – 2B 6.5 kWh Battery

APPENDIX C

COST AND DEMAND CHARGE SUMMARIES FOR ALL WEEK-LONG SIMULATIONS

Table C.1 Dispatch Strategy Load and Cost Summary – 26 kWh Battery

Season	Dispatch Strategy	Peak Load (kW)	Load Factor	Usage Cost ($)	Demand Charge ($)	Total Charge ($)
Winter	Base	10.37	0.09	18.02	63.80	81.82
Winter	1A	10.37	0.09	19.19	63.80	82.99
Winter	1B	4.12	0.22	18.60	25.34	43.94
Winter	2A	10.37	0.09	19.24	63.80	83.04
Winter	2B	6.67	0.14	18.70	41.03	59.74
Spring	Base	13.18	-0.14	-36.99	81.06	44.07
Spring	1A	13.18	-0.14	-36.51	81.06	44.54
Spring	1B	7.81	-0.24	-37.69	48.03	10.34
Spring	2A	13.18	-0.14	-36.44	81.06	44.62
Spring	2B	8.18	-0.23	-37.96	50.33	12.37
Summer	Base	18.63	0.03	8.74	114.58	123.33
Summer	1A	18.63	0.03	6.52	114.58	121.10
Summer	1B	11.81	0.05	7.64	72.66	80.30
Summer	2A	18.63	0.03	6.16	114.58	120.75
Summer	2B	13.56	0.04	5.84	83.40	89.24
Autumn	Base	11.80	0.00	-5.59	72.57	66.98
Autumn	1A	11.80	0.00	-6.65	72.57	65.92
Autumn	1B	9.67	0.01	-4.42	59.46	55.04
Autumn	2A	11.80	0.00	-5.71	72.57	66.85
Autumn	2B	9.67	0.01	-4.02	59.46	55.43

Table C.2 Dispatch Strategy Load and Cost Summary – 13 kWh Battery

Season	**Dispatch Strategy**	**Peak Load (kW)**	**Load Factor**	**Usage Cost ($)**	**Demand Charge ($)**	**Total Charge ($)**
Winter	Base	10.37	0.09	17.97	63.80	81.77
Winter	1A	10.37	0.09	18.82	63.80	82.62
Winter	1B	7.38	0.12	18.51	45.40	63.91
Winter	2A	10.37	0.09	18.65	63.80	82.45
Winter	2B	8.47	0.11	18.25	52.11	70.36
Spring	Base	13.18	-0.14	-36.99	81.06	44.07
Spring	1A	13.18	-0.14	-36.77	81.06	44.29
Spring	1B	12.57	-0.15	-37.36	77.33	39.97
Spring	2A	13.18	-0.14	-36.82	81.06	44.24
Spring	2B	12.57	-0.15	-37.65	77.33	39.69
Summer	Base	18.63	0.03	8.74	114.58	123.33
Summer	1A	18.63	0.03	7.34	114.58	121.92
Summer	1B	18.63	0.03	6.73	114.58	121.31
Summer	2A	18.63	0.03	7.26	114.58	121.84
Summer	2B	18.63	0.03	7.96	114.58	122.55
Autumn	Base	11.80	0.00	-5.59	72.57	66.98
Autumn	1A	11.80	0.00	-6.93	72.57	65.64
Autumn	1B	6.87	0.01	-3.96	42.27	38.31
Autumn	2A	11.80	0.00	-7.31	72.57	65.26
Autumn	2B	6.87	0.01	-3.98	42.27	38.29

Table C.3 Dispatch Strategy Load and Cost Summary – 6.5 kWh Battery

Season	**Dispatch Strategy**	**Peak Load (kW)**	**Load Factor**	**Usage Cost ($)**	**Demand Charge ($)**	**Total Charge ($)**
Winter	Base	10.37	0.09	17.97	63.80	81.77
Winter	1A	10.37	0.09	18.37	63.80	82.17
Winter	1B	10.26	0.09	18.01	63.09	81.10
Winter	2A	10.37	0.09	18.24	63.80	82.04
Winter	2B	10.26	0.09	17.94	63.09	81.03
Spring	Base	13.18	-0.14	-36.99	81.06	44.07
Spring	1A	13.18	-0.14	-36.96	81.06	44.09
Spring	1B	13.18	-0.14	-37.08	81.06	43.98
Spring	2A	13.18	-0.14	-37.05	81.06	44.01
Spring	2B	13.18	-0.14	-37.21	81.06	43.85
Summer	Base	18.63	0.03	8.74	114.58	123.33
Summer	1A	18.63	0.03	6.30	114.58	120.88
Summer	1B	18.63	0.03	8.52	114.58	123.10
Summer	2A	18.63	0.03	7.71	114.58	122.30
Summer	2B	18.63	0.03	8.80	114.58	123.39
Autumn	Base	11.80	0.00	-5.59	72.57	66.98
Autumn	1A	11.80	0.00	-6.96	72.57	65.60
Autumn	1B	9.67	0.00	-5.01	59.46	54.44
Autumn	2A	11.80	0.00	-6.95	72.57	65.62
Autumn	2B	9.67	0.00	-4.24	59.46	55.21