PNNL-ACT-10125

Energy Northwest – Horn Rapids Solar and Storage

A Techno-economic Assessment

August 2022

X Ma
D Wu
A Crawford

U.S. DEPARTMENT OF ENERGY

Prepared for the U.S. Department of Energy
Under contract DE-AC05-76RL01830

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Pacific Northwest National Laboratory
Richland, Washington 99352

Executive Summary

Chartered in 1957 as a joint action agency of the state, Energy Northwest is a consortium of 27 public utility districts and municipalities across Washington state. Energy Northwest takes advantage of economies of scale and shared services to help utilities run their operations more efficiently and at lower costs, to benefit more than 1.5 million customers. Energy Northwest develops, owns, and operates a diverse mix of electricity-generating resources, including hydro, solar, and wind projects, along with the Northwest's only active nuclear energy facility. These projects provide enough reliable, affordable, and environmentally responsible energy to power more than a million homes each year, and that carbon-free electricity is provided at the cost of generation. The agency continually explores new generation projects to meet its members' needs.

In 2017, as part of the second round of funding from the Washington State Clean Energy Fund (CEF), the Washington State Department of Commerce granted up to $3 million in matching funds to develop an estimated $6.3 million project to deploy a 1 MW/4 MWh[1] battery energy storage system (BESS) in Richland, Washington. The BESS is paired with a 20-acre 4 MW direct current solar generating array of photovoltaic (PV) panels that can provide enough energy to power about 600 Richland homes. The combination of PV and BESS will provide a predictable, renewable generating source and serve as a training ground for solar and battery technicians throughout the nation. The project offers Washington state its first opportunity to integrate a large-scale solar and storage facility into its clean mix of hydro, nuclear, and wind resources.

In 2018, Pacific Northwest National Laboratory worked with Energy Northwest to perform a preliminary assessment of the integrated PV and BESS for representative use cases that could benefit the City of Richland. Between March and May 2022, extensive testing was conducted, and the results were used to assess the technical performance of the BESS subjected to actual field operations. The economic assessment was updated to reflect the actual cost and measured technical performance of the integrated system. This report documents the use cases, modeling and analytical methods, and final economic assessment results. The following key lessons and implications can be drawn from the analysis:

1. The benefits were estimated and compared to the costs of the deployed system in the base case to understand the cost-effectiveness of the project, as plotted in Figure ES.1. Benefits from outage mitigation are excluded because microgrid capability was not built into the design of the deployed system. As can be seen, the total present value benefits are $7.15–7.39 million, depending on the assumption and dispatch strategy used for assessment. Among all the benefits, demand charge reduction and load shaping charge reduction account for 46% and 45%, respectively, while the remaining 9% comes from transmission charge reduction. In particular, PV production contributes to 98% of load shaping charge reduction benefits. The benefit-cost ratio (BCR) of the deployed system is around 0.57. With the $3 million grant from the CEF, the outstanding cost for the City of Richland becomes $9.8 million. The corresponding BCR increases to around 0.74.

2. The yearly optimal dispatch method assumes perfect foresight of load and PV generation for the entire year. The estimated benefits using this method represent a theoretical upper bound of the integrated system and were used as a benchmark to quantify the impacts of operational uncertainties and to evaluate the proposed operational dispatch method.

[1] The deployed lithium-iron-phosphate battery is designed with 5.5 MWh of total usable energy. While about 4.3 MWh can be discharged within the recommended 10–90% state of charge range, the allowed daily discharged energy is limited to 4 MWh according to the capacity maintenance agreement.

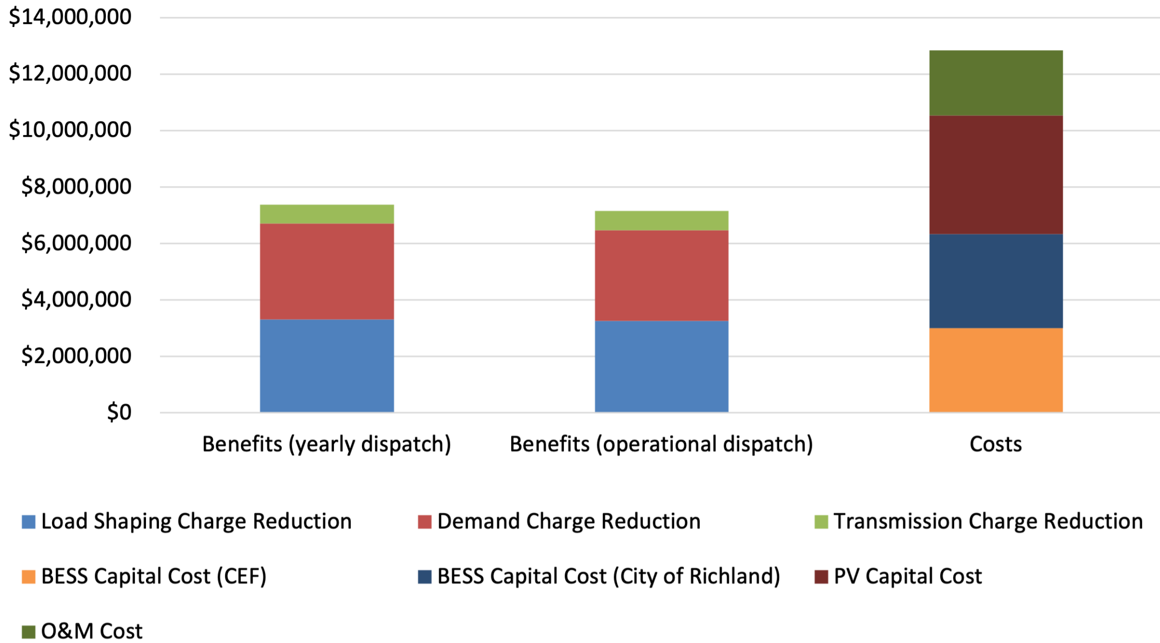

Figure ES.1. Present value benefits vs. costs of the deployed system in the base case.

3. To come up with a more realistic estimate, a practical operational dispatch method was proposed to model and address operational uncertainties. Advanced load modeling and forecasting methods were developed to generate the required inputs. Different thresholds were explored to examine the demand reduction effectiveness and the associated battery degradation. It was found that a threshold of 3% yields the best results, recovering about 97% of the benefits estimated using the yearly dispatch method. Specifically, load shaping reduction benefits decrease from $3.31 million to $3.26 million, and demand charge reduction benefits decrease from $3.40 million to $3.22 million. The BESS is cycled about 20% less frequently than the yearly optimal dispatch method. Therefore, the proposed operational dispatch helps mitigate BESS degradation, and can be used to identify the most appropriate capacity maintenance agreement with the optimal cycle life to maximize the net benefits..

4. To understand the potential benefits of the integrated system with a different design, we evaluated a hypothetical microgrid scenario where outage mitigation is considered in addition to the use cases for electricity bill reduction of the deployed system in the base case. The estimated benefits versus costs are plotted in Figure ES.2. The additional cost required for enabling microgrid operation was estimated at $0.85 million in present value. With the microgrid capability, the system can also be operated in island mode to mitigate the impacts of an outage from the main grid. Even though the BESS paired with PV can only partially mitigate an outage event, it could help the City of Richland avoid about 3 MWh of unserved load each year and bring in an additional $3.70 million of benefits in present value. With the outage mitigation benefits included, the total present value benefits become about $11 million. With the $3 million grant from the CEF, the corresponding BCR for the City of Richland increases to 1.03.

5. In the preliminary assessment performed at the planning stage, typical BESS performance and cost parameters were used, and the operation and maintenance (O&M) cost was not explicitly considered. Compared to the preliminary assessment results, the present value

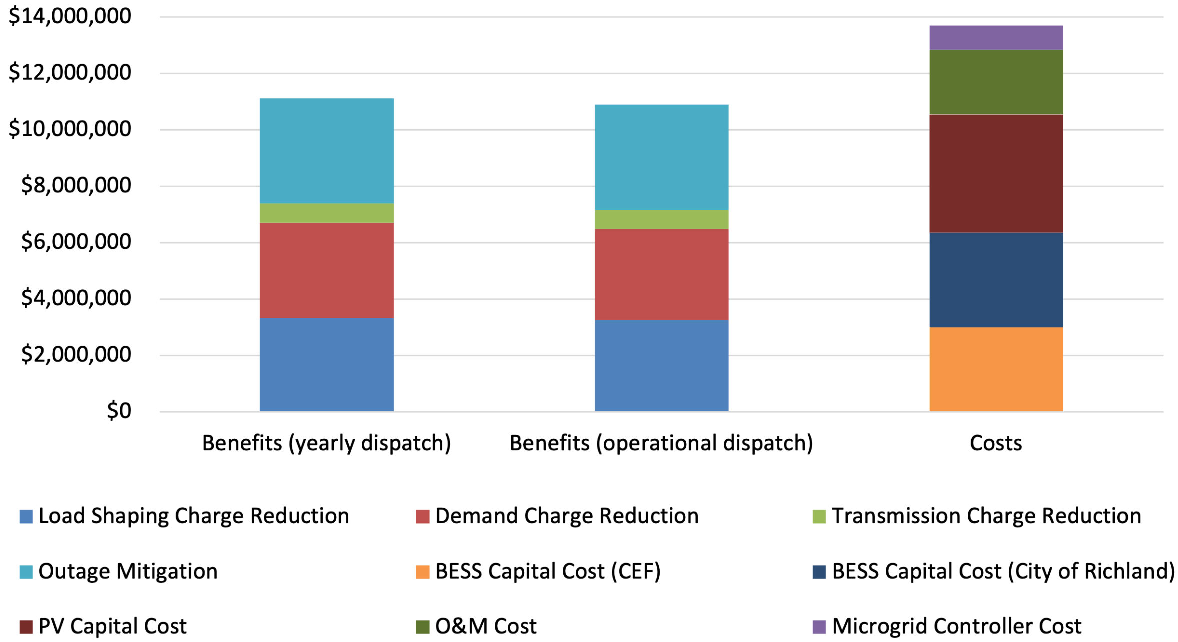

Figure ES.2. Present value benefits vs. costs in a hypothetical microgrid scenario.

benefits and cost in the final assessment results increase by $0.35 million and $0.64 million, respectively. The BCRs estimated in the preliminary analysis were 0.56 and 0.74 without and with considering the $3 million grant from the CEF, respectively, close to the numbers in the final assessment results.

Acknowledgments

We are grateful to Mr. Bob Kirchmeier, former Program Manager for the Clean Energy Fund (CEF) Grid Modernization Program, and Mr. Jeremy Berke, Senior Commerce Specialist and Program Manager for the CEF Grid Modernization Program at the Washington State Department of Commerce, for their leadership and support on this and other CEF projects. We are also grateful to Dr. Imre Gyuk, Director of the Energy Storage Program in the Office of Electricity at the U.S. Department of Energy, for providing financial support and leadership on this and related work at PNNL. Finally, we wish to acknowledge the team members from Energy Northwest, including Gabriel Smith, Kristine Cavanah, Jared Knode, Jennifer Harper, and Ross Rebich, and team members from Doosan, including Emiliano Parizzi and Michael Hamilton.

Acronyms and Abbreviations

BCR	benefit-cost ratio
BESS	battery energy storage system
BPA	Bonneville Power Administration
C&I	commercial and industrial
CDQ	contract demand quantity
CEF	Clean Energy Fund
CSP	customer system peak
DCR	demand charge rate
HLH	heavy load hour
LLH	light load hour
MPC	model predictive control
O&M	operation and maintenance
PNNL	Pacific Northwest National Laboratory
PV	photovoltaic(s)
RHWM	rate period high water mark
RMS	root mean square
SOC	state of charge
TSP	transmission system peak

Notation

Sets

$\mathcal{D}$	A set that contains hours from the beginning of a month to the current time
$\mathcal{K}$	A set that contains all hours within the optimal dispatch time frame
$\mathcal{L}$	A set that contains all month indices
$\mathcal{O}$	A set that contains all minute indices during an outage event
$\mathcal{T}$	A set that contains all transmission peak hours
$\mathcal{W}$	A set that contains all hours within the receding time horizon

Indices

k	Hour index
l	Month index
m	Minute index
t	Transmission peak hour index

Parameters

c^{lim}	BESS annual cycle limit
$E^{\text{batt}}_{\text{max}}$	BESS energy capacity
$E^{\text{day}}_{\text{max}}$	Maximum discharged energy every day
L_k	System native load at hour k
L^{act}_k	Actual load at hour k
L^{for}_k	Forecasted load at hour k
L_m	System native load at minute m during an outage event
$p^{\text{batt}}_{\text{max}}$	BESS rated power
$p^{\text{pv}}_{\text{max}}$	PV rated power
r^{pv}_k	Normalized generation per unit rated power of the PV at hour k
S_{min}	BESS minimum SOC
S_{max}	BESS maximum SOC
TH	Threshold for the peak-day probability
δT	Variation around the temperature break point
ΔT	Time step size
η^+	BESS discharging efficiency
η^-	BESS Charging efficiency
λ_k	Energy charge rate at hour k
μ_l	Demand charge rate of month l
ν_t	Transmission charge rate at peak hour t

Decision Variables

C_{op}	Total cost of the electricity bill
d_l	Peak demand of month l
e_k^{batt}	Energy stored in the BESS at the end of hour k
e_m^{batt}	Energy stored in the BESS at the end of minute m during an outage event
L_k^{net}	System net load at hour k
L'_{unserv}	Total unserved load without the integrated system during an outage event
L''_{unserv}	Total unserved load with the integrated system during an outage event
p_k^+	BESS discharging power at hour k
p_k^-	BESS charging power at hour k
p_k^{batt}	BESS power output at hour k
p_k^{pv}	PV power output at hour k
p_k^{out}	Power output of the integrated system at hour k
p_k^{sol}	Dispatch solution at hour k
p_m^{batt}	BESS power output at minute m during an outage event
p_m^{pv}	PV power output at minute m during an outage event

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CHAPTER 1

Introduction

The Washington State Clean Energy Fund (CEF) is a publicly funded program that provides grants to support the development of clean energy technologies in Washington state. Since 2013, the Washington State Legislature has authorized $122 million for the fund (Kirchmeier, 2018), including Energy Revolving Loan Fund Grants, Smart Grid and Grid Modernization Grants to Utilities, Federal Clean Energy Matching Funds, and Credit Enhancement for Renewable Energy Manufacturing. The funding levels for the first three rounds are plotted in Figure 1.1. In 2021, the Washington State Department of Commerce announced $3.9 million in grants as part of the fourth round of CEF funding for the early-stage project development of 18 grid modernization projects led by utilities across the state to advance a variety of renewable energy technologies and electricity system innovations. To date, CEF funds have been distributed to electric utility companies, vendors, universities, and research organizations for projects that integrate intermittent renewables, improve grid reliability, expand grid modernization activities, reduce the costs associated with distributed energy resource deployments, and lower emissions. Additional information on CEF and the Grid Modernization Program can be found in Washington State Department of Commerce (2017, 2021).

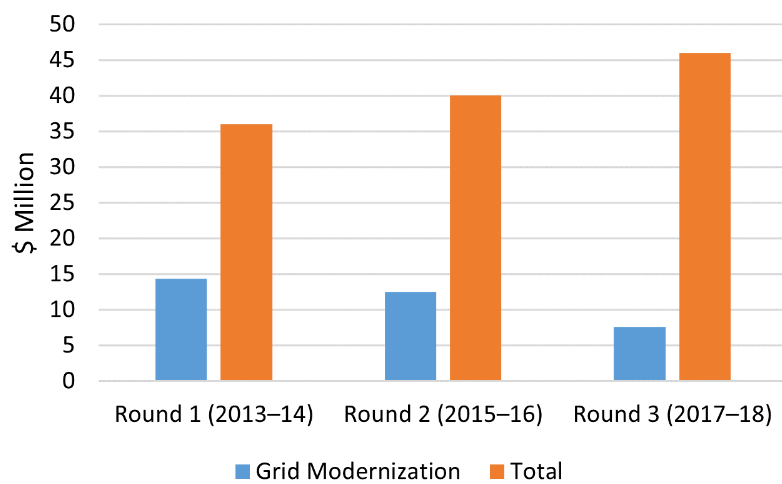

Figure 1.1. Washington State Clean Energy Fund funding levels.

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In 2018, Pacific Northwest National Laboratory (PNNL) worked with Energy Northwest to assess the PV paired with BESS for representative use cases that could benefit the City of Richland. Construction began in February 2020 and completed in the fall of 2020. The deployed combination is shown in Figure 1.2. The project energized in November 2020. Between March and May 2022, extensive testing was conducted, and the results were used to assess the technical performance of the BESS subjected to actual field operations. PNNL has worked closely with Energy Northwest in assessing the economic benefits of the integrated system that combines PV and BESS. This report documents the economic assessment of the integrated system, including the definition of use cases and applications, collection and preparation of data and input parameters, development of modeling and optimization methods, case studies, and analysis results.

Figure 1.2. Large-scale PV and BESS at Horn Rapids.

CHAPTER 2

Use Cases

The combination of PV and BESS can be used for various grid and end-user services. PNNL has previously developed an energy storage valuation taxonomy that includes bulk energy, ancillary, transmission, distribution, and customer energy management services (Balducci et al., 2018). The potential use cases and applications of energy storage vary by stakeholder and typically require different modeling and analytical methods (Wu and Ma, 2021). In this project, PNNL has worked with Energy Northwest to identify a list of high-value applications intended to benefit the City of Richland.

The City of Richland purchases energy from the Bonneville Power Administration (BPA) and is subject to BPA's rate structure. The City of Richland's monthly electricity bill includes four components: i) customer base charge, ii) load shaping charge, iii) demand charge, and iv) transmission charge.

- The customer base charge is independent of the monthly peak demand and the time when energy is consumed. Instead, it is a pre-calculated amount based on a forecasted load. For this reason, the customer base charge remains unaffected regardless of BESS operations. Hence, it will not be described in detail here, as it is simply a previously established charge that the City of Richland must pay each month.

- The load shaping, demand, and transmission charges would be affected by BESS operations. The load shaping and demand charges are components of the City of Richland's electricity bill from BPA that fluctuate every month. Load shaping appears as either a charge or a credit, depending on whether the City of Richland purchases more or less energy than the amount expected by BPA. On the other hand, the demand charge is a fee the City of Richland incurs that is tied to energy purchases during the utility's most load-intensive hour each month. The transmission charge is a small monthly charge that depends on the City of Richland's total MWh energy usage during BPA's transmission system peak (TSP).

Therefore, the following three use cases were identified for the deployed system to reduce the electricity bill paid by the City of Richland: 1) *load shaping charge reduction*, 2) *demand charge reduction*, and 3) *transmission charge reduction*. Note that microgrid capability was not built into the design of the deployed system. Microgrid controllers and associated upgrades are required to operate BESS and PV to support the local load as an islanded microgrid when there is an outage from the main grid. To capture the potential benefits of the BESS and PV for strengthening the distribution resilience and reducing power interruptions of critical facilities, an alternative scenario is designed to include *outage mitigation*. Each of these use cases is described as follows.

2.1 Load Shaping Charge Reduction

BPA offers its customers a tiered rate structure that consists of multiple levels, each of which is differentiated by a MWh energy usage quantity and priced individually. The cutoff at which it crosses from a lower level to the next is established to align with the current generation capabilities of BPA's system. Tier 1 is a lower price level in BPA's structure, and the City of Richland is allocated a limited quantity of energy (in MWh) that they may purchase at this rate. The reasoning behind the purchase cap is that Tier 1 is constrained by BPA's total current generation capability and the level of demand it can readily meet with available resources. Tier 2 rates, on the other hand, are established to cover the City of Richland's remaining demand beyond what is covered under Tier 1, and are higher as they are priced according to the cost of BPA obtaining more generation to meet the additional demand. The amount of energy that the City of Richland has to purchase at Tier 2 rates is called the above rate period high water mark (RHWM) obligation. It is set at a fixed amount based on a forecast of how much Tier 2 energy BPA expects the City of Richland to require. The combination of PV and BESS can effectively affect monthly energy consumption during different hours and thereby can be used to reduce load shaping charges. The calculation of heavy load hour (HLH) and light load hour (LLH) load shaping charges are described as follows, with all parameters listed in Table 2.1.

Table 2.1. The City of Richland's Monthly Load Shaping Charge Parameters

Month	HLH Shaped Load (MWh)	LLH Shaped Load (MWh)	HLH above RHWM Obligation (MWh)	LLH above RHWM Obligation (MWh)	HLH Rate ($/MWh)	LLH Rate ($/MWh)
Jan.	44,471.193	27,510.022	5,563.200	4,784.352	29.30	23.94
Feb.	37,275.805	21,734.829	5,340.672	4,005.504	28.54	23.94
Mar.	44,181.462	25,684.985	6,008.256	4,325.388	23.75	20.80
Apr.	43,185.688	23,966.131	5,563.200	4,450.560	19.67	17.54
May	62,805.228	35,735.314	5,785.728	4,561.824	16.63	11.25
June	50,860.875	26,885.009	5,785.728	4,228.032	17.71	9.31
July	44,631.845	23,635.566	5,563.200	4,784.352	24.66	19.05
Aug.	50,582.801	25,026.089	6,008.256	4,339.296	28.11	22.61
Sept.	43,786.989	24,711.659	5,563.200	4,450.560	27.94	22.19
Oct.	44,874.570	24,119.334	5,785.728	4,561.824	26.74	22.49
Nov.	53,730.386	31,540.835	5,563.200	4,464.468	27.27	24.74
Dec.	52,481.838	31,765.377	5,563.200	4,784.352	30.28	26.60

2.1.1 Heavy Load Hour Load Shaping Charge

This is a monthly charge or credit to customers that depends on whether their total energy demand during all HLHs is greater or less than expected each month. HLHs are all hours between 6 a.m. and 10 p.m., Monday through Saturday, excluding holidays. For customers that purchase less than expected, they receive a credit on their bill, whereas customers that purchase more are penalized. In this work, holidays are not differentiated from other days in modeling for simplicity as they would have a minimal impact on the results.

The monthly HLH load shaping charge/credit can be calculated as:

$$\begin{aligned} HLH\ load\ shaping\ charge = \big(&HLH\ energy - HLH\ above\ RHWM\ obligation \\ &- HLH\ shaped\ load\big) \times HLH\ load\ shaping\ rate, \end{aligned} \tag{2.1}$$

where

- $HLH\ energy$ is the total amount of energy purchased during all HLHs in a month, which is the only non-predetermined value that is affected by PV and BESS.
- $HLH\ above\ RHWM\ obligation$ is the monthly amount of HLH energy that the City of Richland has made the obligation to purchase at higher Tier 2 rates. This energy will be charged in a separate part that the combination of PV and BESS cannot affect. It must be subtracted from this calculation so that only Tier 1 amounts are included. The HLH above RHWM amount is different each month and is calculated as the product of the total number of HLHs that month and the set Tier 2 amount of energy the customer has agreed to pay per hour.
- $HLH\ shaped\ load$ is the total amount of energy across all HLHs that BPA expected the City of Richland to purchase that month. This value changes monthly but is predetermined for each month of the year and is based on the percent of BPA's total system cost the customer makes up.
- $HLH\ load\ shaping\ rate$ is the price at which the HLH billing determinant is charged/credited.

2.1.2 Low Load Hour Load Shaping Charge

Similar to the HLH load shaping charge, this is a monthly charge or credit to customers that depends on whether their energy demand is greater or less than expected during LLHs, which include all other hours on those same days as well as all hours on Sundays and holidays. The LLH load shaping charge/credit for each month can be determined by:

$$\begin{aligned} LLH\ load\ shaping\ charge = \big(&LLH\ energy - LLH\ above\ RHWM\ obligation \\ &- LLH\ shaped\ load\big) \times LLH\ load\ shaping\ rate, \end{aligned} \tag{2.2}$$

where $LLH\ energy$ is the only non-predetermined value that is affected by PV and BESS. The description of other parameters are similar to those of the HLH and is thereby omitted.

2.2 Demand Charge Reduction

The City of Richland faces a demand charge on its bill every month. The monthly demand charge is determined by four factors: i) its customer system peak (CSP), ii) its Tier 1 average HLH load, iii) its contract demand quantity (CDQ), and iv) BPA's demand charge rate (DCR). These four components come together through the following formula:

$$demand\ charge = (CSP - above\ RHWM - aHLH - CDQ) \times DCR, \tag{2.3}$$

where

- CSP is the City of Richland's single highest demand each month. It does not get adjusted to a Tier 1 value, but is simply the peak itself. CSP is a decision variable that can be affected by PV and BESS operations.
- $above\ RHWM$ follows the same logic as the above RHWM obligation for the load shaping charge: a portion of the demand charge must be separated out to be charged at Tier 2 rates. This value is constant at 13,908 kW each month, which is the amount the City of Richland is obligated to purchase at Tier 2 rates on a per-hour basis.
- $aHLH$ is the average HLH load in a given month. This component requires a Tier 1 adjustment and can be calculated by dividing all Tier 1 HLH energy by the number of HLHs that month. Taking October 2018 as an example, the City of Richland's total energy consumption during all HLHs in that month was 42,145.683 MWh. To obtain a Tier 1 portion of that value, the Tier 2 amount must be subtracted out, and then the difference is divided by the total number of HLHs, giving the overall average:

$$\begin{aligned} aHLH &= \frac{HLH\ energy - HLH\ above\ RHWM\ obligation}{total\ number\ of\ HLHs\ in\ the\ month} \\ &= \frac{42{,}145.683 \text{ MWh} - 5{,}785.728 \text{ MWh}}{416 \text{ hours}} \\ &= 87.404 \text{ MW} \end{aligned}$$

- CDQ is the amount of demand that is set in the City of Richland's original energy contract with BPA. This value is preset but can be different each month of the year, as listed in Table 2.2.
- DCR is the price at which the demand charge billing determinant is charged. This value changes monthly but is predetermined, as listed in Table 2.2.

Table 2.2. The City of Richland's Monthly Demand Charge Parameters

Month	CDQ (kW)	DCR ($/kW)
Jan.	36,106	11.45
Feb.	46,079	11.15
Mar.	28,189	9.28
Apr.	19,141	7.68
May	30,020	6.49
June	33,452	6.92
July	28,305	9.63
Aug.	28,121	10.98
Sept.	25,628	10.91
Oct.	28,360	10.45
Nov.	37,921	10.65
Dec.	25,476	11.83

2.3 Transmission Charge Reduction

The City of Richland incurs a small transmission charge each month of $2.103/kW that is dependent on its energy purchases during BPA's TSP. By using the PV and BESS to reduce load during TSP, costs can be reduced. For example, the economic benefits of reducing 500 kW during TSP are $1,050 per month or $12,600 per year.

2.4 Outage Mitigation

Microgrid capability was not built into the design of the deployed system. Therefore, in addition to the deployed BESS, PV, and existing control and communication infrastructure, microgrid controllers and associated upgrades are needed to enable islanding and transiting between grid-connected mode and island mode. Provided that the system is capable of forming a microgrid, the combination of PV and BESS can be used to serve the local load when there is an outage of the main grid. This would result in benefits accruing for the City of Richland's customers located in the area of the outage and can be monetized in terms of avoided loss of load. According to the City of Richland, approximately 80% of its customers are large commercial and industrial (C&I), and 20% are small C&I.

Historical outage events at Horn Rapids (Feeder 113) and relevant data has been collected from 2014 to 2017, as summarized in Table 2.3, to evaluate outage mitigation benefits. Based on the historical events, outage statistics in terms of timing and duration can be extracted. On average, Feeder 113 experienced three unplanned outages affecting 23 customers annually, with each outage lasting 98 minutes. Note that all outage events could only be partially mitigated because the feeder load exceeds the capacity of PV and BESS.

Table 2.3. Historical Outage Events at Horn Rapids

Year	Date	Start Time	Duration (Hours)	Customers Affected
2017	12/2/17	16:00	2.167	4
2016	5/15/16	07:00	2.500	1
2016	1/29/16	09:36	0.783	100
2015	11/17/15	15:26	1.833	1
2015	10/26/15	04:45	2.250	5
2015	8/30/15	05:52	1.167	1
2015	6/27/15	04:59	0.000	80
2015	2/24/15	08:15	4.500	1
2014	1/26/14	07:50	1.667	22
2014	1/22/14	14:50	0.667	22
2014	1/22/14	08:00	1.333	22
2014	1/20/14	08:45	0.750	22

CHAPTER 3

System Modeling and Optimal Dispatch

This chapter presents the mathematical modeling of the integrated system, along with an optimization-based assessment framework proposed and used to assess the integrated system. In particular, two dispatch and assessment methods are proposed to quantify the economic benefits:

- The first method assumes perfect knowledge of the system load information for the entire year. A large optimization problem is formulated with hourly BESS dispatch as decision variables. The optimization problem is solved to determine optimal hourly operations of BESS for the entire year and to maximize the annual benefits, subject to BESS operational and cycling constraints. Because scheduling a BESS over a year is impractical, this method generates a theoretical upper bound of the economic benefits.
- The second method simulates daily or hourly operational dispatch typically used in practice. Dispatch decisions are made based on i) the day-ahead load forecast and ii) a prediction about when the monthly peak demand will occur. An optimal dispatch method based on model predictive control (MPC) is proposed and used to incorporate operational uncertainties into modeling and valuation. A flow chart is provided in Figure 3.1 to illustrate the proposed method. Specifically, we predict the probability that the monthly peak demand will occur during the next day, which is named as *peak-day probability*. A threshold is designed and used to control whether to activate BESS dispatch: if the predicted peak-day probability exceeds the threshold, the BESS will be dispatched on the operating day. Otherwise, the BESS will not be used for demand charge reduction. A higher threshold leads to less usage of the BESS and therefore slower degradation. In this way, we can achieve a good balance between peak demand reduction effectiveness and battery degradation.

The two optimal dispatch methods are compared in Table 3.1. While the yearly optimization based on the load and PV profile throughout a year helps us understand the potential value, the operational dispatch method better models and addresses operational uncertainties and estimates practically achievable benefits. The former formulates all 8760 hourly BESS operations within a single optimization problem, while the latter repeatly formulate and solve smaller operational dispatch problems with a 24-hour look-ahead window for 24 $\times$ $N(TH)$ times, where $N(TH)$ denotes the number of active days and depends on the preset threshold TH. In an extreme case when TH is set as zero, for example, the BESS will be activated every day for demand charge reduction. Therefore, we have $N(0) =$ 365. If we increase the threshold TH, the value of $N(TH)$ will decrease monotonically, which means that the BESS has more time to be set aside and thus degrades slowly.

The rest of this chapter is organized as follows. The BESS and PV models used for optimal dispatch and assessment are provided in Section 3.1. Section 3.2 presents the load forecasting method that is used to generate the required inputs for the operational dispatch method. The two assessment methods are detailed in Section 3.3. Finally, Section 3.4 presents a model for calculating the benefits of outage mitigation.

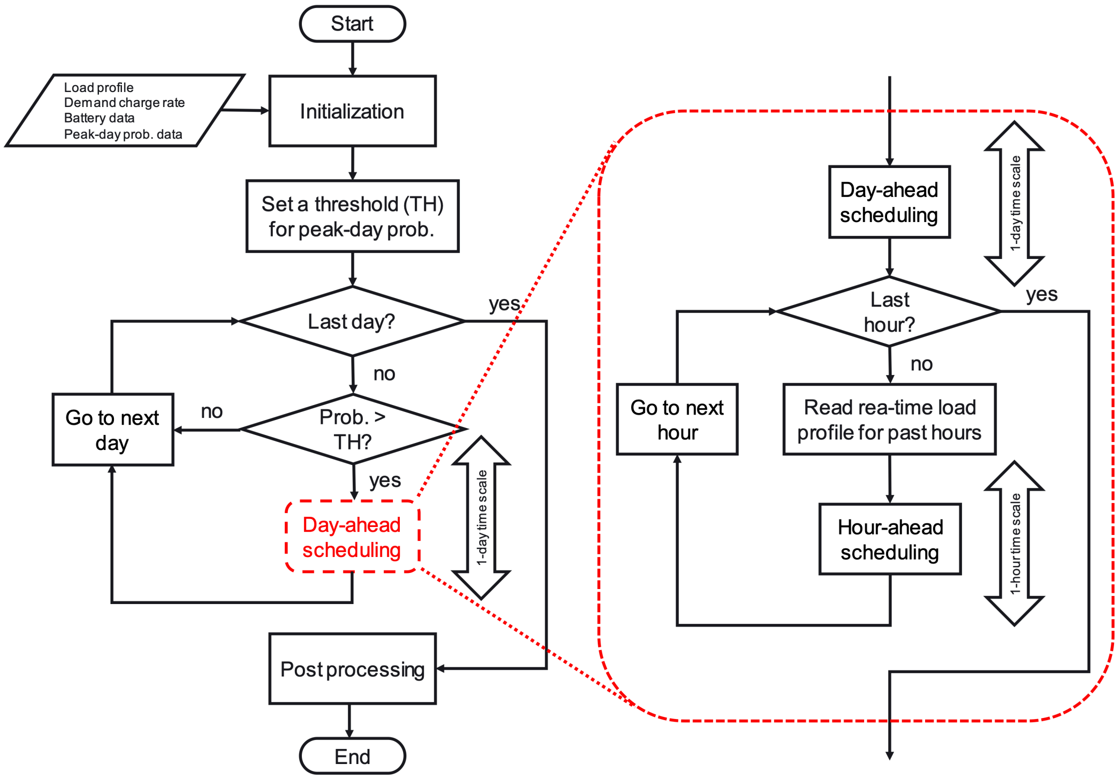

Figure 3.1. A flow chart of the practical operational dispatch.

Table 3.1. Comparisons between Two Optimal Dispatch Methods

	Yearly Optimal Dispatch	**Practical Operational Dispatch**
System Load Information	perfectly known	forecast load with uncertainties
Number of Optimizations	1	24 $\times$ $N(TH)$
Time Horizon (in Hours)	8760	24
Peak-day Probability	No	Yes

3.1 BESS and PV Models

A BESS can be modeled as a scalar linear dynamical system that resembles simplified energy state dynamics parameterized by charging and discharging power limits, energy state limits, and efficiencies (Wu et al., 2021). To capture one-way efficiencies, two non-negative auxiliary variables p_k^+ and p_k^- can be introduced to represent discharging and charging power at the point of common coupling, respectively. The discharging and charging power ranges are given by:

$$0 \le p_k^+ \le p_{\text{max}}^{\text{batt}}, \quad 0 \le p_k^- \le p_{\text{max}}^{\text{batt}}, \quad \forall k \in \mathcal{K}, \tag{3.1}$$

where $p_{\text{max}}^{\text{batt}}$ is the BESS rated power and $\mathcal{K}$ is a set that contains all scheduling hours. The BESS power output can be expressed as:

$$p_k^{\text{batt}} = p_k^+ - p_k^-, \quad \forall k \in \mathcal{K}, \tag{3.2}$$

where a positive p_k^{batt} means discharging. The dynamics of the BESS energy state can be modeled as:

$$e_k^{\text{batt}} = e_{k-1}^{\text{batt}} - (p_k^+/\eta^+ - p_k^-\eta^-)\Delta T, \quad \forall k \in \mathcal{K}, \tag{3.3}$$

where e_k^{batt} is the energy state at the end of hour k, η^+ and η^- are discharging and charging efficiencies, respectively, and ΔT is the hour size. A range for the energy state is given by:

$$S_{\text{min}} E_{\text{max}}^{\text{batt}} \leq e_k^{\text{batt}} \leq S_{\text{max}} E_{\text{max}}^{\text{batt}}, \quad \forall k \in \mathcal{K}, \tag{3.4}$$

where $E_{\text{max}}^{\text{batt}}$ is the BESS energy capacity, and S_{min} and S_{max}, respectively, are the minimum and maximum requirements for the state of charge (SOC) of the BESS. The total amount of BESS discharged energy during all hours should also be bounded by:

$$\sum_{k \in \mathcal{K}} p_k^+ \Delta T/\eta^+ \leq c^{\text{lim}} E_{\text{max}}^{\text{batt}}, \tag{3.5}$$

where c^{lim} is an annual cycle limit, i.e., a given upper bound to restrict how many cycles we can use the BESS annually. Moreover, to add a constraint on daily discharged energy, we have:

$$\sum_{k=24(d-1)+1}^{24d} p_k^+ \Delta T/\eta^+ \leq E_{\text{max}}^{\text{day}}, \quad \forall d = 1, \cdots, 365, \tag{3.6}$$

where $E_{\text{max}}^{\text{day}}$ denotes a maximum discharged energy allowed each day. A range of the PV power output can be expressed as:

$$0 \leq p_k^{\text{pv}} \leq r_k^{\text{pv}} p_{\text{max}}^{\text{pv}}, \quad \forall k \in \mathcal{K}, \tag{3.7}$$

where r_k^{pv} is the normalized power output in maximum power point tracking mode at hour k, and $p_{\text{max}}^{\text{pv}}$ is the PV rated power. Finally, the power output from the integrated system into the grid becomes:

$$p_k^{\text{out}} = p_k^{\text{batt}} + p_k^{\text{pv}}, \quad \forall k \in \mathcal{K}. \tag{3.8}$$

3.2 Load Forecasting

PNNL has developed a probabilistic load forecasting model to capture operational uncertainties in the optimal dispatch and economic assessment. On each given day, the load forecasting model predicts the hourly load for the remainder of the month based on calendar variables such as hour of the day, day of the week, and day of the year, as well as the outdoor temperature. The error from the load model and the uncertainty in predicting temperature are incorporated to produce a model that predicts the probability of a given hour being the monthly peak hour. This is valuable for demand charge reduction, as the demand charge is based on the maximum load of the entire month, while a typical look-ahead scheduling can only cover one or a few days.

Hourly load profiles for all the feeder meters from 2015 to 2019 were obtained from the City of Richland and then aggregated to estimate the total load from the City of Richland. Hourly temperature over the same time period was scraped from Weather Underground Weather Underground (2022). These were combined into one time series dataset of aggregate load and temperature.

3.2.1 Load Modeling

The load forecasting model is a weighted multilinear regression of time and temperature variables, which are explained and defined in this section. Several aspects of the model are chosen to minimize out of sample error, which is defined and discussed in Section 3.2.1.4.

To capture the periodicity of the load with respect to the hour of the day, a Fourier series is utilized, and these terms are defined in (3.9). It was found that the first five frequencies minimize model error prediction out of sample.

$$F_{daily} = \sum_{n=1}^{5} \left(\cos \frac{2\pi nt}{24h} + \sin \frac{2\pi nt}{24h} \right). \tag{3.9}$$

To capture the periodicity of the load with respect to the time of the year, we again utilize a Fourier series as per (3.10). It was found that the first three frequencies minimize model error prediction out of sample.

$$F_{yearly} = \sum_{n=1}^{3} \left(\cos \frac{2\pi nt}{1yr} + \sin \frac{2\pi nt}{1yr} \right). \tag{3.10}$$

We use exponential weighted time series points in the multilinear regression, as shown in (3.11), in which the recent data points are assigned a greater weighting, whereas past data points are assigned less weighting:

$$W = \exp \left(\frac{t}{\tau} \right), \tag{3.11}$$

where τ is a characteristic time used for weighting. The smaller τ is, the more heavily a recent data point is weighted compared to an older data point. If τ is too large, the model does not respond quickly enough to the most recent load data. If τ is too small, the model reads too much into recent changes and is at risk of overfitting to noise. In our model, τ was designed to minimize the out of sample error.

The model also incorporates the hourly temperature of the City of Richland to predict load, which is scraped from Weather Underground (Weather Underground, 2022). Ideally, the model would use the hourly temperature forecast instead of the observed temperature. Nevertheless, historical load forecast is not available and therefore observed temperature was used. In the following sections, we describes three different models depending on how the temperature is used for load forecast. The temperature-based model uses the observed temperature as a predictor, and therefore has perfect knowledge of future temperatures. The climate-based model does not explicitly use any temperature information, and therefore has zero knowledge of future temperatures. The realistic case is somewhere in the middle, and therefore we also introduce an ensemble model that mixes the two. The ensemble model is the most realistic and hence was used in the economic assessment.

3.2.1.1 Temperature-Based Model

We observed a piecewise linear dependence of load on temperature, which makes physical sense, as Newton's law of cooling predicts the heat flow between a building and its surroundings is linearly proportional to the temperature difference. Therefore, the load required to operate the heater or air conditioning and keep the building at room temperature should also be proportional to this temperature difference. The break point for this piecewise linear function was found using the segmented package in R, a programming language for statistical computing and graphics. This break point is subtracted from the temperature to produce δT, such that $\delta T = 0$ corresponds to this break point. The temperature terms are given in (3.12), and include quadratic and cubic terms around this break point:

$$T_{terms} = \delta T(\delta T > 0) + \delta T(\delta T \leq 0) + (\delta T)^2 + (\delta T)^3. \tag{3.12}$$

We also included temperature smoothing to account for lag between ambient temperature and load required for heating or cooling. We use exponential smoothing, with the exponential factor chosen to minimize out of sample error. The smoothed temperature was fed into (3.12) to produce the same terms for smoothed temperature.

With these time and temperature terms defined, we combine this into our temperature-based load model, given in (3.13):

$$Load = t + F_{daily} \times \big(F_{yearly} + Weekday + T_{terms} + T_{terms,smooth}\big). \tag{3.13}$$

where t is used to capture the average load increasing linearly with time, and $Weekday$ is a category capturing the day of the week. We also include the interaction terms, so the load dependence on the weekday, day of the year, and temperature can vary over the course of a day.

3.2.1.2 Climate-Based Model

One weakness of the temperature-based model is that it takes for granted perfect knowledge of temperature. This is unrealistic, as when deployed, only temperature forecasts are available. Temperature forecasts have higher uncertainty the further out you are predicting, and after a number of days, a climate-based forecast based on historical average temperatures is more accurate than a weather forecast. Since we are interested in predicting load toward the end of the month, it is vital to develop a forecast model that does not fully rely on perfect knowledge of temperature.

To address the challenge, a climate-based model is proposed, as given in (3.14):

$$Load = t + F_{daily} \times \big(F_{yearly} + Weekday\big). \tag{3.14}$$

The model is the same as (3.13), but with the temperature-dependent terms removed. The climate-based model is a temperature-ignorant model, only depending on historical load data and calendar variables.

3.2.1.3 Ensemble Model

The temperature-based model assumes perfect prediction of hourly temperature, which is unrealistically optimistic. On the other hand, the climate-based model assumes zero knowledge of hourly temperature, which is unrealistically pessimistic. The true measure of the model's uncertainty is somewhere in the middle.

We therefore combined these two models into an ensemble model, which is a weighed average of the temperature-based model and the climate-based model. The weights vary based on how many days ahead the model is predicting. We discovered that the ability to forecast temperature only beats historical averages up to 10 days ahead. The root mean square (RMS) error of temperature forecast error is about half of the historical average error when predicting only one day ahead. As an approximation, we weighed the two models in the ensemble to capture this, with the weight for the climate-based model increasing from approximately 0.5 at 1 day ahead to 1 for 10 days ahead, and the temperature-based model weight decreasing from 0.5 at 1 day ahead to 0 for 10 days ahead. The ensemble model gives the most realistic depiction of operational uncertainty and is used for optimal dispatch and economic assessment.

3.2.1.4 Validation

The model was validated by using a rolling time horizon. For each day in the dataset, the model was trained on all previous days, and used to predict the next 1–31 days. This is because the application of this model was to predict the rest of the month's load, and hence this is the relevant horizon for forecasting the load. This is repeated for each day of the year to fully evaluate the model's predictive capability.

The modeling error (the predicted load minus the actual load) is organized by how many days ahead the model was predicting. This gives us a distribution of modeling error for 1 day ahead, 2 days ahead, etc. As expected, the error range is wider the further ahead the model predicts.

To evaluate the model, all the modeling error for 1–31 days ahead is consolidated into the RMS error. When choosing parameters such as exponential weighing factor, temperature smoothing factor, or number of Fourier terms to use, we seek to minimize the out of sample RMS error so we can optimize the model's predictive capability. All continuous hyperparameters (such as the smoothing factor and weighing factor) are optimized using the Nelder-Mead algorithm.

3.2.2 Probabilistic Modeling

To deploy this model for economic assessment, it must predict the probability of each remaining hour of the month being the peak load for the month. This section describes the procedure for using the load model to produce a probabilistic model that predicts the probability of each hour being the peak load for the month.

For each day of the month, the load for the remainder of the month is forecast using the ensemble model, giving a deterministic load forecast. Next, the error distribution corresponding to each prediction period (such as 1 day ahead, 2 days ahead, etc.) is obtained. The out of sample error distribution for each time period of prediction of the ensemble model is given in Figure 3.2. This demonstrates the error distribution spreading out the further into the future the model has to predict, and the increase in accuracy the weather forecast allows over a period of several days.

By bootstrapping from the actual error distribution, we have to make far fewer assumptions about the properties of the error distribution than if we used Gaussian noise. Each of the forecast hourly load has an error randomly drawn and added to its load to represent the uncertainty. This is repeated with 1000 trials.

After the 1000 trials have been performed, each hour is evaluated to determine the fraction of trials for which it is the peak load (considering both the predicted loads, and the loads observed earlier in the month). This is returned as the probability of this hour being the peak load for the month. This procedure is repeated for each day of the month, giving an updating estimate of the probability of each remaining hour being the peak load for the month.

3.3 Optimal Dispatch

Two methods were proposed for optimal dispatch and economic assessment of the combination of BESS and PV: i) a yearly optimal dispatch and ii) an operational practical dispatch. Both methods rely on the models presented in Section 3.1. While the yearly optimal dispatch method requires perfect knowledge of the load profile, the operational practical dispatch takes load

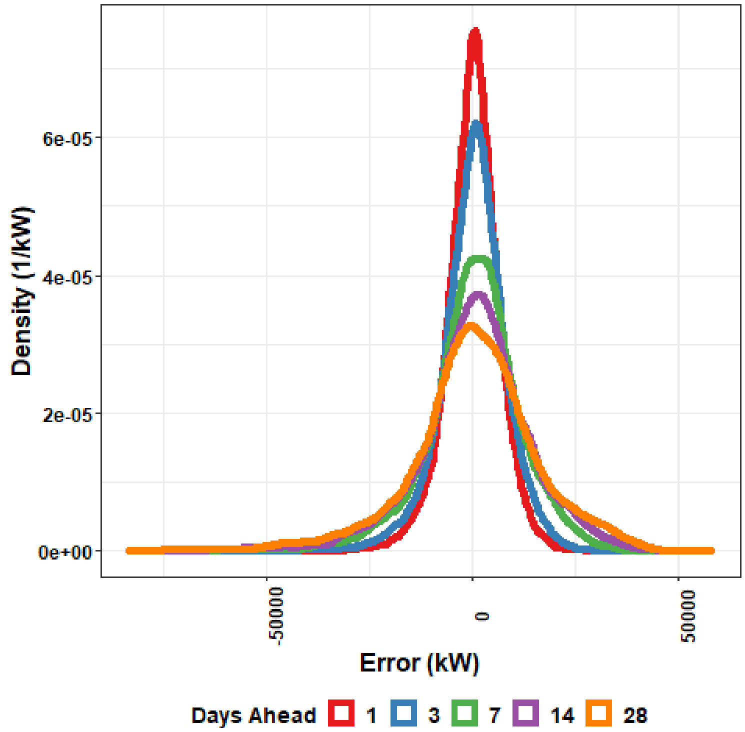

Figure 3.2. Ensemble load forecasting model prediction error for predicting 1, 3, 7, 14, and 28 days ahead.

forecast produced by the ensemble model and probabilistic modeling in Section 3.2 to make charging/discharging decisions over a 24-hour time window.

3.3.1 Yearly Optimal Dispatch

The yearly optimal dispatch assumes to know a perfect load profile and considers all hourly system operations throughout the year as its decision variables. Mathematically, it optimizes over a time span $\mathcal{K} := \{k \mid k = k_1, k_2, \cdots, k_n\}$, with $k_1 < k_2 < \cdots < k_n$ being n consecutive time step indices within a year. We define $\mathcal{L} := \{l \mid l = l_1, l_2, \cdots, l_m\}$, with $1 \leq l_1 < \cdots < l_m \leq 12$, as a set including m month indices that correspond to the same time span of $\mathcal{K}$. For each month index $i = 1, \cdots, m$, we further define $\boldsymbol{s}(l_i)$ and $\boldsymbol{e}(l_i)$, respectively, as the starting and ending hour indices of month l_i. More specifically, we should have $\boldsymbol{s}(l_1) \leq k_1$ and $k_n \leq \boldsymbol{e}(l_m)$. Let t_i denote the index of the transmission peak hour that occurs within month l_i, for all $i = 1, \cdots, m$. We define $\mathcal{T} := \{t \mid t_i \in \mathcal{K}\}$ as a set that collects all of these transmission peak hour indices contained in $\mathcal{K}$.

Given the native load L_k and the integrated system's output p_k^{out}, the net load L_k^{net} is:

$$L_k^{\text{net}} = L_k - p_k^{\text{out}}, \quad \forall k \in \mathcal{K}. \tag{3.15}$$

The monthly peak d_l of month l can be expressed as:

$$d_l = \max\{L_k^{\text{net}} : \boldsymbol{s}(l) \leq k \leq \boldsymbol{e}(l)\}. \tag{3.16}$$

Written in an epigraph form, constraint (3.16) can be equivalently transformed into:

$$d_l \geq L_k^{\text{net}}, \quad \text{for all } \boldsymbol{s}(l) \leq k \leq \boldsymbol{e}(l). \tag{3.17}$$

The total electricity bill over the time span $\mathcal{K}$ is given by:

$$C_{\text{op}} = \sum_{k \in \mathcal{K}} \lambda_k L_k^{\text{net}} + \sum_{l \in \mathcal{L}} \mu_l d_l + \sum_{t \in \mathcal{T}} \nu_t L_t^{\text{net}}, \tag{3.18}$$

where λ_k, μ_l, and ν_t denote the energy charge rate at hour k, DCR for month l, and transmission charge rate for peak hour t, respectively. Finally, the yearly optimal dispatch can be formulated as a linear programming problem:

$$\begin{aligned} \text{(P0)} \qquad \text{minimize} \quad & (3.18) \\ \text{subject to} \quad & (3.1) - (3.8),\ (3.15),\ (3.17). \end{aligned}$$

3.3.2 Operational Practical Dispatch

Different from the yearly optimal dispatch, the operational practical dispatch uses load forecast and optimizes over a 24-hour time span. The inputs are the load and peak-day forecast produced using the methods presented in Section 3.2. We also set a threshold for the peak-day probability to control whether or not to activate the dispatch. More specifically, at the beginning of each day, the peak-day probability is compared to the threshold. If the probability exceeds the threshold, it means that the monthly peak demand will occur during that day with a high likelihood and therefore the MPC-based dispatch is executed to reduce the peak demand. Further, if the peak-day probability does not exceed the threshold, but a predefined transmission peak hour will occur during the day, we run a regular daily dispatch without considering the peak demand reduction. Otherwise, if neither of the two conditions occurs, the BESS will not be cycled. When a BESS dispatch is activated on an operating day, in each hourly dispatch, the actual load for the current hour and all previous hours is known. Imperfect forecast can be generated for all the remaining hours of the look-ahead scheduling window. We obtain the BESS dispatch for the entire look-ahead window but only execute dispatch for the current hour.

The dispatch and control procedures are summarized in Algorithm 1. To execute the algorithm, one has to solve two optimization problems, (P1) and (P2), which are described as follows.

3.3.2.1 MPC-Based Dispatch for Peak Days

Suppose the peak-day probability of a given day exceeds the threshold, and the MPC-based optimal dispatch is activiated. The time span set $\mathcal{K}$, in this special case, can be written as $\mathcal{K} = \{k_1, \cdots, k_{24}\}$, which include all 24 hour indices within the day. The set $\mathcal{L}$ only contains one month index, i.e., $\mathcal{L} = \{l_1\}$, with l_1 being the current month. Let t_1 denote the transmission peak hour index corresponding to month l_1. If $t_1 \in \mathcal{K}$, we have $\mathcal{T} = \{t_1\}$. Otherwise, we have $\mathcal{T} = \emptyset$.

At the beginning of each hour k_h, for all $1 \leq h \leq 24$, we repeatedly solve the optimal dispatch (P1) over a receding prediction horizon:

$$\mathcal{W} = \begin{cases} \{k_{h+1}, \cdots, k_{24}\}, & \text{if } 1 \leq h \leq 23 \\ \emptyset, & \text{if } h = 24. \end{cases}$$

The MPC-based optimal dispatch takes the actual load to calculate the net load for the current hour and all previous hours. Either day-ahead or hour-ahead forecast load is used for

Algorithm 1 Daily Dispatch Algorithm with MPC

Input:
1) BESS parameters such as energy/power capacity, round-trip efficiency, etc.
2) Actual/forecast load profile and peak-day prob.
3) Energy charge rate, DCR, and transmission charge rate

Output:
An annual dispatch of the BESS

Initialization
Set a threshold TH for the peak-day prob.
for day $i = 1$ to the last day of the year **do**
  Find all sets $\mathcal{K}$, $\mathcal{L}$, $\mathcal{T}$, and peak-day prob. for day i
  if day i's peak-day prob. $\geq TH$ **then**
    for all hour $h = 1$ to 24 **do**
      Define the prediction horizon $\mathcal{W}$
      Solve the proposed MPC-based dispatch (P1) with prediction horizon $\mathcal{W}$
      Implement the dispatch solution $p^{\text{sol}}_{k_h}$ only
    end for
  else
    if transmission peak will occur **then**
      Solve the simplified optimal dispatch (P2)
      Implement all the dispatch solution
    end if
  end if
end for
Post processing: Record all optimal dispatch solutions for the year

the remaining hours of the day. Therefore, the load balance equations can be written as:

$$L^{\text{net}}_k = \begin{cases} L^{\text{act}}_k - p^{\text{sol}}_k, & \forall k \in \mathcal{K} \setminus (\mathcal{W} \cup \{k_h\}) \\ L^{\text{act}}_k - p^{\text{out}}_k, & \text{for } k = k_h \\ L^{\text{for}}_k - p^{\text{out}}_k, & \forall k \in \mathcal{W}, \end{cases} \tag{3.19}$$

where p^{sol}_k, for $k \in \mathcal{K} \setminus (\mathcal{W} \cup \{k_h\})$, is the dispatch decision for the previous hour k ("$\setminus$" denotes the subtraction of two sets). The net load variable L^{net}_k can be used to update the first and third terms in the objective function (3.18).

Next, we explain how to calculate the monthly demand charge. As we mentioned earlier, the $\mathcal{L}$ set only contains one element l_1 for the daily dispatch. Let $\boldsymbol{s}(l_1)$ denote the starting hour index of month l_1, with $\boldsymbol{s}(l_1) \leq k_1$, and $\mathcal{D} := \{k \mid \boldsymbol{s}(l_1) \leq k \leq k_{24}\}$ be a set that contains all the hour indices from the beginning of month l_1 to the end of that given day. The monthly peak demand can be expressed as:

$$d_{l_1} \geq \begin{cases} L_k^{\text{act}} - p_k^{\text{sol}}, & \forall k \in \mathcal{D} \setminus (\mathcal{W} \cup \{k_h\}) \\ L_k^{\text{act}} - p_k^{\text{out}}, & \text{for } k = k_h \\ L_k^{\text{for}} - p_k^{\text{out}}, & \forall k \in \mathcal{W}. \end{cases} \tag{3.20}$$

Finally, the MPC-based optimal dispatch for peak days can be formulated as:

$$\begin{aligned} \text{(P1)} \quad & \text{minimize} \quad (3.18) \\ & \text{subject to} \quad (3.1) - (3.8),\ (3.19),\ (3.20). \end{aligned}$$

3.3.2.2 Dispatch without Demand Charge Reduction

There exists another situation where the peak-day probability does not exceed the threshold, but a transmission peak is expected to occur on an operating day. In this case, the BESS dispatch is not as complicated as the MPC-based dispatch. Instead of running the MPC-based dispatch 24 times with receding prediction horizons, we only need to run a regular optimal dispatch for the entire day based on the predicted system peak hours.

Let $\mathcal{K} = \{k_1, \cdots, k_{24}\}$ denote the hour index set and $\mathcal{T} = \{t_1\}$ denote the transmission peak hour index set. Excluding demand charge reduction, the objective function (3.18) becomes:

$$C_{\text{op}} = \sum_{k \in \mathcal{K}} \lambda_k L_k^{\text{net}} + \sum_{t \in \mathcal{T}} \nu_t L_t^{\text{net}}. \tag{3.21}$$

Moreover, based on the load forecast, net load can be expressed as:

$$L_k^{\text{net}} := L_k^{\text{for}} - p_k^{\text{out}}, \quad \forall k \in \mathcal{K}. \tag{3.22}$$

The daily optimal dispatch for transmission charge reduction can be formulated as:

$$\begin{aligned} \text{(P2)} \quad & \text{minimize} \quad (3.21) \\ & \text{subject to} \quad (3.1) - (3.8),\ (3.22). \end{aligned}$$

3.4 Outage Mitigation

This section describes how we monetize the economic benefits of outage mitigation using the BESS and PV models presented in 3.1. We first estimate the cost of unserved load during an unplanned outage event. Based on the Interruption Cost Estimate (ICE) Calculator developed by Lawrence Berkeley National Laboratory (2018), we have developed a cost estimation function for the City of Richland through regression:

$$y = -4 \times 10^{-13} x^5 + 2 \times 10^{-9} x^4 - 3 \times 10^{-6} x^3 + 2.3 \times 10^{-3} x^2 - 0.7574x + 140,$$

where y denotes the cost of unserved load (in \$/kWh) and $0 \leq x \leq 300$ is the outage duration (in minutes). With this function and the historical outage events listed in Table 2.3, we can estimate the outage cost without and with the BESS and PV, and thereby estimating the benefits of outage mitigation.

We record the starting time and duration for each outage event and check the available BESS energy level when an outage occurs. In particular, the available BESS energy level is determined by the BESS' dispatch results in grid connected mode. Then we can simulate how BESS and PV can be used to serve the local load by following the procedure described below.

Suppose that an outage event i lasts for N_i minutes. Let $\mathcal{O}_i = \{m_1, \cdots, m_{N_i}\}$ be a set that contains all minute indices during this outage event. Without using the integrated system, the total unserved load (in kWh) during this outage can be calculated as:

$$L'_{\text{unserv}} = \sum_{m \in \mathcal{O}_i} \frac{L_m}{60}, \tag{3.23}$$

where L_m is the system load (in kW) at minute m. When the integrated system is considered, on the other hand, the total unserved load can be expressed as:

$$L''_{\text{unserv}} = \sum_{m \in \mathcal{O}_i} \frac{L_m - p_m^{\text{batt}} - p_m^{\text{pv}}}{60}, \tag{3.24}$$

where p_m^{batt} and p_m^{pv}, respectively, are the power output (in kW) of the BESS and PV at minute m. Here, the BESS and PV operations at minute m are characterized by:

$$p_m^{\text{batt}} = \begin{cases} \min\left(L_m,\ p_{\text{max}}^{\text{batt}},\ 60 e_{m-1}^{\text{batt}}\right), & \text{if } e_{m-1}^{\text{batt}} > S_{\text{min}} E_{\text{max}}^{\text{batt}}, \\ 0, & \text{if } e_{m-1}^{\text{batt}} \le S_{\text{min}} E_{\text{max}}^{\text{batt}}, \end{cases} \tag{3.25a}$$

$$e_m^{\text{batt}} = e_{m-1}^{\text{batt}} - \frac{p_m^{\text{batt}}}{60\eta^+}, \quad \forall m \in \mathcal{O}_i, \tag{3.25b}$$

$$p_m^{\text{pv}} = r_m^{\text{pv}} p_{\text{max}}^{\text{pv}}, \quad \forall m \in \mathcal{O}_i. \tag{3.25c}$$

Based on the difference between the unserved load with and without the integrated system, we can estimate the outage mitigation benefits as $y(L'_{\text{unserv}} - L''_{\text{unserv}})$.

CHAPTER 4

Case Studies and Assessment Results

Various tools have been developed for energy storage valuation (Vinod et al., 2022). The Energy Storage Evaluation Tool developed at PNNL was customized and used for this analysis. This chapter presents the economic assessment results for the solar and storage system at Horn Rapids, along with the key findings and insights. Since the microgrid capability was not built into the deployed system, we first present the economic benefits of the deployed system in the base case without considering outage mitigation. Two optimal dispatch methods, i.e., the yearly and practical operational dispatch, were used to simulate the integrated system and estimate the corresponding benefits. By assuming perfect foresight of the system load information, the former method generates results representing a theoretical upper bound of the benefits. The latter provides an estimate of practically achievable benefits. Next, we present the assessment results in the microgrid scenario where the cost for enabling a microgrid and the potential benefits from outage mitigation were included. Lastly, the preliminary analysis results are presented and compared with the final assessment results.

4.1 Assumptions and Inputs

4.1.1 Economic Parameters and Assumptions

The economic life is assumed to be 25 years and the discount rate is assumed to be 4%. The inflation rate for both energy cost and annual O&M cost is assumed to be 5%.

4.1.2 System Costs

The costs include both capital cost and O&M cost. The BESS capital cost is $6,343,322, including Energy Northwest labor and overhead, legal support, Small Generator Interconnection Application, engineering, archaeological survey and State Environmental Policy Act (SEPA), owner's engineer, PNNL analytics, site infrastructure, BESS' engineering, procurement, and construction (EPC) contract, construction, warranty, equipment, BPA interconnection, and City of Richland interconnection. The CEF grant from the Washington State Department of Commerce is $3,000,000. Therefore, the BESS outstanding cost for the City of Richland is $3,343,322. According to Potelco, Inc., the company that provides utility construction services for this project, the capital cost of Horn Rapids' PV system is $4,200,000. The total capital cost of the BESS and PV is $10,543,322. The O&M cost is approximately $85,000 and escalates each year. This includes the annual maintenance payment $18,000 to Doosan, weed control, transmission costs, labor and overhead, lease payment, decommissioning, etc. With the 5% escalation rate, the O&M cost over 25 years is $2,297,368 in present value. Summing them up yields a total project cost of $12,840,690 in present value.

For the hypothetical microgrid scenario, the cost associated with microgrid controllers has to be estimated and included on the top of the deployed system. Microgrid project and controller costs are reviewed and summarized in Giraldez et al. (2018). The cost varies much by the type of distributed energy resources, market segment such as campus, commercial, community, and utility, and control complexity level. The average cost of microgrid controllers for energy storage and PV with load management capability is about $162,477 per MW, leading to $812,385 for the 1 MW BESS and 4 MW PV system. The average microgrid controller cost was also estimated at 7% of the total project cost. Based on this percentage, the additional cost for microgrid controllers is $898,848 for the deployed system at Horn Rapids. In this study, we assume that the additional cost for microgrid capability is $850,000.

4.1.3 BESS Parameters

We have incorporated the BESS testing results and measured performance (Crawford et al., 2022) into the economic assessment. The key parameters of the linear BESS models are summarized as follows. The BESS rated power is 1 MW. The BESS is designed with 5.5 MWh of total usable energy. While about 4.3 MWh can be discharged within the recommended 10–90% SOC, the allowed daily discharged energy is limited to 4 MWh according to the capacity maintenance agreement for 25 years. To guarantee this, we constrained the BESS to operate between 10% and 90% SOC with no more than 4 MWh of discharged energy each day. The BESS round-trip efficiency is 87.6%, with the same charge and discharge efficiencies. Therefore, we have $\eta^+ = \eta^- =$ 93.6%.

4.1.4 PV Parameters

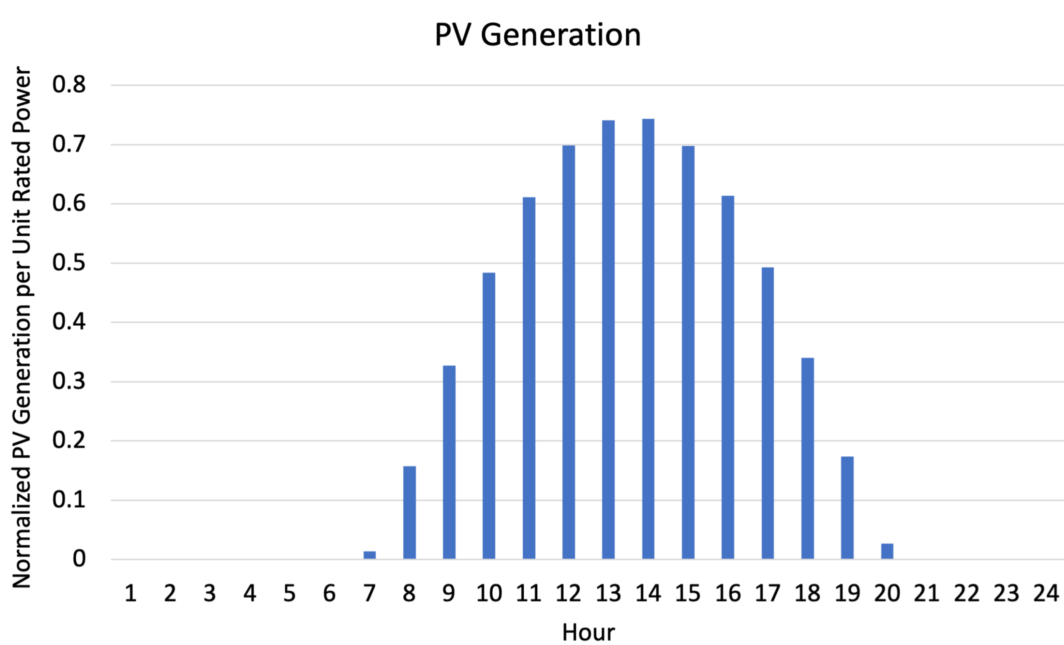

Figure 4.1. PV generation at Horn Rapids on an example summer day.

The DC power rating of the solar panel is 4 MW and the AC power rating at the grid connection point is about 3.2 MW. Locational normalized PV generation profiles are generated for Horn Rapids using the `pvlib` library (Holmgren et al., 2018), which is a community-supported tool for simulating the performance of PV systems. The required input parameters of `pvlib` include PV module and inverter parameters, PV installation parameters, as well as parameters that depend on weather conditions. The parameters such as hourly clear sky global horizontal irradiance, direct normal irradiance, ambient temperature, and wind speed are generated using a stochastic model with historical weather data from National Solar Radiation Database (Wilcox, 2012) as inputs.

The PV generation at Horn Rapids on an example summer day is shown in Figure 4.1, where the y-axis represents a normalized generation per unit rated power of the PV system. PV generation is available between 7 a.m. and 8 p.m., with the peak output occurring around 1–2 p.m. According to `pvlib` simulation, the average hourly PV generation is 0.6 MWh and about 5,221 MWh annually.

4.1.5 System Load

The City of Richland's system load from 2015 to 2019 were obtained and used for load modeling and economic assessment. The 2018 load plotted in Figure 4.2 was used to simulate the system operation and assess the economic benefits. In particular, in the *yearly optimal dispatch* method, the 2018 load was used for both dispatch decision making and benefit calculation. In the *practical daily or hourly dispatch* method, the load forecast and peak-day probability were used for dispatch decision making while the 2018 load was used for benefit calculation. The average load is 108 MW. The system peak is 189 MW, which occurred around mid-August.

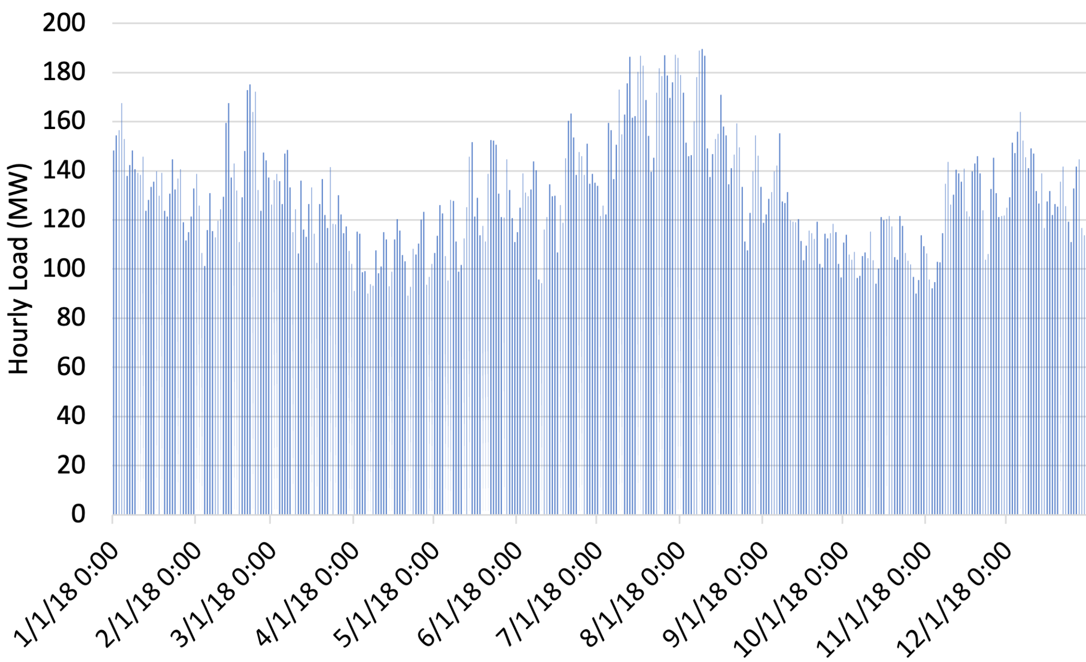

Figure 4.2. The City of Richland's 2018 load profile.

4.2 Base Case

This section presents the economic assessment results in the base case considering the electricity bill reduction use cases only. Outage mitigation is excluded because microgrid capability was not built into the design of the deployed system. We first estimate the benefits using the yearly optimal dispatch method, where the City of Richland's system load in 2018 was used to determine the optimal dispatch for the entire year at once. With the perfect foresight of load information, the economic assessment results using this method inform us of the theoretical upper bound of the benefits.

An economic assessment was also performed using the practical operational dispatch, without assuming perfect knowledge of the load. In this case, the City of Richland's system load from 2015 to 2019 was obtained and used for load modeling and forecast to capture operational uncertainties in the BESS dispatch decision-making process. The 2018 load was used to simulate the system operation after dispatch decisions were made and to assess the corresponding economic benefits. Different thresholds were explored and evaluated, and the optimal threshold was selected to maximize the benefits.

4.2.1 Benefits vs. Costs

The present value benefits and costs evaluated using both dispatch methods in the base case are plotted and compared in Figure 4.3. A detailed breakdown of costs can be found in Section 4.1.2. Key findings are highlighted as follows:

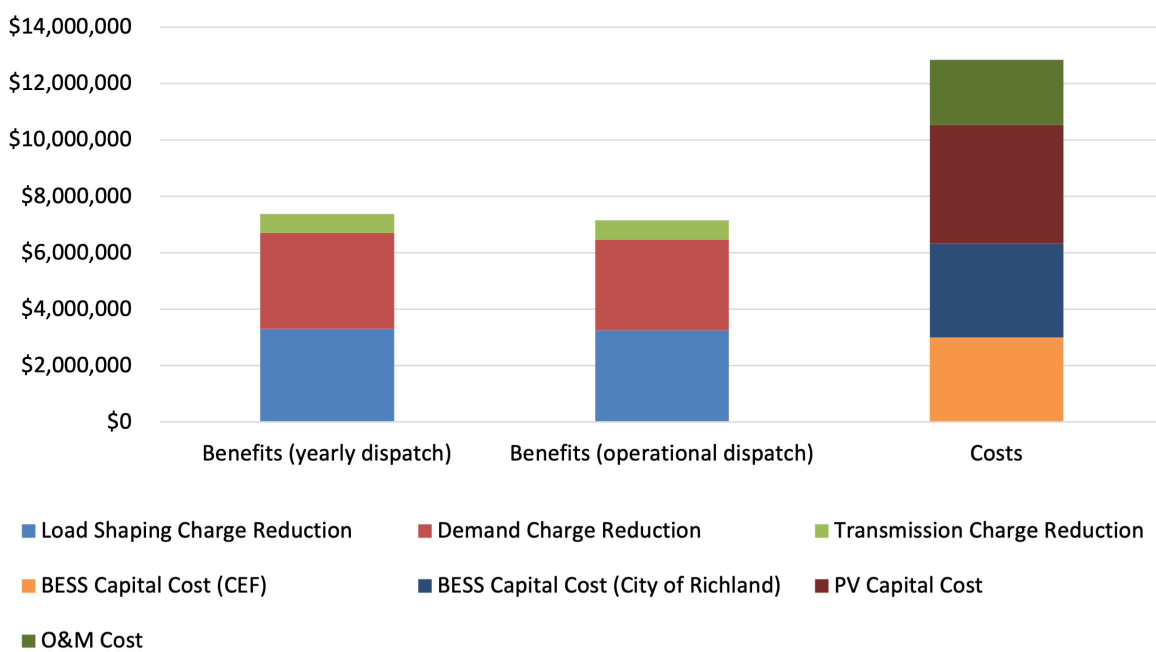

Figure 4.3. Present value benefits vs. costs in the base case.

- Using the yearly optimal dispatch, the total present value benefits from electricity bill reduction, including load shaping charge reduction, demand charge reduction, and transmission charge reduction, are $7,386,098. In particular, demand charge reduction and load shaping charge reduction together account for 91% of electricity bill reduction.

  - Without considering the CEF grant and outage mitigation benefits, the present value net cost is $5,454,592, and the benefit-cost ratio (BCR) is 0.58.
  - With the $3,000,000 grant from the CEF, the outstanding cost of the BESS and PV for the City of Richland becomes $9,840,690. The corresponding present value net cost become $2,454,592, and the BCR increases to 0.75.

- Using the practical operational dispatch with a 3% threshold, the total estimated benefits from electricity bill reduction are $7,154,748 in present value. Compared with results yielded from the yearly dispatch method, the benefits received from load shaping reduction decrease from $3,312,950 to $3,257,155. The demand charge reduction benefits decrease from $3,392,924 to $3,217,370. Such decreases of benefits are mainly caused by the imperfect load forecast and peak-day prediction.
  - Without considering the CEF grant, the present value net cost is $5,685,942, and the BCR becomes 0.56.
  - With the $3,000,000 CEF grant, the corresponding present value net cost becomes $2,685,942, and the BCR increases to 0.73.

Note that an appropriate threshold needs to be determined to maximize the total benefits when using the practical operational dispatch. Results with different thresholds are plotted in Figure 4.4 together with the benefits estimated using the yearly optimal dispatch. As can be seen, the benefits increase and then decrease as the threshold increases from 0 to 1 using the practical operational dispatch. The best performance is achieved with a threshold of 3%, which recovers more than 95% of the electricity bill reduction benefits estimated using the yearly optimal dispatch.

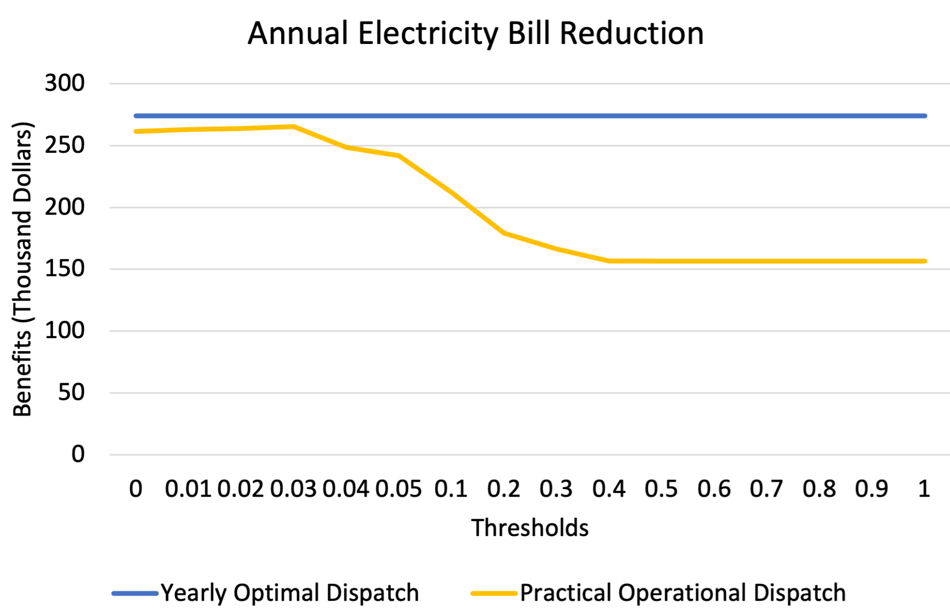

Figure 4.4. Annual electricity bill reduction using the practical operational dispatch method with different thresholds.

4.2.2 Annual Electricity Bill Reduction Breakdown

Figure 4.5 visualizes a breakdown of the savings in the City of Richland's electricity bill using the yearly optimal dispatch method. The breakdown of results obtained using the operational dispatch method is similar and therefore is omitted to save space.

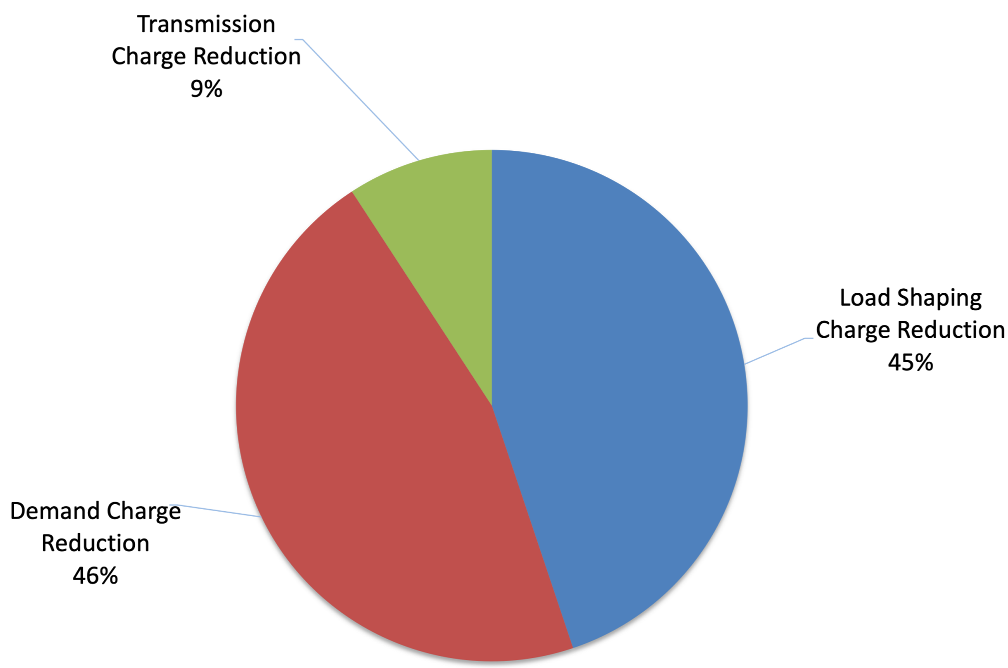

Figure 4.5. A breakdown of the electricity bill reduction using the yearly optimal dispatch.

Using the yearly optimal dispatch, the annual benefits of load shaping charge reduction are \$122,909, which are equivalent to \$3,312,950 in present value, accounting for 45% of the total benefits in electricity bill reduction. In particular, about 98% of these benefits are received from PV production. The present value benefits from demand and transmission charge reductions are \$3,392,924, and \$680,224, respectively. In general, it is difficult separate benefits between the BESS and PV for demand and transmission charge reductions, as the two subsystems are coupled in the two use cases.

Using the practical operational dispatch with the 3% threshold, the present value benefits received from load shaping charge, demand charge, and transmission charge reduction are \$3,257,155, \$3,217,370, and \$680,224, respectively. These numbers are very close to the theoretical upper bounds estimated using the yearly optimal dispatch, suggesting that the 3% threshold is indeed an optimal. Due to such small differences between the two results, we will only present the yearly optimal dispatch results as an example to explain how these benefits are generated.

Note that PV production has the effect of increasing demand charges by reducing load during HLHs. Such impact is due to the presence of the $aHLH$ component in the demand charge calculation described in Section 2.2, where a lower value of $aHLH$ leads to a more significant deviation between CSP and $aHLH$ and thereby increases the basis of the demand charge.

The BESS can be used to shift load from HLHs to LLHs to take the advantage of different charge rates considering BESS cycling losses, and thereby reducing the overall load shaping charges. The monthly LLH and HLH load are plotted in Figures 4.6 and 4.7, respectively.

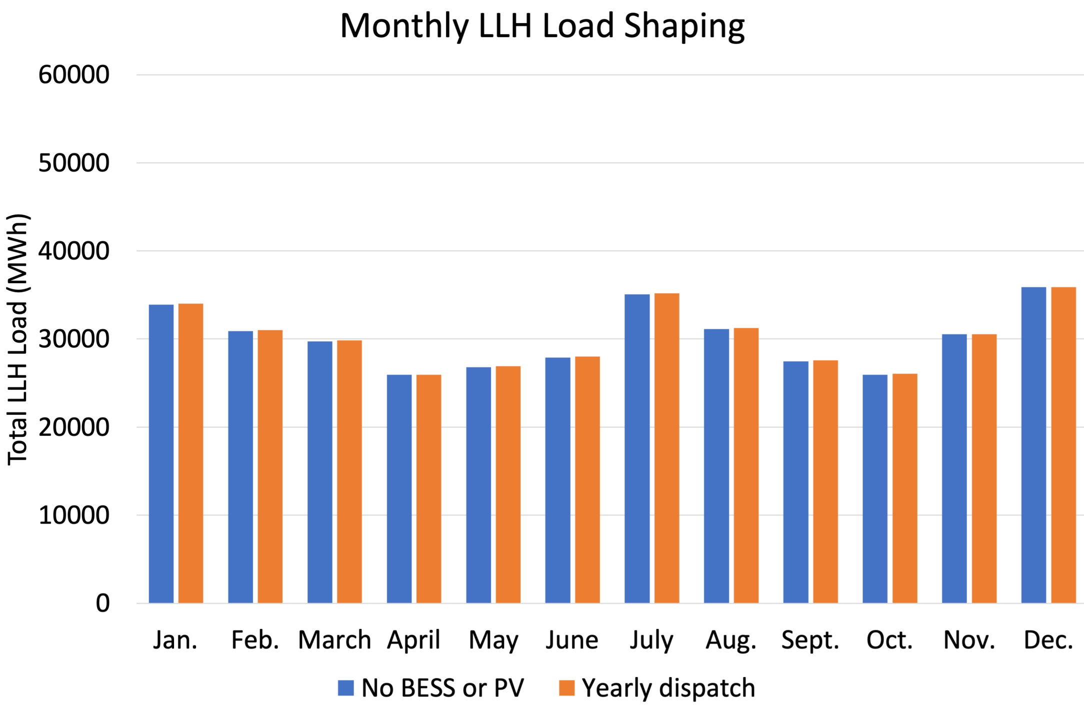

Figure 4.6. LLH load for each month.

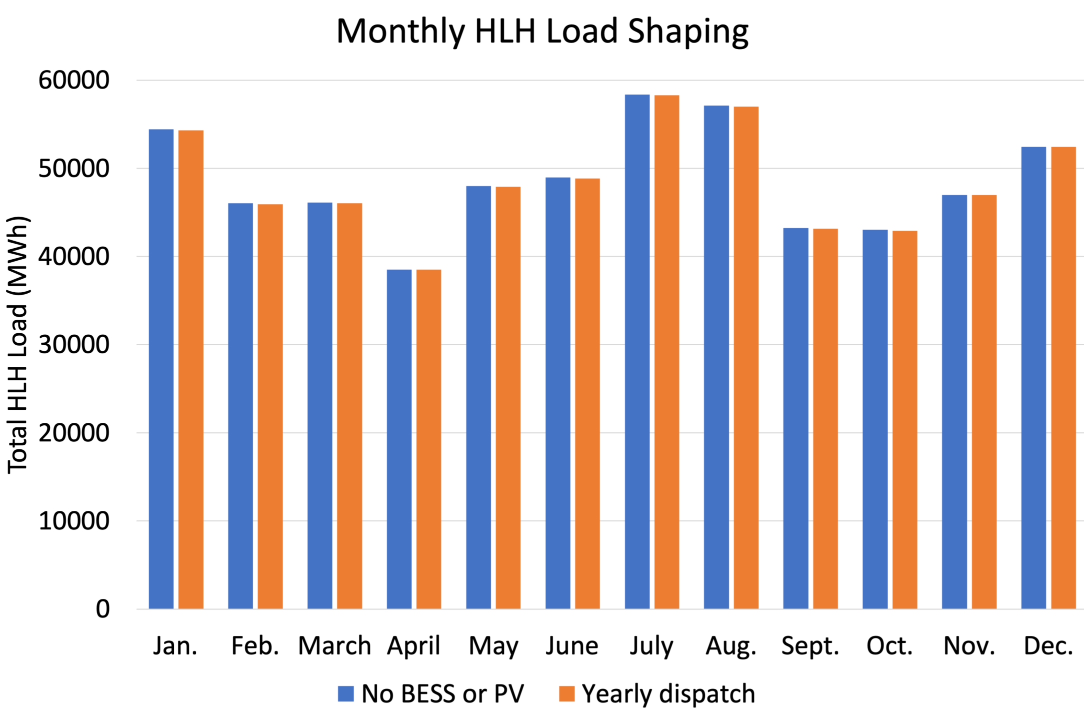

Figure 4.7. HLH load for each month.

In both figures, net load without and with BESS are compared. It was found that the total monthly LLH load increases by 89 MWh on average, while the monthly HLH load decreases by 78 MWh. The changes are small compared to the baseline and thereby are difficult to observe in the plots. The BESS provides load shifting only when the ratio between LLH and HLH rates (see Table 2.1) is lower than its round-trip efficiency, so the benefits received from load shifting can cover the BESS cycling losses. In months such as March, April, November, and December, their corresponding ratios between LLH and HLH rates are all higher than 0.87, and thereby the BESS does not provide load shifting during these months. On the other hand, the BESS mainly shifts loads during the summer months (from May to August). In the meantime, the optimal BESS dispatch solutions also balance the trade-offs between load shifting and demand charge reduction, not making a high value of $aHLH$ to affect the demand charge reduction benefits.

Demand charge reduction represents a significant value stream, since the DCR is much higher than the load shaping or transmission charge rate. Figure 4.8 compares the original monthly system peaks to those equipped with the integrated system. With perfect knowledge of the system load, the optimal BESS dispatch strategy can accurately capture all monthly peak demand.

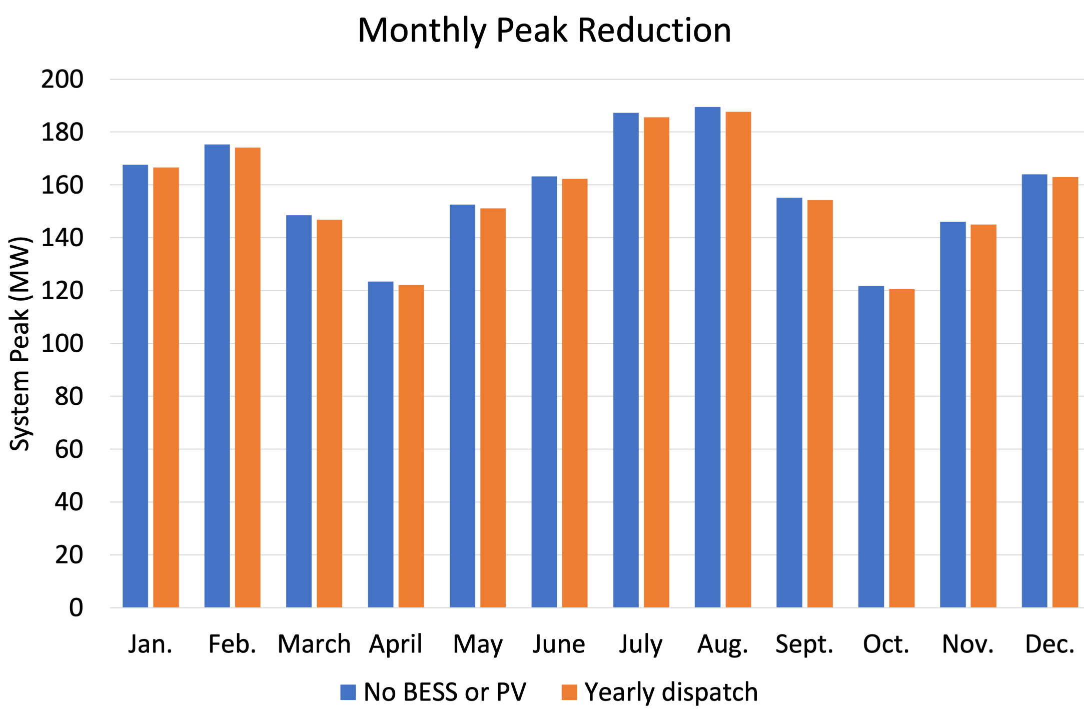

Figure 4.8. System peak demand for each month.

Table 4.1. Peak Demand Reduction for Each Month

Month	Jan.	Feb.	Mar.	Apr.	May	June
Peak Day & Hour	1/4 8:00	2/21 8:00	3/7 8:00	4/27 17:00	5/22 18:00	6/21 18:00
Reduced Peak (MW)	1.00	1.16	1.67	1.27	1.37	1.00
Month	July	Aug.	Sept.	Oct.	Nov.	Dec.
Peak Date & Hour	7/30 18:00	8/9 17:00	9/7 18:00	10/22 8:00	11/20 18:00	12/6 8:00
Reduced Peak (MW)	1.69	1.85	1.00	1.19	1.00	1.00

Table 4.1 also lists detailed information about when the system peak occurred in each month of 2018 and how much reduction can be provided by the integrated system. Note that all monthly peaks of 2018 occurred either in the early morning (8 a.m.) or late afternoon (5–6 p.m.), during which the PV production was usually weak. As a result, PV does not contribute much to the demand charge reduction. The integrated system can reduce the monthly system peak by 1.27 MW on average, with a maximum reduction of 1.85 MW in August and a minimum reduction of 1 MW in January, June, September, November, and December, because the PV production was zero during the peak hour in all these five months. The annual benefits from demand charge reduction are $125,876, about $3,392,924 in present value.

Lastly, the benefits received from transmission charge reduction can be easily calculated. We also assume here the perfect knowledge about when the BPA's transmission peak hours occur. Under such an assumption, the integrated system can reduce the transmission charge by $25,236 annually, equivalent to $680,224 in present value.

4.2.3 BESS Usage

The annual BESS usage statistics in the operational dispatch (by thresholds) and the yearly dispatch method are compared in Figure 4.9. As can be seen, the BESS is dispatched on 255 days using the yearly dispatch method. Using the practical operational dispatch method, the annual BESS usage decreases monotonically as the threshold increases. For example, when the threshold is set to 0, any peak-day probability is bigger than the threshold and the BESS is activated every day. When the threshold is set to be 1, the BESS is only used for 12 days in a year. With a threshold of 3%, the BESS is dispatched on 199 days, 22% less than the yearly dispatch method.

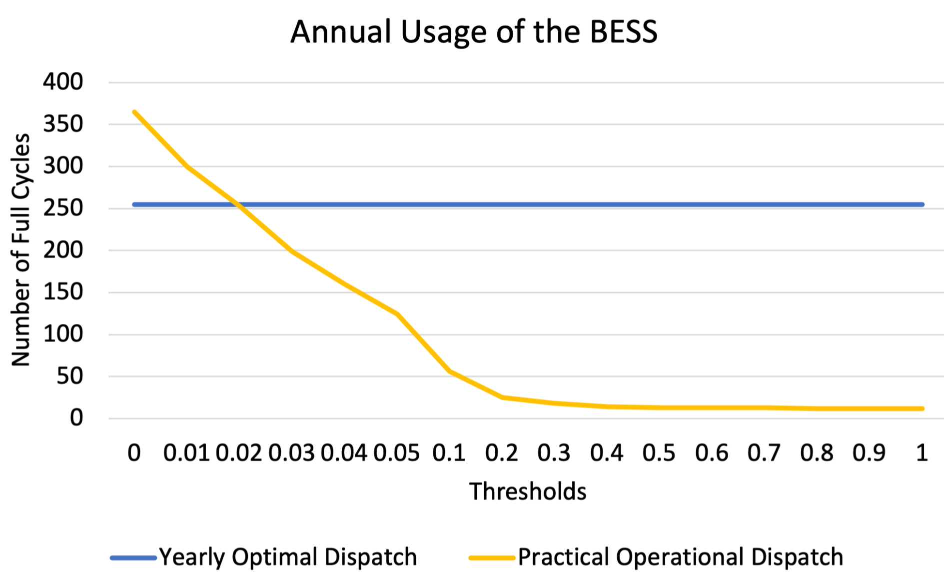

Figure 4.9. Annual BESS usage using the practical operational dispatch method with different thresholds.

4.3 Microgrid Scenario

When equipped with microgrid controllers and associated updates, the integrated system can form a microgrid to serve the local load when there is an outage of the main grid. To understand the benefits of the integrated system with a different design, we evaluated a hypothetical microgrid scenario where outage mitigation was considered in addition to the use cases for electricity bill reduction in the base case. Additional benefits and costs associated with outage mitigation are estimated using the approach proposed in Section 3.4. The total present value benefits and costs in this scenario are plotted below in Figure 4.10, from which we can observe:

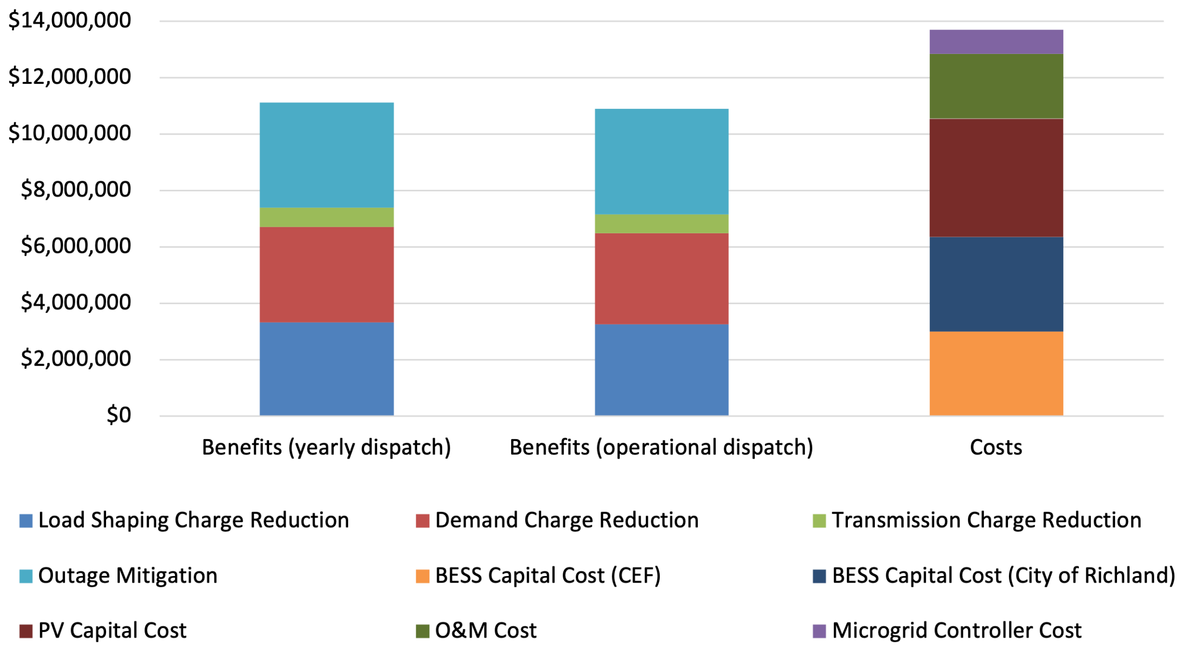

Figure 4.10. Present value benefits vs. costs in the microgrid scenario.

- The additional cost was estimated at $850,000 to enable microgrid operation, and the total project cost becomes $13,690,690 in present value. With the $3,000,000 grant from the CEF, the outstanding cost for the BESS and PV becomes $10,690,690. On the other hand, the estimated annual benefits from outage mitigation is $239,042, which is equivalent to $3,734,333 in present value.

- With outage mitigation benefits included, the total present value benefits estimated using the yearly dispatch become $11,120,432, increased by 50.6% compared to the base case.
  - Without considering the CEF grant, the present value net cost is $2,570,258, and the BCR becomes 0.82.
  - With the $3,000,000 grant from the CEF, the corresponding present value net cost becomes $429,742, and the BCR increases to 1.04.

- With outage mitigation benefits included, the total present value benefits estimated using the operational dispatch become $10,889,082, increased by 52.2% compared to the base case.
  - Without considering the CEF grant, the present value net cost is $2,801,608, and the BCR becomes 0.80.

– With the $3,000,000 CEF grant, the corresponding present value net cost becomes $198,392, and the BCR increases to 1.02.

The estimated unserved load without and with the PV paired with BESS are summarized in Table 4.2. The difference between the two is the total unserved load avoided using the integrated system as a microgrid. Recall that the cost of unserved load is estimated using a curve-fitting calculator described in Section 3.1, which represents a nonlinear relationship between the unserved load cost and outage duration. The BESS initial energy level is obtained from our simulation using the yearly optimal dispatch. On average, the integrated system can help the City of Richland to avoid 3.3 MWh of unserved load each year, with an annual benefit of $239,042. This results in $3,734,333 benefits in present value from outage mitigation.

Table 4.2. Outage Events and Unserved Load

Date	Start Time	Duration (Hours)	Cost of Unserved Load ($/kWh)	BESS Initial Energy (kWh)	Unserved Load w/o PV & BESS (kWh)	Unserved Load w/ PV & BESS (kWh)
12/2/17	16:00	2.167	74.37	4,838	264,827	262,660
5/15/16	07:00	2.500	69.00	2,538	256,706	254,706
1/29/16	09:36	0.783	109.19	538	85,928	85,581
11/17/15	15:26	1.833	80.82	4,838	184,035	182,202
10/26/15	04:45	2.250	72.93	4,538	204,849	202,599
8/30/15	05:52	1.167	97.26	3,538	120,531	119,364
6/27/15	04:59	0.000	0.00	4,850	0	0
2/24/15	08:15	4.500	54.18	1,538	571,050	570,050
1/26/14	07:50	1.667	84.45	1,538	217,129	216,129
1/22/14	14:50	0.667	113.19	538	74,701	74,138
1/22/14	08:00	1.333	92.68	1,538	169,804	168,804
1/20/14	08:45	0.750	110.31	538	91,726	91,726

4.4 Comparison with Preliminary Assessment

At the project planning stage in 2018, a preliminary economic assessment was performed using typical BESS performance and cost parameters. The cost, service life, and performance parameters used in the preliminary analysis are different from those of the deployed system reported in Section 4.1. For example, in the preliminary analysis, the project life was assumed to be 20 years, and the BESS was modeled as a 1 MW/4 MWh vanadium redox flow battery with no constraints on its operational SOC range. The BESS O&M cost was not explicitly modeled.

The preliminary assessment results are plotted in Figure 4.11. The capital costs of BESS and PV were estimated at $5,515,265 and $6,681,683, respectively, leading to a total project cost of $12,196,948. Without considering outage mitigation, the total present value benefits were estimated at $6,803,134. These benefits were primarily driven by demand and load shaping reduction, which were about $2.5 and $3.8 million, respectively. Outage mitigation could bring in additional benefits of $3.9 million.

Without considering the CEF grant and outage mitigation benefits, the BCR was 0.56. With outage mitigation benefits included, the corresponding BCR increased to 0.88. With the $3,000,000 grant from the CEF, the outstanding cost for the BESS and PV became $9,193,541. The corresponding net benefits were $1,536,775 and the BCR increased to 1.16. These net benefits/cost and BCR obtained in the preliminary assessment are close to the updated results. The preliminary versus final assessment results are detailed in Table 4.3.

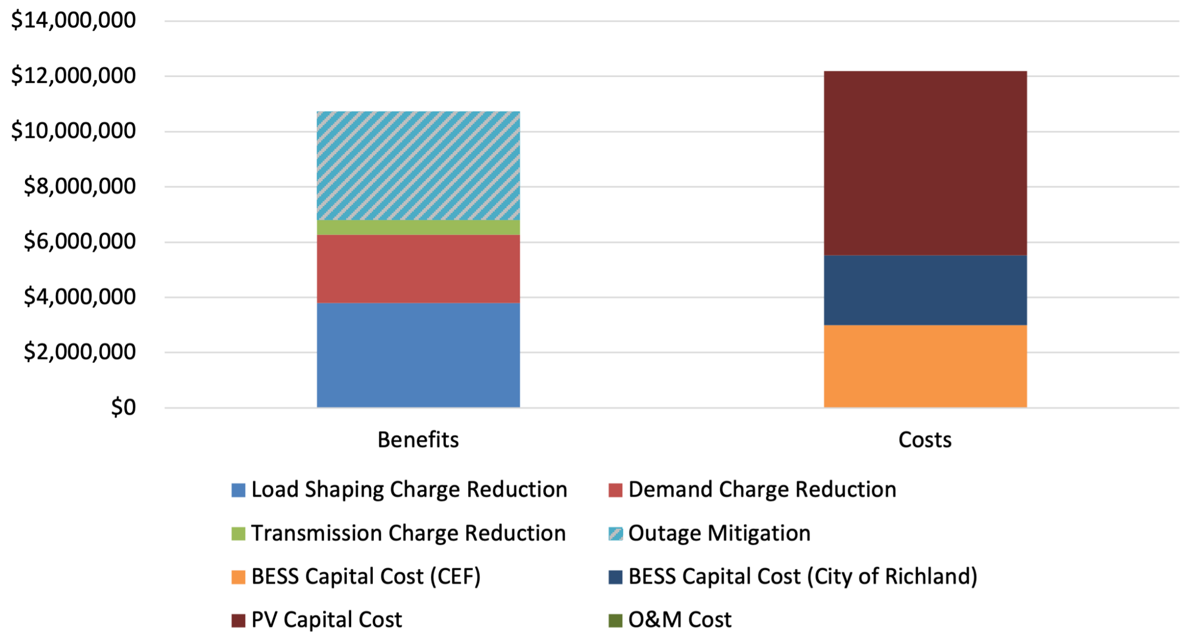

Figure 4.11. Present value benefits vs. costs from the preliminary economic assessment.

Table 4.3. Preliminary vs. Final Assessment

		Deployed System in the Base Case				Hypothetical Microgrid Scenario			
		w/o CEF Funding		w/ CEF Funding		w/o CEF Funding		w/ CEF Funding	
		Preliminary	Final	Preliminary	Final	Preliminary	Final	Preliminary	Final
Benefits ($million)	Load Shaping Charge Reduction	3.8	3.3	3.8	3.3	3.8	3.3	3.8	3.3
	Demand Charge Reduction	2.5	3.2	2.5	3.2	2.5	3.2	2.5	3.2
	Transmission Charge Reduction	0.5	0.7	0.5	0.7	0.5	0.7	0.5	0.7
	Outage Mitigation	N/A				3.9	3.7	3.9	3.7
Costs ($million)	BESS Capital Cost	5.5	6.3	2.5	3.3	5.5	6.3	2.5	3.3
	PV Capital Cost	6.7	4.2	6.7	4.2	6.7	4.2	6.7	4.2
	O&M Cost	0.0	2.3	0.0	2.3	0.0	2.3	0.0	2.3
	Microgrid Controller Cost	N/A				0.0	0.9	0.0	0.9
Net Benefits ($million)		–5.4	–5.6	–2.4	–2.6	–1.5	–2.8	1.5	0.2
BCR		0.56	0.56	0.74	0.73	0.88	0.80	1.16	1.02

CHAPTER 5

Conclusions

This report presented economic assessments of an integrated PV and BESS system deployed at Horn Rapids in the City of Richland, considering various use cases in grid-connected mode and outage mitigation in island mode. The system configuration and use cases were detailed. To define technically achievable benefits, advanced modeling and optimal dispatch methods were developed to capture the technical characteristics and operational constraints of the integrated system, rules and requirements of different use cases, as well as their couplings. Comprehensive analyses were performed to understand the cost-effectiveness the integrated system, considering the coupling among various use cases. It was found that the total benefits of the deployed integrated system are $7.2 million. With the $3 million grant from the CEF, the outstanding cost for the City of Richland is $9.8 million and the corresponding BCR is about 74%. It was also found that with an appropriate threshold, the practical operational dispatch can reduce BESS cycling by 20% compared to the yearly optimal dispatch and help mitigate BESS degradation. The proposed method and assessment results can be used to determine the optimal cycle life that maximizes the net benefits, and thereby help select the most appropriate capacity maintenance agreement. Compared to the preliminary assessment results, the present value benefits and cost in the final assessment results increase by $0.35 million and $0.64 million, respectively. The BCRs estimated in the preliminary analysis are close to the numbers in the final assessment results.

CHAPTER 6

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